Do Incentives to Industrial R&D Enhance Research Productivity and Firm Growth? Evidence from the Italian Case

By MONICA MERITO†, SILVIA GIANNANGELI†, and ANDREA BONACCORSI‡

†*Sant'Anna School of Advanced Studies, Pisa* ‡*University of Pisa*

This paper aims at contributing to the empirical literature about the impact of R&D subsidies on firm performances by providing recent micro-evidence from Italy. We evaluate grant effects on the innovation and market results of firms selected for funding in the short and medium run using a counterfactual approach. Results show that the innovative performance improves only temporarily, and no significant differences between grant recipients and non-recipients emerge as far as labor productivity and sales growth are concerned. Rather, a growth in qualified employment is observed among SMEs.

JEL classification: L2, H2, O3

Keywords: research and development (R&D), subsidies, firm performances, bias-corrected matching

INTRODUCTION

Public support to private R&D has been a traditional measure of industrial policy in Western countries for several decades. In recent years, increasing the overall intensity of innovation activity through stimulating business ventures' R&D investments has been recognized as a key component of innovation policy by many European governments (European Commission, 2004).

As it is well known, the basic argument for public intervention is that R&D investment is subject to a systematic discrepancy between the *private and public rate of return* (Nelson, 1959; Arrow, 1962). The market mechanism does not realize the equilibrium between demand for and supply of new information, due to the fact that the informational product is not appropriable and non rival in consumption. Under these conditions private incentives to invest in R&D are lower than the social optimum. Another argument goes around the idea of *imperfections of financial markets*. Investment into R&D is subject to strong information asymmetries between the inventor or the innovator and the funding agent (Hall, 2002). Financial markets may be thus reluctant to provide debt or equity capital, and raise the cost of external funds reducing significantly the net present value of research projects. By subsidizing the R&D activity, governments expect more projects to be undertaken (Hall and Van Reenen, 2000). Closely related is the argument about *firm size*. The present value of investment in R&D depends on the circumstances that the firm can exclude rivals from the exploitation of results. While excludability also depends on legal and regulatory factors, a crucial dimension is the market power of firms. Small firms, lacking complementary assets and market power in final markets, are often unable to internalize the benefits stemming from research activities and are discouraged to undertake R&D investment (Cohen and Klepper, 1996). At the same time small firms may be subject to more severe financial constraints (Cooley and Quadrini, 2001; Carpenter and Petersen, 2002).

It is interesting to note that, alongside arguments entirely crafted within the market failure framework, most governments and international organizations also developed in the last twenty years policy arguments and de facto new rationales. Among these new rationales we can identify the following.

First, after the deep industrial crises of late ‘70s and early ‘80s, the goal of *employment creation* started to dominate government concerns. Since industrial restructuring was leading to situations of job losses and permanent unemployment, governments assumed the goal of creating new jobs as transversal to many policies, including innovation policies. The employment goal is still visible in governments’ stated goals for R&D and innovation policy (European Commission, 2004). Second, in the ‘90s the notion of *competitiveness* of firms gained prominence in the economic reasoning

(Fagerberg, Guerrieri, Verspagen, 1999). The emphasis on competitiveness became institutionalized via such organisms as the Competitiveness Council in the USA and entered into the European agenda with the Lisbona Summit in 2000. Finally, Lisbona's legacy was a new emphasis on knowledge formation, human capital accumulation and productive use of knowledge, collectively known under the heading of *knowledge economy*. The notion that the productive use of knowledge may lead to increasing returns and to permanent effects of growth in productivity has roots in both endogenous growth and evolutionary theories. According to the former, knowledge is the only productive factor that does not diminish, but rather increases its value with use, producing spillovers and positive externalities. This leads to exclude the classical prediction of diminishing returns, opening the way to sustained growth opportunities (Romer, 1990; Aghion and Howitt, 1992). In particular, this perspective has emphasized the role of productivity in the long run growth of nations, reopening a vast debate on the role of labour productivity and total factor productivity. In the latter perspective, the crucial concern is learning, or the ability to absorb, develop and deploy productively knowledge. This is not done by firms in isolation, but by firms embedded into complex systems of innovation, formed by a large number of both private and public institutions (Freeman, 1987; Nelson, 1990; Edquist, 1997; Carlsson et al., 2002). In this perspective the public intervention adds to the collective and institutionalized learning of systems of innovation. While competitiveness per se may imply a number of infrastructural, labour market, financial market, or fiscal policies, the emphasis on knowledge and learning lead to focus policy goals on individuals.

It is not easy to link expected benefits from public subsidy, as articulated according to the various theoretical underpinnings, with observed variables. First, governments that believe that R&D subsidies may help in addressing unemployment will expect the public subsidy to generate *new employment*. Secondly, emphasis on competitiveness may take a variety of forms in terms of policy goals. One is to assume that R&D subsidy will produce not only an increase in innovation inputs, but also an increase in technological output, for example in terms of *number of patents*. Another one is to expect better competitiveness to be translated into an increase in *turnover*. Thirdly, emphasis on knowledge may lead to the expectation that the public intervention supports the creation of human capital. This may be translated into an increase of *highly qualified personnel*, particularly in firm R&D or innovation-related activities, and of *labor productivity.* All these variables are reasonable operationalizations of the broad policy goal of competitiveness.

Whether public support to private R&D activity really attains one or more of its stated goals is clearly a matter of empirical ex-post investigation. This paper addresses such issue by an in-depth analysis of the impact of a specific R&D incentive measure in a national context. We focus on the last years of the Special Fund for Applied Research (FSRA), the main instrument of industrial research and innovation policy in Italy until 2000, and evaluate its effects on several dimensions of firm performance.

The contribution of this paper to the existing literature is twofold. First, it widens the spectrum of outcome variables through which the effectiveness of R&D public grants on firm performance has been measured by most empirical literature. Second, to the best of our knowledge, the paper is the first formal evaluation exercise of an R&D public support program in Italy[1].

The remainder of the paper is structured as follows. In section 2 we briefly survey the empirical literature about the impact of public R&D subsidies on firm innovative activity and market performance. Section 3 outlines the framework of the public support program we focus on. In section 4 we describe the dataset, the matching estimator for the treatment effect of interest, and the empirical findings. Our main results are then discussed in section 5 and some concluding comments are provided.

I. WHICH ARE THE OBSERVED EFFECTS OF PUBLIC R&D SUBSIDIES? A SURVEY OF THE LITERATURE

As in many other cases in the real world, government wishes do not materialize easily. This is due partly to bad design and implementation of policies, partly to structural problems. The latter have been clearly identified in the literature: it is likely that public subsidies crowd out private investment (David et al., 2000; Jaffe, 2002). This effect may come from different sources. First, if the supply of research inputs, particularly of scientists and engineers, is inelastic in the short run, then allocating inputs to publicly subsidized projects implies reducing activities in other projects (Goolsbee, 1998). Second, government agencies may be biased towards projects with a high rate of success, in order to demonstrate the effectiveness of public policy. These projects are likely to have lower risk profile and would be undertaken by firms even in the absence of any subsidy, opposite to the public incentive's goal of generating additional R&D expenditure. Third, information asymmetries also apply between government agencies and firms. It may happen that public subsidies are captured by *bad* firms, that use public subsidies for other goals than research, still avoiding sanctions.

