Direct public subsidies and the productivity of high-tech start-ups:
exploring the governmental ‘build efficiency’ function

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Abstract

It is widely accepted that firm expenditures in innovation and R&D activities may be lower than the social optimum. The gap between private and social returns to R&D activities has traditionally been used as a theoretical justification for public support to firm innovation activities (Arrow, 1962; Nelson, 1959; Griliches, 1992; Teece, 1986). Another rationale of public direct support to new technology-based firms (NTBFs) is related to the presence of imperfections in the capital market that may lead firms to disregard innovative valuable projects because of problems in raising external financial resources. New and young firms in high-tech sectors are particularly subject to financial constraints for their investment decisions (Carpenter and Petersen, 2002). As suggested by Lerner (1999; 2002), the public financing of small high-technology firms may have a significant role in reducing the information asymmetry between the firm and external investors, by “signalling” the high quality of a firm innovative projects.

Most of the empirical literature evaluates the effectiveness of programs mainly looking at R&D expenditures of subsidized and non-subsidized firms (Klette et al., 2000 and Koga 2005 for contributions that refer to specific NTBFs-targeted schemes). We make a step forward and estimate the impact of subsidies on total factor productivity (TFP) of 238 Italian NTBFs. In order to control for the potentially endogenous nature of public financing we adopt advanced econometric methods such as Olley-Pakes estimator and Blundell-Bond GMM methodology.

The Italian experience is very interesting since Italy, as many other EU countries, has never had any national financial support scheme exclusively targeted to young high-tech firms (Storey and Tether, 1998), but these firms have benefited from public assistance through measures that were also available to broader typologies of firms. Furthermore, there has been no systematic indirect support to NTBFs. So it is legitimate to question whether direct general-purpose policy measures have been effective in supporting NTBFs.

We address the key question, almost neglected by the literature, of the efficacy of policy measures characterized by different evaluation methods. Distinguishing between automatic and selective policy measures, we test the hypothesis that evaluation schemes matter. In particular, our results strongly support the hypothesis that selective schemes are more effective than automatic ones. Moreover, this result is stronger if subsidies have the specific goal to increase firms’ R&D expenses.

In other words, public assistance towards high-tech start-ups seems to exert a “build efficiency” function only when government is able to select competently specific business projects to sustain.
1. Introduction
It is widely accepted that firm expenditures in R&D activities may be lower than the social optimum. Since new knowledge created through privately funded R&D activities is not rival, R&D spillovers may prevent firms from defending their technological innovation in the product market and profiting from it (Arrow, 1962; Nelson, 1959; Griliches, 1992; Teece, 1986). The gap between private and social returns to R&D activities has traditionally been used as a theoretical justification for government support to private R&D through subsidies or tax credits (Stoneman and Vickers, 1988; Hall, 2002).

A different economic rationale points to the presence of capital market imperfections in financing R&D investments as an argument for public support to private R&D. The access to external financing is especially problematic for new technology-based firms (NTBFs). New equity finance in the form of initial public offering, although presenting several advantages over debt, is still subject to capital market imperfections (Carpenter and Petersen, 2002). Venture capital has also shown some limitations in financing NTBFs. Even though venture capitalists are able to overcome information asymmetry problems by developing accurate context-specific screening procedures and monitoring portfolio firms, they generally focus on specific industries and back only a small fraction of firms in high-technology industries (Gompers and Lerner, 1998; Bottazzi and Da Rin, 2002). The financing gap of private R&D investments has often been invoked as a justification for government direct support in the form of R&D tax credits or subsidies.

However, the market failure argument provides a rationale for public support to innovation beyond the role of public funds as financial resources for R&D expenditure. As suggested by Lerner (1999, 2002), the public financing of high-technology firms may have a significant role in reducing the financing gap of R&D activities through its “certification effect”. Government support, by picking projects with high social returns, can signal to external investors the high quality of a firm’s innovative project inducing, therefore, an indirect positive effect on firm ability to attract external capital in the future, especially for NTBFs.

Nonetheless public measures could miss the objective of solving financial market failures if they generate a crowding-out effect in the sector. Crowding-out effects take place whenever public funds substitute private expenditures in financing innovation. This effect may come, first, from government agencies adopting a “pick-the-winner” strategy. Government
may be willing to avoid criticism of wasting public funds (Lach, 2002) and therefore finance projects with lower risk profile and higher private returns that would be undertaken also in the absence of public subsidies. Second, government founded R&D may crowd-out private R&D if it translates in higher costs of research input (David and Hall, 2000). This situation occurs when the supply of research inputs, particularly of scientists and engineers, is quite inelastic (Goolsbee, 1998).