Therefore the net impact of public subsidies on research expenditures is a matter of ex post empirical analysis, being the effect of many countervailing factors. The literature offers mixed results on this issue, a classical situation in which there is need for better design of research.

A group of studies has examined the issue of complementarity vs. substitution between public and private expenditure. David et al. (2000), after a careful review of the literature, conclude that the empirical evidence seems "to be running in favour of finding complementarity of public and private investments". A more recent meta-analysis, however, concludes that findings strongly depend on the level of aggregation at which the analysis is conducted (Garcia-Quevedo, 2004). As an example, Wallsten (2000) finds that public subsidies under the Small Business Innovation Research (SBIR) program in the USA completely crowd out private investment, roughly for the same amount. On the contrary, Branstetter and Sakakibara (2002) conclude that public subsidies to research consortia in Japan have produced an increase in private expenditure of participating firms, a conclusion shared by Lach (2002) for Israelian firms.

Even more ambiguous results have been found when the research design was intended not to examine the impact on expenditures (an input to the innovation process) but on the output and the outcome of the innovation process. Indeed, predicting the impact of R&D public financing on firm technological and economic performance requires a careful assessment of a series of factors that operate at the industry, firm and R&D project level.

The causal relation between firm innovation input and output is the subject of a stream of empirical literature that emphasizes the risk and uncertainty embedded in the R&D process, and investigates the impact of R&D efforts on firm technological activity and productivity (see Crépon et al., 1998 for a formal model). Alongside with structural uncertainty over R&D outputs, the empirical evaluation of the impact of R&D incentives on firm innovative activity may also be blurred by differences in the time-to-market of R&D results due, for instance, to the characteristics of the industry innovation dynamics (Utterback, 1994) or the specific features of the R&D project implemented. Cooper and Kleinschmidt (1994) finds that project organization, pre-development activities, and marketing activities were the most significant drivers of timeliness in a study of chemical engineering firms. Similarly, the timing of commercialization patterns of product innovations or the (un)timeliness for the implementation of process innovations affect the ability of firm R&D and innovation efforts to produce sizeable effects of firm performance, as measured by sales or profitability (Powell and Moris, 2004). Finally, even if public R&D financing translates into an increased level of R&D expenditure and a rise of firm innovative activity, its ultimate effect on employment is far from being clear. The innovative process may induce job creation or destruction because of shifts in factor demand, as well as a change in the skill structure of the firm. Although a positive impact of innovation on employment is possible, Piva et al. (2005) show on a sample of manufacturing Italian firms that upskilling is a function of reorganization strategy rather than a direct effect of technological change. Chennels and Van Reenen (2002) provide a survey of the microeconometric evidence on the effect of technical change on the structure of employment and wages.

Since the effect of public R&D financing programs can differ both in sign and time lag depending on the outcome variable a researcher is willing to study, and since outcomes are subject to trade-offs (for example, it is difficult to reach simultaneously the goals of employment and rise in labor productivity), the empirical evaluation of such effects must include a wider range of outcome variables than the firm R&D efforts alone.

The empirical literature having assessed the impact of public R&D programs on measures of firm performance other than R&D expenditure is relatively scarce and results are not univocal. Hujer and Radic (2005) observe 2714 establishments in East and West Germany that received public support for private R&D in 1997 and 1998 and find no impact on innovative activities, as measured by the introduction of a new product or service during 1999 and 2000. Irwin and Klenow (1996) evaluate the SEMATECH program, a large research consortium established in 1987 in the USA. Examining firm data in the period 1970-1993, they conclude that participating firms grow more than non participating firms in terms of profitability, but not significantly in terms of investments, and labor productivity. Examining firms that received SBIR support in the 1983-1985 period, Lerner (1999) finds that in a fairly long subsequent period (1985-1995) they grew more than the control sample in terms of sales and employment. On the contrary, Wallsten (2000) shows that, once the endogeneity of the awards is controlled for, the employment effect of SBIR awards in the short run is negligible. Recently, Hyytinen and Toivanen (2005) report that in a sample of 519 Finnish firms surveyed in 2001, those receiving public R&D support experience higher R&D investments and perceived growth prospects, especially if they operate in industries that are dependent on external financing.

II. FIRMS' R&D IN ITALY AND THE FSRA FUND

Firms' propension to invest in R&D activities in Italy has always been low. This is mainly due to the local productive structure, characterized by the prevalence of small firms (according to ISTAT, the Italian national statistical office, in 2004 firms with fewer than 20 employees accounted for 92.9% of active ventures in the industrial sector), and a specialization in traditional manufacturing sectors, which are both factors showing a negative correlation with the private sector propensity to innovate. On the other hand, public funds supporting business research are higher than in other Western European countries. In 2003, 14.1% of business enterprises R&D expenditures were financed by the government, compared to 11.1%, 10.9%, and 6.1%, in Spain, UK, and Germany, respectively (EUROSTAT data).

In this paper we will focus on the Special Fund for Applied Research (FSRA), which has been the main instrument of industrial research and innovation policy in Italy for almost 20 years, until the Fund for Research Support (FAR) started to operate in 2001. Waiting for some evidence about the implementation and effectiveness of such reform, we will analyze the last years of activity of the FSRA, 1999 and 2000. As a bottom-up type of intervention, the Fund subsidized both applied research and industrial development projects autonomously presented by business firms after an evaluation procedure largely modified in 1997, in order to guarantee homogenous selection criteria and quick decisions.

Applicants had to highlight the industrial interest of the R&D project in relation to its foreseen economic and occupational impact, as well as its additionality with respect to their ordinary research activities. However, additionality was presumed for SMEs. Firms located in Southern regions and SMEs could also benefit of larger grants (out of the total costs of the projects). In the selection procedure the Italian Ministry for Research and Innovation (MURST) evaluated firms' claims about the expected growth benefits, together with the adequacy of financial resources to be devoted to the project. In addition, the public evaluator assessed several technical aspects of the proposal, ranging from the novelty and originality of the project, to its technical feasibility, firms' specific competencies, and the likely applications of the new knowledge to product or process innovations increasing firm competitiveness and market success.

III. METHODS AND DATA

Econometric methodology

Our empirical analysis aims at assessing whether public subsidies to business R&D boosted firm performance in subsequent years. Ideally, we would want to observe what would have happened to each grant recipient's innovative activity, productivity and growth had it not been subsidized by the

FSRA. This counterfactual outcome is clearly unobservable, leaving those firms that were not subsidized as the only feasible comparison group for our subsidized firms. A major problem of using non recipients as a control group in this ex-post evaluation exercise is that subsidies are not assigned at random. Rather, on the one hand, firms with specific ex-ante characteristics may self select into the application process (Lichtenberg, 1984). On the other hand, the public agency granting the funds purposely selects recipients among the applicants according to given selection criteria (Busom, 2000; Wallsten, 2000). Eventually, those firms funded by the government are likely to be those with the best ideas or a recognized competence for certain kinds of R&D, meaning that they will have more incentives to privately invest in research, as well as more ability to raise third parties funds than those that are not funded, and that their projects would have the largest expected output even in the absence of funding. Generally speaking, in estimating the impact of R&D support programs a selection bias arises when the same latent firm characteristics affect both grant assignment and the final outcome. Dealing with such selection bias requires the imputation of an appropriate counterfactual outcome for the sample of grant recipients.

Formally, we are interested in estimating the causal effect of a binary treatment ($T = 0,1$) – no subsidy/subsidy – on a continuous scalar outcome (Y) – innovative activity, productivity, or growth – in our non random sample of treated firms. This impact measure is known as the sample average treatment effect on the treated (SATT). Let ($Y_i(0)$, $Y_i(1)$) denote the two potential outcomes for units i, i.e. $Y_i(0)$ is the outcome of firm i when it is not exposed to the treatment, and $Y_i(1)$ is the outcome of firm i when it is exposed to the treatment, and let N_1 be the number of treated units, the SATT is equal to:

$$\tau = \frac{1}{N_1} \sum_{i|T_i=1} (Y_i(1) - Y_i(0)) .$$

To ensure that the treatment effect of interest can be identified and consistently estimated we shall assume a relaxed form of "strong ignorability" (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2002): (i) conditional on observable pre-treatment characteristics X, assignment to treatment is independent of the outcome $Y(0)$ (*unconfoundedness for controls*); and (ii) the probability of assignment is bounded away from one (*overlap*). The average treatment effect on the treated can then be recovered by first estimating the average treatment effect for all x in the support of X for the treated, and then averaging over the distribution of X conditional on $T = 1$.

We now face the problem of estimating the untreated outcome, $Y_i(0)$, for firm i with covariates x which was exposed to the treatment. We shall use a matching approach that imputes the missing outcome for each treated firm in the data with the average outcome among control firms whose pre-treatment covariates were most similar. Abadie and Imbens (2002) show that this simple matching estimator will be biased in finite samples when the matching is not exact. In order to address this problem, they develop a bias-corrected matching estimator adjusting the difference within the matches for the difference in covariate values through a consistent estimate of the conditional expectation:

$\mu_0(x) = \mathrm{E}[Y(0)|X = x]$.

They use a nearest neighbors matching estimator with replacement, allowing each unit to be used as a match more than once. Let $J_M(i)$ be the set of indices for the matches of treated unit i that are at least as close as the Mth match according to a pre-defined distance metric. The missing potential outcome, $Y_i(0)$, is then imputed as

$$\hat{Y}_i(0) = \frac{1}{\# J_M(i)} \sum_{l \in J_M(i)} (Y_l(0) + \hat{\mu}_0(X_i) - \hat{\mu}_0(X_l))$$

where $\#J_M(i)$ is the number of elements of $J_M(i)$, and $\hat{\mu}_0(x)$ denotes the regression imputation estimates for the controls with covariate values $X = x$. The corresponding estimator for the SATT is:

$$\hat{\tau}_{M,bcm} = \frac{1}{N_1} \sum_{i|T_i=1} (Y_i(1) - \hat{Y}_i(0)),$$

where *bcm* stands for bias-corrected matching.

Abadie and Imbens (2002) show that their bias-corrected matching estimator is consistent and has a sampling distribution that is asymptotically normal. In addition, they provide expressions for computing the variance of the bias-corrected estimator making it possible to test the significance of the treatment effect without relying on bootstrapping.

In this study we applied their bias-corrected matching estimator with one match and Mahalanobis norm as distance metric between different values for the covariates. Mahalanobis distance weights the difference in covariate pre-treatment values by the inverse of their variance-covariance matrix. The bias correction was estimated through linear regression on the matched units in the comparison group. All of the analysis was implemented via the *nnmatch* module in Stata (Abadie et al., 2001). Besides computing the treatment effect at the average output values, we also investigated whether treated and matched control units differed with respect to the whole post-treatment distribution of outcome variables, by plotting the cumulative distribution functions of our performance measures in the two groups of firms and testing for their equality.

Samples and data

Information about R&D projects and firms selected for funding between 1999 and 2000 came from the Italian Ministry of Research. Treated firms were then searched in the database Amadeus (Bureau van Dijk), the most widespread source of financial data for European firms, which also includes the financial statements of Italian firms with a turnover of at least 500 thousand Euro. We were able to find the financial records of 208 out of the 380 grant recipients. Due to the small number of service firms among subsidized firms (according to their main NACE code of economic activity reported in Amadeus), and to the incompleteness of their financial information, as well as for comparability with most of the international applied literature, we focused the empirical analysis on manufacturing ventures only[2]. The final sample of treated units consisted of 185 manufacturing firms selected for funding by the FSRA between 1999 and 2000 and for which financial records were available.

A control group was then selected through a stratified random sampling procedure from the population of Italian manufacturing firms in Amadeus. The sampling was stratified according to size class, i.e. whether the firm had at least 250 employees or fewer, being a large enterprise or a SME, respectively. Differences in accessing FSRA grants between SMEs and large enterprises (identified by the Italian law according to the previous threshold), as well as a size distribution of treated firms biased upward compared to the general population of Italian firms, called for such a stratification criterion. Within each stratum five control units were drawn for each treated firm among those who did not receive any grant.

The final dataset included 1110 firms whose balance sheets and income statements data span the period 1998-2004. In addition, from the database Delphion (Thomson) we collected information about the number of patent applications submitted worldwide to national and international patent offices (Italian Patent Office, USPTO, other national patent offices, EPO, and WIPO) between 1998 and 2004 by each firm in the treated and control groups.

Based on the availability of financial data, we estimated the average treatment effect on the following performance variables measuring, respectively, employment growth, market success, labor productivity, and labor force composition: log-number of employees; log-turnover (in thousand €); log-added value per employee (in thousand € per employee); and log-average labor cost (in thousand € per employee).

In addition, we estimated the average treatment effect of public subsidies on the innovative performance as measured by the number of patent applications.

In order to distinguish temporary and long-lasting effects of R&D subsidies on firms' performances, the impact on the outcome variables was assessed both in 2002 and 2004, i.e., at least two and four years, respectively, after the subsidy was assigned.

Our set of matching variables included several pre-treatment firm characteristics as of 1998 that are likely to affect both treatment assignment and performance results:

- An indicator for *size class* (large enterprises vs. SMEs) identified the two strata of SMEs and large firms, differing both for access conditions to FSRA funds and the expected benefit from R&D public support (Blanes and Busom, 2004).

- Firm *age* (in years) took account of size and experience effects, such as managerial skills and the ability to obtain external resources (Wallsten, 2000; Busom, 2000; Almus and Czarnitzki, 2003; Hussinger, 2003; Görg and Strobl, 2006).
- The ratio between tangible fixed assets and turnover stood for firm capital intensity, which in turn is a proxy of both access to capital market, and embedded stock of knowledge and technological upgrade (Hyytinen and Toivanen, 2005)
- The number of *patent applications* controlled for firm's past innovative activities. However, small firms usually face high application costs that reduce their propensity to patent (Acs and Audretsch, 1988; Arundel and Kabla, 1998). We used then *intangibles intensity*, expressed as intangible fixed assets over turnover, as a proxy for R&D capitalization in SMEs. Indeed, if one assumes a "pick-the-winner" strategy in allocating public R&D funds, the probability of receiving a grant is affected by the innovative history of the firm, both as accumulated R&D competencies and as innovative output produced (Wallsten, 2000; Hussinger, 2003).
- *Cash flow* scaled by turnover proxies for possible liquidity constraints. As we discussed above, financial markets imperfections can limit R&D investments, and liquidity constraints may become an important determinant of the propensity to apply for a public subsidy.
- Firm *localization* by geographical area (North-East, North-West, Centre and South) controlled for the unequal distribution of business R&D in the country and the easier access to public support for firms located in southern regions.
- Being a *group holding*, as recovered from the information on consolidated financial statements reporting, was included as an indication of firm organizational complexity.
- A categorical variable for *sectoral technological intensity*, based on OECD classification of high tech, medium tech, and low tech sectors, took into consideration the large sectoral differences in the propensity to regularly perform R&D and, thus, apply for public grants (Busom, 2000; Almus and Czarnitzki, 2003; Blanes and Busom, 2004). It also controlled for

different sectoral market trends over time, e.g., the declining performance in recent years of Italian traditional manufacturing industries under an increased international competitive pressure.