Most of the empirical literature evaluates the effectiveness of programs mainly looking at the R&D expenditures of subsidized and non-subsidized firms (Klette et al., 2000 and Koga, 2005 for contributions that refer to specific NTBFs-targeted schemes). We make a step forward and study the impact of subsidies on NTBFs’ total factor productivity (TFP).

We estimate the effect of public financing on 238 Italian NTBFs in the period 1994-2003 and control for the potential endogeneity of public financing by adopting a GMM-system estimation. Assessing the success of Italian technology policy on NTBFs is very interesting. In fact Italy, as many other EU countries, has never had any national financial support scheme exclusively targeted to young high-tech firms (Storey and Tether, 1998), but these firms have benefited from public assistance through measures that were also available to broader typologies of firms. Furthermore, there has been no systematic indirect support to NTBFs. So it is legitimate to question whether direct general-purpose policy measures have been effective in supporting NTBFs.

In particular we address the key question, almost neglected by the literature, of the efficacy of policy measures characterized by different evaluation methods. Distinguishing between automatic and selective policy measures, we test the hypothesis that evaluation schemes matter. In particular, our results strongly support the hypothesis that selective schemes are more effective than automatic ones. Moreover, this result is stronger if selective subsidies have the specific goal to increase firms’ R&D expenses.

The paper is structured as follows. In Section 2 we review the extant literature and illustrate the conceptual framework that leads to the theoretical hypotheses. In Section 3 we give some remarks on Italian direct subsidy schemes towards entrepreneurship and describe the way we collected information on the sample of NTBFs on which is based the empirical analysis. In Section 4 we specify the econometric models, and describe the variables of our specification. In Section 5 we illustrate the results of the econometric estimates. Section 6 concludes the paper.
2. The impact of public financing on NTBFs’ productivity

2.1 Literature review

Evaluation studies on the impact of policy measures aimed at stimulating firm’s innovation activities have suggested that industrial R&D expenditure is positively influenced by government support (Hall and Van Reenen, 2000). A large number of studies have explicitly addressed the question of whether public innovation expenditure is complementary or tends to substitute private innovation. David et al. (2000) provide a careful taxonomy of the econometric evidence accumulated over several decades, and conclude that overviewed results, although considerably depending on the level of aggregation at which the analysis was performed, suggest that “complementarity” appears more prevalent. This conclusion is confirmed by the most recent literature on the public R&D expenditure “additionality” issue (Lach, 2002; Czarnitzki and Fier 2002; Almus and Czarnitzki, 2003; Hussinger, 2003; Duguet, 2004; Koga, 2005; Lööf and Heshmati, 2005; Hyytinen and Toivanen, 2005).

A less developed literature extends the analysis of the effectiveness of public subsidies by looking at the innovation output and subsequent market performance of subsidized and non-subsidized firms. Indeed, the relation between innovation inputs, such as R&D expenditures, and firm technological and economic performance is not straightforward (Patel and Pavitt, 1995). The impact of public financing on observable innovation, growth and productivity measures is especially interesting in the case of small firms that operate in high-tech sectors, that often do not have a dedicated R&D department, but still engage in high-technology investments (Hujer and Radic, 2005). 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) find no impact of public support for private R&D on innovative activities in East and West Germany establishments. Irwin and Klenow (1996), evaluating the SEMATECH program, conclude that participating firms grow more than non-participating firms in terms of profitability, but not significantly in terms of investments and labour productivity. Czarnitzki et al. (2004) examine the effect of R&D tax credits on a series of innovation indicators of Canadian manufacturing firms and they conclude that fiscal incentives lead to additional innovation output. Czarnitzki and Hussinger (2004) analyze the effect of public R&D funding on R&D expenditure and
patenting behaviour of German firms. The direct impact of subsidies on R&D and the indirect effect on innovation output measured by patent applications are explicitly modelled in a system of equations. Girma et al. (2007), using a unique plant-level dataset from Ireland, find that only subsidies with the goal to increase R&D, capital and training investments, and to promote technology acquisition increase firms’ total factor productivity. Czarnitzki and Licht (2006) estimate the input and output additionality of public R&D subsidies in Western and Eastern Germany and they find a large degree of additionality in public R&D grants with regard to innovation input measured as R&D and innovation expenditures, as well as with regard to innovation output measured by patent applications. Czarnitzki et al. (2007) apply the matching in a multiple treatment setting analyzing the effects of R&D collaboration and public R&D funding on R&D per sales and patent outcome for Germany and Finland. Hussinger (2008) applies parametric and semiparametric two-step selection models in her analysis on the effect of public R&D subsidies on firms’ private R&D investment per employee and new product sales in German manufacturing. The results show that the average treatment effect on the treated firms’ R&D intensity is positive. Furthermore publicly induced R&D spending is as productive as private R&D investment in generating new product sales. Examining small and high-technology firms that received SBIR support in the 1983-1985 period, Lerner (1999) finds that in a fairly long subsequent period subsidized firms 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. Also Busom (2000) finds that, for 30% of participants in her cross-section sample of Spanish firms, full crowding-out effects cannot be ruled out.