Since, on the one hand, treatment effect may not be constant at different output values, and, on the other hand, our performance measures may be highly persistent over time (Bottazzi et al., 2006), lagged outcome variables as of 1998 were also among pre-treatment variables in all matching estimations.

In order to account for the likely heterogeneity of the effects of R&D grants depending on firm size, the evaluation exercise was performed on the whole dataset and, separately, for SMEs alone. Table 1 reports main descriptive statistics of pre-treatment variables in the treated and control groups before matching both for all firms and for SMEs only.

-Table 1 about here-

As specified in the legend of Table 2, sometimes higher order terms of the above variables were included as pre-treatment covariates both in the matching exercise and in the linear regression for bias adjustment in addition to linear terms.

All nominal variables were appropriately deflated to 2000 prices. For turnover, value added, tangible fixed assets, intangible fixed assets, and cash flow appropriate sectoral (at NACE 2-digit code) deflators were employed, whereas labor costs were adjusted according to the consumer price index.

IV. EMPIRICAL RESULTS

The empirical results reported in Table 2 highlight that, after two years from receiving grants, subsidized firms did not experienced any increase in size or labor productivity. Looking at the whole sample, some effects of public R&D grants can be registered in the short term rise of patent applications and, rather surprisingly, in a decrease in the average labor cost. While the negative average effect of R&D subsidies on granted firms' labor cost is a puzzling result, the positive effect on the number of patent applications by granted firms is consistent with the hypothesis that grants stimulated innovative activities in subsidized firms. However, the impact of grants on the number of patent applications was not found to be significant in the medium/long run, thus suggesting that firms with R&D projects already on-going at the time of the grant benefited the most from it, producing significantly more innovative output than it would have been observed in the counterfactual situation of no subsidy. More generally, none among the outcome variables under study was found to be fostered by R&D subsidies four years after receiving them.

This combined evidence suggests that, in the whole database, public R&D subsidies were able to produce only little effects on the innovative activity of subsidized firms, casting some doubts on the overall efficacy of the public instrument.

-Table 2 about here-

A partially different picture emerges, however, when considering the impact of R&D grants on SMEs. In the short run, public R&D grants provision significantly fostered average labor cost in small and medium-sized subsidized firms. This result is consistent with the hypothesis that in the short run publicly subsidized SMEs shift their employment structure toward more skilled workers. Moreover, the long run effect of receiving a grant on average labor cost is almost three times as much as in the two-year horizon. This means that the process of upskilling is reinforced over time. Matching results also show that public subsidies increased the employment level in subsidized SMEs after four years from receiving the grant. The reinforcement over time of the process of upskilling and the delayed effect of subsidies on employment in granted SMEs may suggest that the intervening organizational changes stimulated by the grant might need time to take place and fully develop their effect. Finally, as for the whole sample, in the case of SMEs we observe some positive short run effect of R&D support on the number of patent applications of subsidized firms. However, we recall that in the case of small and medium sized firms, a very low share of process as well as product innovations are patented: very few among subsidized and, to a larger extent, non subsidized firms ever applied for a patent. This feature of the data resulted in a poor matching process that makes it very difficult to identify any average effect of R&D grants on the number of patent applications by subsidized firms[3].

By looking at simple average effects of subsidies on firm activity, one might conclude that the zero impact often found in the analysis could be driven by averaging out significantly different (and possibly opposite in sign) firm-specific effects. If this is the case, a substantial distance should be detected between the distribution of the outcome variables for the treated and the control group, at least for some portions of the support. Figure 1 and 2 show the cumulative distribution functions for treated and matched control firms of performance variables examined so far, in 2002 and 2004, respectively: Panel A refers to the whole dataset and Panel B to SMEs only.

-Figure 1 and Figure 2 about here-

A simple visual inspection of the figures suggests that, with the only exception of average labour cost (year 2002), patent applications (year 2002), and employment (year 2004) in SMEs, there is no clear evidence of first order stochastic dominance of one distribution over the other. This finding is confirmed by the results of the Wilcoxon rank-sum test, according to which the probability of a better outcome in the treated group compared to the matched control group is never greater than 0.65[4]. Moreover, no dramatic differences emerges between the outcome distribution for the treated and matched control groups in any portion of the support, rejecting the hypothesis that the zero average impact of R&D subsidies on firm activity was driven by an averaging effect.

V. CONCLUDING REMARKS

We investigated the relationship between government support for business R&D and firm innovative and market performance in the short and medium run using micro-level data on Italian manufacturing firms. In order to deal with the potential selection problem inherent to the ex-post empirical evaluation, we combined a non-parametric matching procedure with an auxiliary regression for bias-correction. Our results suggest that on average public grants have no significant effects on firm productivity or growth and only temporarily foster innovation output, yielding a rather discouraging picture of the overall impact of R&D subsidies. However, the provision of public funds to small and medium manufacturing firms seems to stimulate employment and upskilling in the medium-long run.

Our empirical analysis represents the first formal ex-post evaluation of R&D grants policy in Italy. Moreover, it contributes to the international empirical literature on the impact of this policy instrument by widening the range of outcome measures and, thus, allowing a direct assessment of R&D subsidies' adequacy with regard to their stated or implied multiple objectives. It is worth mentioning that the present study examined the overall policy intervention, including both the selection process of private research projects to be awarded public grants and the impact of such grants on firms' research activities, productivity and growth. Indeed, since we did not have any information about the technical quality of each candidate project we could only control for a "firm effect" on the impact of the subsidies.

The economic relevance of public grants to business R&D within the framework of industrial policy, as well as their broad range of possible effects, encourage further evaluation exercises at the national level along two main research lines: first, arguably it is not only whether a firm receives a R&D grant that matters, but also how much it receives; second, the timing of actual grant receipt over multi-year research projects may play an important role for subsidized business ventures in the presence of binding financial constrains.

NOTES

[1] Among empirical studies on the issue of public support schemes to firm activity in Italy, Del Monte and Scalera (2001) study the effectiveness of start-up programs on firm life duration, Santarelli and Vivarelli (2002) discuss the effects of such programs in the light of the process of market selection and post-entry scale adjustments. Colombo and Grilli (2006) provide a taxonomy of Italian national direct support schemes and question the allocative efficiency of public funds through horizontal general-purpose support mechanisms.

[2] We could not find among Italian firms any suitable control for STMicroelectronics srl, a worldwide producer of semiconductors, thus we excluded it from the evaluation exercise.

[3] The poor matching quality achieved in this case is pointed out by the high value of the standardized percentage difference between SMEs' patent applications by treated firms and matched controls, shown in Table A1 and A2 in the Appendix. This drawback is hard to overcome due to the predominance in the Italian manufacturing sector of very small firms with a low propension to protect their innovations through patents.

[4] We were unable to perform a Kolmogorov-Smirnov type test of first-order stochastic dominance due to the insufficient number of available observations.

REFERENCES

ABADIE, A. and IMBENS, G. W. (2002). Simple and bias-corrected matching estimators. Mimeo, Department of Economics, UC Berkeley.

ABADIE, A., DRUKKER, D., HERR LEBER J. and IMBENS, G. W. (2001). Implementing matching estimators for average treatment effects in Stata. The Stata Journal, 1, 1-18.

ACS, Z.J. and AUDRETSCH, D.B. (1988). Innovation in large and small firms: an empirical analysis. American Economic Review, 78, 678–690.

AGHION, P. and HOWITT, P. (1992). A model of growth through creative distruction. Econometrica, 60, 323-351.

ALMUS, M. and CZARNITZKI, D. (2003). The effects of public R&D subsidies on firms' innovation activities: the case of Eastern Germany. Journal of Business & Economic Statistics, 21, 226-236.

ARROW K. (1962). Economic welfare and the allocation of resources for invention. in R. Nelson (ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton: Princeton University Press.

ARUNDEL, A. and KABLA, I. (1998). What percentage of innovations are patented? empirical estimates for European firms. Research Policy, 27, .127–141.

BLANES, J. V. and BUSOM, I. (2004). Who participates in R&D subsidy programs?: The case of Spanish manufacturing firms. Research Policy, 33, 1459-1476.

BOTTAZZI, G., CEFIS, E., DOSI, G., and SECCHI, A. (2006). Invariances and diversities in the evolution of Italian manufacturing industry. Small Business Economics, forthcoming.

BRANSTETTER, L. G. and SAKAKIBARA, M. (2002). When do research consortia work well and why? Evidence from Japanese panel data. American Economic Review, 92, 143-159.

BUSOM, I. (2000). An empirical evaluation of the effects of R&D subsidies. Economics of Innovation and New Technology, 9, 111–148.

CARLSSON B., JACOBSSON, S., HOLMEN, M. and RICKNE, A. (2002). Innovation systems : Analytical and methodological issues. Research Policy, 31, pp. 233-245.

CARPENTER, R.E. and PETERSEN, B.C. (2002). Is the growth of small firms constrained by internal finance? The Review of Economics and Statistics, 84, 298-309.

CHENNELS, L. and VAN REENEN, J. (2002). Technical change and earnings in British establishments. Economica, 64, 587-604.

COHEN, W.M., and KLEPPER, S. (1996). A reprise of size and R&D. Economic Journal. 106, 925–951

COLOMBO, M. and GRILLI, L. (2006). Supporting high-tech start-ups: lessons from Italian technology policy. International Entrepreneurship and Management Journal, 2, 189-209.

COOLEY, T. and QUADRINI, V. (2001). Financial markets and firm dynamics. American Economic Review, 91, 1286-1310.

COOPER, R.G. and KLEINSCHMIDT, E.J. (1994). Determinants of timeliness in product development. Journal of Product Innovation Management, 11, 381–396.

CREPON, B., DUGUET, E. and MAIRESSE, J. (1998). Research, innovation and productivity : an econometric analysis at the firm level, NBER Working Paper 6696.

DAVID, P. A., HALL, B. H., and TOOLE, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Research Policy, 29, 497-529.

DEL MONTE, A. and SCALERA, D. (2001). The life duration of small firms born within a start-up programme: evidence from Italy. Regional Studies, 35, 13-24.

EDQUIST, C. (ed.) (1997). Systems of innovation. Technologies, institutions and organizations. London: Pinter.

EUROPEAN COMMISSION (2004). Innovation Policy in Europe 2004. DG Enterprise and Industry, Bruxelles.

FAGERBERG, J., GUERRIERI, P. and VESPAGEN, B. (eds.) (1999). The economic challenge for Europe. Cheltenham: Edward Elgar, 1999.

FREEMAN, C. (1987). Technology policy and economic performance. Lessons from Japan. London: Pinter.

GARCIA-QUEVEDO, J. (2004). Do public subsidies complement business R&D? A meta-analysis of the econometric evidence, KYKLOS, 57, 87-102.

GOOLSBEE, A. (1998). Does government R&D policy mainly benefit scientists and engineers?.American Economic Review, 88, 298-302.

GÖRG, H. and STOBL, E. (2006). The Effect of R&D Subsidies on Private R&D. Economica, forthcoming.

HALL, B. (2002). The financing of research and development. Oxford Review of Economic Policy, 18, 35–51.

____ and VAN REENEN, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence, Research Policy, 29, 449–469.

HUJER, R. and RADIC, D. (2005). Evaluating the impacts of subsidies on innovation activities in Germany, Scottish Journal of Political Economy, 52, 565-586.

HUSSINGER, K. (2003). Crowding out or stimulus? The effect of public R&D subsidies on firms' R&D expenditure. Mimeo, ZEW.

HYYTINEN, A. and TOIVANEN, O. (2005). Do financial constraints hold back innovation and growth? Evidence on the role of public policy. Research Policy, 34, 1385-1403.

IRWIN, D.A. and KLENOW, P. J. (1996). High-tech R&D subsidies: estimating the effects of Sematech. Journal of International Economics, 40, 323-344.

JAFFE, A. B. (2002). Building program evaluation into the design of public research support program. Oxford Review of Economic Policy, 29, 471-495.

LACH, S. (2002). Do R&D subsidies stimulate or displace private R&D? Evidence from Israel. The Journal of Industrial Economics, L(4), 369-390.

LERNER, J. (1999). The government as venture capitalist: the long-run impact of the SBIR program. Journal of Business, 72, 285-318.

LICHTENBERG, F. (1984). The relationship between federal contract R&D and company R&D. American Economic Review, 74(2), 73-78.

NELSON, R. R. (1959). The simple economics of basic scientific research. Journal of Political Economy, 67, 297-306.

___ (1990). Capitalism as an engine of progress. Research Policy, 19, 193-214.

PIVA, M., SANTARELLI, E. and VIVARELLI, M. (2005). The skill bias effect of technological and organisational change: Evidence and policy implications, Research Policy, 34, 141-157.

POWELL, J. and MORIS F. (2004). Different timelines for different technologies. Journal of Technology Transfer, 29, 125–152.

ROMER P.M. (1990) Endogenous technological change. Journal of Political Economy, 5, S71-S102.

ROSENBAUM, R. R. and RUBIN, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70,1-55.