2.2 The role of public agencies’ evaluation methods and goals
This paper examines the effectiveness and efficiency of public subsidies for NTBFs’ economic performance. However, we do not intend to evaluate single programmes, looking instead at the average impact of public subsidies on firm’s TFP. Quite surprisingly, very little attention has been paid by the literature to the issue of the evaluation mechanisms through which public funds are actually allocated, and in particular to the possible backlashes in terms of subsidy effectiveness that different allocation mechanisms might imply. The evaluation methods adopted by public authorities are indeed a crucial component of technology policies design, and empirical studies should take into account the way government funds
are allocated (Klette et al., 2000). Structural models have been proposed to attempt merging the analysis of firm performance with the allocation choices by public agencies (Wallsten, 2000; Takalo et al., 2005). We propose an empirical evaluation comparing the impact of public technology policies adopting different screening and selection procedures. The ultimate goal of our study is to verify whether or not different government subsidies are able to enhance firms’ productivity.

Evaluation procedure embedded in different subsidization programs may differ under many aspects (e.g. the design of technical evaluation, the relative importance of applicant’s size and location, etc.): for the purpose of our analysis, we adopt a simple classification of policy measures into automatic and selective ones. An automatic scheme gives financial assistance to all applicants fulfilling all the requirements specified in the law. Instead, a selective scheme provides financial support to selected applicants. In this latter case, applicants compete for receiving a financial subsidy and their projects are judged by committees formed by experts who are nominated by the national authority.

Selective and automatic procedures adopted by public agencies may have substantially different impacts on firm performance for two reasons. First, the design of a dedicated technical committee and strict competition rules allow for a more precise screening of projects so to reduce information asymmetry problems and to award projects with positive social returns. On the contrary, automatic subsidies are awarded after a procedural assessment of firms fulfilling the required criteria specified by the law (e.g. financial solidity requirements, etc.). Second, selective subsidies may provide awarded firms with a relevant certification of their projects’ quality. Signalling a firm good quality through public financial support may overcome the asymmetric information problems and thus facilitate a subsequent access to debt and equity capital markets. Selective awards, differently from automatic ones, have a “halo effect” that attracts private investors, who see the awards as a certification of technical quality, reducing the uncertainty inherent in early-stage investment. Thus, we want to test if government agencies would have better information than the market. In second instance, we want to test if companies are willing to disclose more to such an agency in the context of a competition than they would disclose to the market in general. In our vision, to disclose information to a government agency is less risky than to a private investor. In the latter case, there is a serious risk of appropriability; in fact, private
investors (e.g. banks or financial venture capitalists\(^1\)) could be able to spill-over firm’s technology and give it to other portfolio companies. In this case companies are not willing to disclose information about their innovative idea and thus information asymmetries are high. Instead, in the former case there is no such risk because government is not a profit maximizing entity but it is a social welfare maximizing one. We therefore posit the following hypothesis.