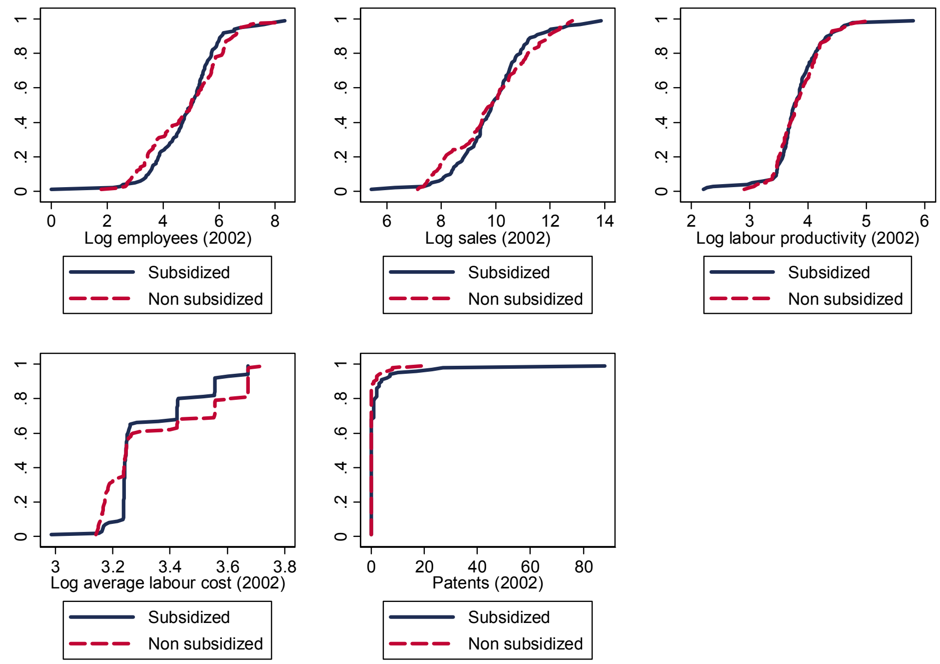
SANTARELLI, E. and VIVARELLI, M. (2002). Is subsidizing entry an optimal policy? Industrial and Corporate Change, 11, 39-52.

UTTERBACK, J.M. (1994). Mastering the dynamics of innovation: how companies can seize opportunities in the face of technological change. Boston: Harvard Business School.

WALLSTEN, S. J. (2000). The effects of government-industry R&D programs on private R&D: the case of Small Business Innovation Research program. *RAND Journal of Economics*, 31 (1), 82-100.

Figure 1. Cumulative distribution functions for treated and control firms of performance variables in 2002.

Panel A – All firms



Panel B – SMEs

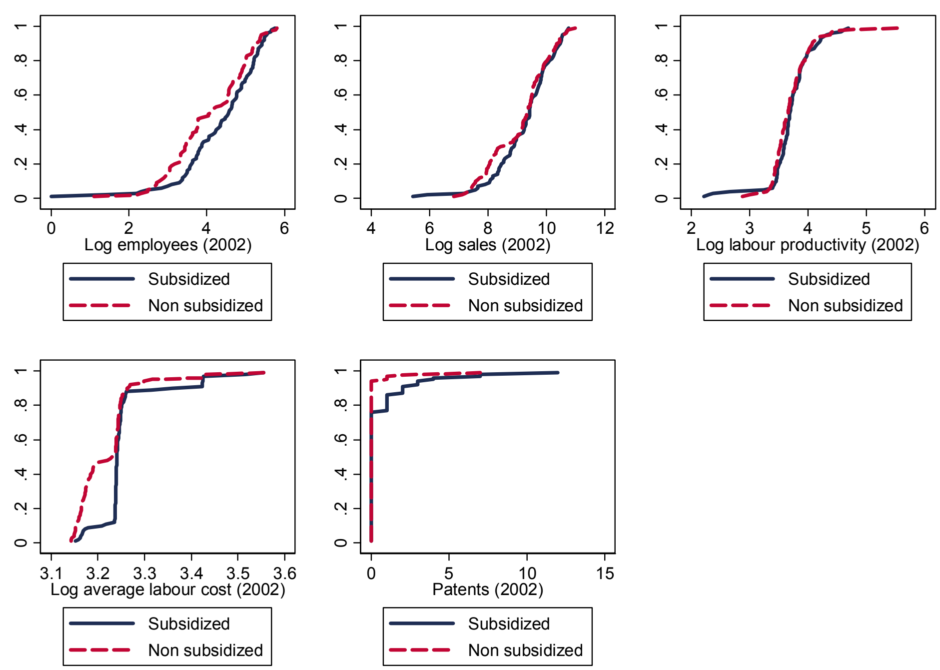
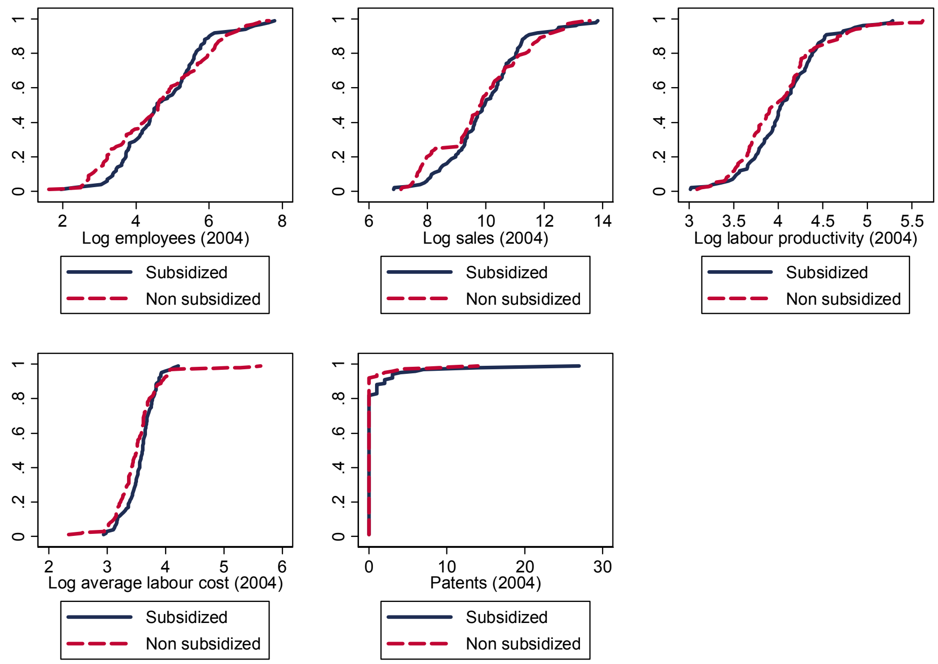


Figure 2. Cumulative distribution functions for treated and control firms of performance variables in 2004.

Panel A – All firms



Panel B – SMEs

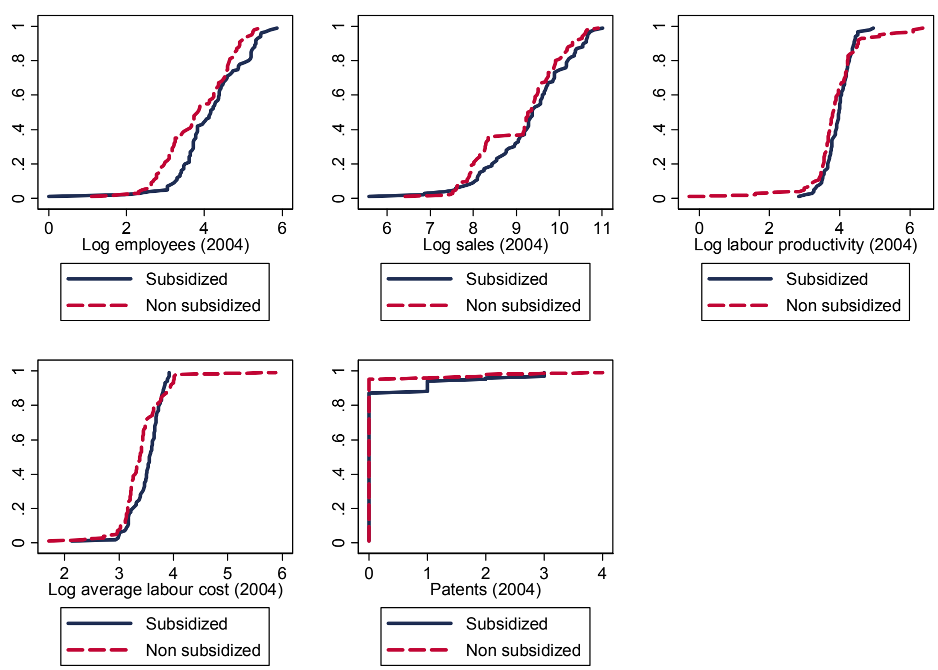


Table 1. Comparison between pre-treatment characteristics of treated and control firms before matching (1998).

	All firms							
	Subsidized			Non subsidized			P	Standardized
	N	Mean	S.D.	N	Mean	S.D.	value*	Difference (%)**
Log employment	185	4.626	1.259	925	4.071	1.794	0.000	35.8
Log sales	185	9.850	1.329	925	9.333	1.793	0.000	32.8
Log labour productivity	185	4.065	0.457	919	3.954	0.507	0.003	23.0
Log average labour cost	185	3.562	0.329	922	3.446	0.336	0.000	34.9
Number of patent applications	185	3.454	12.570	925	1.085	7.335	0.014	23.0
Log age	185	2.851	0.755	925	2.793	0.764	0.337	7.6
Capital intensity	185	0.212	0.202	925	0.229	0.303	0.343	-6.6
Intangibles intensity	185	0.035	0.071	925	0.019	0.048	0.004	26.4
Scaled cash flow	185	0.066	0.075	925	0.061	0.070	0.372	6.9
	N	Proportion		N	Proportion			Difference (%)
Geographical area	185			925			0.125	
North-East		0.405			0.332			7.3
North-West		0.465			0.542			-7.7
Centre and South		0.130			0.126			0.4
Holding	185	0.195		925	0.118		0.005	7.7
Sectoral technological intensity	185			925			0.000	
High-tech		0.676			0.379			29.7
Medium-tech		0.221			0.297			-7.6
Low-tech		0.103			0.324			-22.1

	SMEs							
	Subsidized			Non subsidized			P	Standardized
	N	Mean	S.D.	N	Mean	S.D.	value*	Difference (%)**
Log employment	124	4.023	0.841	620	2.995	1.026	0.000	109.6
Log sales	124	9.207	0.849	620	8.300	1.023	0.000	96.5
Log labour productivity	124	4.018	0.489	615	3.918	0.453	0.037	21.2
Log average labour cost	124	3.534	0.366	617	3.393	0.273	0.000	43.7
Log age	124	2.775	0.757	620	2.692	0.687	0.260	11.5
Capital intensity	124	0.209	0.214	620	0.217	0.316	0.744	-3.0
Intangibles intensity	124	0.039	0.080	620	0.016	0.038	0.003	36.7
Scaled cash flow	124	0.060	0.078	620	0.056	0.059	0.532	5.8
	N	Proportion		N	Proportion			Difference (%)
Applies for patents	124	0.274		620	0.026		0.000	24.8
Geographical area	124			620			0.429	
North-East		0.419				35.8		41.9
North-West		0.452				50.5		45.2
Centre and South		0.129				13.7		12.9
Holding	124	0.073		620		0.018	0.001	7.3
Sectoral technological intensity	124			620			0.000	
High-tech		0.709				0.331		70.9
Medium-tech		0.210				0.313		21.0
Low-tech		0.081				0.356		8.1

* Two sample t-test with unequal variance for continuous variables, χ^2 test for categorical variables

** The standardized percentage difference is defined as the mean difference between subsidized and non subsidized firms as a percentage of the standard deviation: $\left[100(\bar{x}(1)-\bar{x}(0))\right]/\left[\sqrt{(s^2(1)+s^2(0))/2}\right]$, where $\bar{x}(1)$ and $\bar{x}(0)$ are the sample means in the two groups, and $s^2(1)$ and $s^2(0)$ are the corresponding sample variances.

Table 2. Matching estimates of the average treatment effect of public subsidies to R&D.

Firm performance in 2002										
	*All firms**					*SMEs***				
	N subsidized	N non subsidized	SATT	S.E.	P value	N subsidized	N non subsidized	SATT	S.E.	P value
Log employment	185	141	0.008	0.061	0.893	124	93	0.050	0.066	0.447
Log sales	185	144	-0.111	0.070	0.115	124	94	-0.117	0.091	0.198
Log labour productivity	183	144	-0.051	0.049	0.301	122	96	-0.047	0.052	0.360
Log average labour cost	183	151	-0.034	0.016	0.037	122	98	0.034	0.010	0.001
Number of patent applications	185	151	2.141	1.269	0.092	124	91	0.516	0.272	0.058
Firm performance in 2004										
	*All firms**					*SMEs***				
	N subsidized	N non subsidized	SATT	S.E.	P value	N subsidized	N non subsidized	SATT	S.E.	P value
Log employment	127	107	-0.008	0.076	0.914	83	70	0.131	0.076	0.085
Log sales	126	105	-0.027	0.077	0.730	82	71	-0.067	0.086	0.435
Log labour productivity	123	106	0.052	0.074	0.487	79	65	0.047	0.120	0.695
Log average labour cost	126	110	0.053	0.047	0.261	82	69	0.106	0.062	0.088
Number of patent applications	185	151	0.320	0.290	0.271	124	91	-0.024	0.092	0.798

* For all outcome but patent applications, matching based on Mahalanobis distance on lagged (1998): outcome variable, log age, capital intensity, patent applications, scaled cash flow. For patent applications, matching based on Mahalanobis distance on lagged (1998): outcome variable, log age, capital intensity, intangibles intensity, intangibles intensity squared, scaled cash flow. Exact matching on indicator variables (SME, geographical area, holding, sectoral technological intensity).

** For all outcome but log employment, matching based on Mahalanobis distance on lagged (1998): outcome variable, log age, capital intensity, intangibles intensity, scaled cash flow. For log employment, matching based on Mahalanobis distance on lagged (1998): outcome variable, outcome variable squared, log age, capital intensity, intangibles intensity, scaled cash flow. Exact matching on indicator variables (geographical area, holding, sectoral technological intensity).

APPENDIX

Table A1. Descriptive statistics of continuous pre-treatment (1998) matching variables in matched samples for 2002 SATT estimates

	All firms						
	Subsidized			Non subsidized			Standardized
	N	Mean	S.D.	N	Mean	S.D.	Difference (%)
Outcome variable: log employment	185			141			
Log employment		4.626	1.259		4.615	1.432	0.8
Log age		2.851	0.755		2.918	0.664	-9.4
Capital intensity		0.212	0.202		0.204	0.214	3.8
Number of patent applications		3.454	12.570		2.170	13.346	9.9
Scaled cash flow		0.066	0.075		0.064	0.061	2.9
Outcome variable: log sales	185			144			
Log sales		9.850	1.329		9.731	1.489	8.4
Log age		2.851	0.755		2.911	0.665	-8.4
Capital intensity		0.201	0.212		0.212	0.202	-5.3
Number of patent applications		3.454	12.570		1.938	13.044	11.8
Scaled cash flow		0.066	0.075		0.064	0.061	2.9
Outcome variable: log labour productivity	183			144			
Log labour productivity		4.075	0.445		4.053	0.360	5.4
Log age		2.868	0.729		2.874	0.663	-0.9
Capital intensity		0.211	0.201		0.195	0.209	7.8
Number of patent applications		3.481	12.636		2.083	13.091	10.9
Scaled cash flow		0.070	0.054		0.069	0.047	2.0
Outcome variable: log average labour cost	183			151			
Log average labour cost		3.564	0.330		3.541	0.208	8.3
Log age		2.868	0.729		2.911	0.655	-6.2
Capital intensity		0.211	0.201		0.180	0.200	15.5
Number of patent applications		3.481	12.636		1.960	12.776	12.0
Scaled cash flow		0.070	0.054		0.068	0.047	4.0
Outcome variable: number of patent applications	185			151			
Number of patent applications		3.454	12.570		1.821	12.750	12.9
Log age		2.851	0.755		2.846	0.629	0.7
Capital intensity		0.212	0.202		0.192	0.205	9.8
Intangibles intensity		0.035	0.071		0.023	0.047	19.9
Scaled cash flow		0.066	0.075		0.063	0.060	4.4

	SMEs						
	Subsidized			Non subsidized			Standardized
	N	Mean	S.D.	N	Mean	S.D.	Difference (%)
Outcome variable: log employment	124			93			
Log employment		4.023	0.841		3.793	0.939	25.8
Log age		2.775	0.757		2.841	0.613	-9.6
Capital intensity		0.209	0.214		0.196	0.237	5.8
Intangibles intensity		0.039	0.080		0.024	0.052	22.2
Scaled cash flow		0.060	0.078		0.055	0.065	7.0
Outcome variable: log sales	124			94			
Log sales		9.207	0.849		9.003	0.950	22.6
Log age		2.775	0.757		2.836	0.656	-8.6
Capital intensity		0.209	0.214		0.193	0.228	7.2
Intangibles intensity		0.039	0.080		0.024	0.052	22.2
Scaled cash flow		0.060	0.078		0.058	0.066	2.8
Outcome variable: log labour productivity	122			96			

Log labour productivity		4.032	0.475		3.978	0.370	12.7
Log age		2.798	0.720		2.799	0.679	-0.1
Capital intensity		0.208	0.213		0.175	0.238	14.6
Intangibles intensity		0.034	0.052		0.023	0.047	22.2
Scaled cash flow		0.067	0.046		0.061	0.045	13.2
Outcome variable: log average labour cost	122			98			
Log average labour cost		3.536	0.368		3.482	0.205	18.1
Log age		2.798	0.720		2.816	0.649	-2.6
Capital intensity		0.208	0.213		0.166	0.231	18.9
Intangibles intensity		0.034	0.052		0.023	0.047	22.2
Scaled cash flow		0.067	0.046		0.057	0.042	22.7
Outcome variable: number of patent applications	124			91			
Number of patent applications		1.306	3.661		0.242	1.177	39.1
Log age		2.775	0.757		2.806	0.651	-4.4
Capital intensity		0.209	0.214		0.196	0.243	5.7
Intangibles intensity		0.039	0.080		0.026	0.053	19.2
Scaled cash flow		0.060	0.078		0.056	0.065	5.6

Table A2. Descriptive statistics of continuous pre-treatment (1998) matching variables in matched samples for 2004 SATT estimates

	All firms						
	Subsidized			Non subsidized			Standardized
	N	Mean	S.D.	N	Mean	S.D.	Difference (%)
Outcome variable: log employment	127			107			
Log employment		4.664	1.360		4.584	1.411	5.8
Log age		2.849	0.783		2.905	0.668	-7.7
Capital intensity		0.217	0.216		0.210	0.233	3.1
Number of patent applications		4.630	14.959		2.477	15.111	14.3
Scaled cash flow		0.062	0.081		0.062	0.065	0.0
Outcome variable: log sales	126			105			
Log sales		9.932	1.431		9.783	1.492	10.2
Log age		2.872	0.743		2.905	0.686	-4.6
Capital intensity		0.214	0.215		0.208	0.231	2.7
Number of patent applications		4.651	15.017		2.552	15.239	13.9
Scaled cash flow		0.068	0.051		0.065	0.045	6.2
Outcome variable: log labour productivity	123			106			
Log labour productivity		4.093	0.495		4.066	0.379	6.1
Log age		2.856	0.742		2.842	0.668	2.0
Capital intensity		0.212	0.214		0.201	0.227	5.0
Number of patent applications		4.764	15.183		2.689	15.195	13.7
Scaled cash flow		0.067	0.051		0.069	0.047	-4.1
Outcome variable: log average labour cost	126			110			
Log average labour cost		3.582	0.366		3.556	0.206	8.8
Log age		2.872	0.743		2.810	0.686	8.7
Capital intensity		0.214	0.215		0.192	0.220	10.1
Number of patent applications		4.651	15.017		2.664	14.925	13.3
Scaled cash flow		0.068	0.051		0.067	0.047	2.0
Outcome variable: number of patent applications	185			151			
Number of patent applications		3.454	12.570		1.821	12.750	12.9
Log age		2.851	0.755		2.846	0.629	0.7
Capital intensity		0.212	0.202		0.192	0.205	9.8
Intangibles intensity		0.035	0.071		0.023	0.047	19.9
Scaled cash flow		0.066	0.075		0.063	0.060	4.4

	SMEs						
	Subsidized			Non subsidized			Standardized
	N	Mean	S.D.	N	Mean	S.D.	Difference (%)
Outcome variable: log employment	83			70			
Log employment		3.988	0.870		3.770	0.950	23.9
Log age		2.799	0.773		2.855	0.607	-8.1
Capital intensity		0.214	0.232		0.210	0.264	1.6
Intangibles intensity		0.044	0.091		0.023	0.050	28.6
Scaled cash flow		0.054	0.087		0.048	0.067	7.7
Outcome variable: log sales	82			71			
Log sales		9.206	0.852		8.945	0.911	29.6
Log age		2.833	0.712		2.816	0.722	2.4
Capital intensity		0.210	0.231		0.192	0.257	7.4
Intangibles intensity		0.036	0.053		0.025	0.044	22.6
Scaled cash flow		0.063	0.041		0.057	0.041	14.6
Outcome variable: log labour productivity	79			65			
Log labour productivity		4.039	0.544		3.978	0.405	12.7
Log age		2.808	0.707		2.764	0.702	6.2

Capital intensity		0.206	0.230		0.176	0.270	12.0
Intangibles intensity		0.036	0.053		0.020	0.035	35.6
Scaled cash flow		0.062	0.040		0.056	0.042	14.6
Outcome variable: log average labour cost	82			69			
Log average labour cost		3.556	0.420		3.495	0.215	18.3
Log age		2.833	0.712		2.810	0.680	3.3
Capital intensity		0.210	0.231		0.167	0.263	17.4
Intangibles intensity		0.036	0.053		0.022	0.044	28.7
Scaled cash flow		0.063	0.041		0.054	0.040	22.2
Outcome variable: number of patent applications	124			91			
Number of patent applications		1.306	3.661		0.242	1.177	39.1
Log age		2.775	0.757		2.806	0.651	-4.4
Capital intensity		0.209	0.214		0.196	0.243	5.7
Intangibles intensity		0.039	0.080		0.026	0.053	19.2
Scaled cash flow		0.060	0.078		0.056	0.065	5.6