Hypothesis 1: \textit{selective subsidies have a larger impact on NTBFs’ total factor productivity than automatic ones.}

Different goals of the public agencies in awarding subsidies to applicant firms may have substantially different impacts on productivity, especially if ventures operate in high technology industries. In fact, one of the main rationales invoked for providing government subsidies is the existence of market failure. Thus, it may be still difficult to finance R&D using capital from sources external to the firm. Unless a firm is already profitable, some innovations will fail to be provided purely because the cost of external capital is too high. Public subsidies may help firms overcome financial constraints in investment and, in particular, encourage firms to adopt new technologies. If governments’ goal is to increase R&D investments of awardees, a subsidy with this scope should enhance a positive impact on productivity via R&D investments (Griliches, 1995; Hall and Mairesse, 1992; Parisi et al., 2006). In fact, the common objective of public R&D support is to increase the size and the number of R&D projects performed by private sector firms. For this reason, it is important to understand how public policies like R&D subsidies influence private incentives for R&D investment. Theoretically, public support focuses on projects whose private benefit-cost ratios are small and will hence only be undertaken if government subsidies are available. As a consequence, public support is expected to induce additional private R&D investment because of the lower private costs. That way, companies could perform the difficult and arduous work necessary to convert promising research results into products and services that satisfy customers’ needs. This reasonably generates fundamental backlashes on revenues and, because part of the production costs is covered by governmental subsidies, on productivity. This can be

\(^1\) We do not include corporate venture capitalists because they do not have only financial goals but also strategic goals. See Bertoni, Colombo and Grilli (2007).
possible because R&D subsidies should increase R&D investments and thus the probability to introduce a product or process innovation. In fact, R&D efforts should favor the absorption of new and more advanced technologies (Cohen and Levinthal, 1989). The productivity effect of a process innovation should be larger than the one of a product innovation.

In order to increase NTBFs’ productivity this kind of award must be provided in a selective way. In fact, only high quality firms engage in high quality innovation activities enhancing positive and significant backlashes on productivity. Thus, it is fundamental that government programs are driven by economic criteria and are not influenced by pressure groups for political influence (Becker, 1983). Public agencies would only grant subsidies for projects in which the private rate of return is insufficient to induce investment but the social return exceeds the R&D cost of investment. Due to asymmetric information between borrowers and lenders a financing gap for R&D emerges. Potential lenders like banks are reluctant to fund R&D due to the inherent risk, even if the borrower has argued that there are high expected returns. Unlike investment in physical capital, R&D is treated as a current expense and there is no capitalized value on firms’ balance sheets to use as collateral in credit negotiations. Thus R&D must be supported predominantly by internal financial resources. This causes a financing gap for small and medium sized firms that do not have sufficient cash-flow to fund R&D. Hyytinen and Toivanen (2005) and Czarnitzki (2006) find that R&D subsidies reduce the underinvestment problem stemming from financial constraints. Moreover, R&D subsidies can mitigate the incentive effect of uncertainty on firm level R&D investment. While these policies do not act directly to reduce uncertainties, they can offset the incentive to delay investment by increasing the expected return on the firm’s R&D investment. Therefore, firms getting subsidies should invest more in R&D today than those firms that do not receive them. Selective public policies intended to increase private R&D investment can achieve this objective by reducing the degree of uncertainty in the innovative process or in the product market. Selective public incentives are expected to increase the private R&D engagement in the business sector and that such additionally induced R&D activities lead to new products and processes improving NTBFs’ economic performance, as explained above. Public funding reduces the price for private investors and thus the innovations are carried out. In case of profit maximizing companies, we can assume that firms first conduct those projects from their research portfolio that have highest expected profits. For this reason, it is important that R&D subsidies are provided in a selective way, that is government agencies must select
only projects with high social returns. We therefore posit the following hypothesis.

Hypothesis 2: selective subsidies enhancing R&D investments have a larger impact on NTBFs’ total factor productivity than the other ones

3. Data

3.1 Italian national direct support schemes
Italy lacks any direct policy measure that explicitly targets NTBFs. Furthermore there has not been any systematic indirect support to this typology of firms. Nonetheless, Italian new high-tech firms may benefit from all the national horizontal schemes implemented. Overall, 28 national laws have provided some type of financial facilitation to Italian NTBFs (for a taxonomy of the different measures of Italian technology policy see Colombo and Grilli, 2006). National support schemes differ as for the main purpose of the scheme, namely investments in R&D, general-purpose investments (i.e. machineries, new plants, employment, etc.) and support of underdeveloped areas. Our analysis distinguishes between policy programs explicitly aimed at stimulating private R&D from other types of interventions (general investment and support of depressed areas). Moreover, as mentioned before, we distinguish between selective and automatic subsidies

3.2 Sample
In this paper we use a unique hand collected longitudinal dataset relating to a sample composed of 238 Italian NTBFs that are observed over a ten year period (1994-2003). Most sample firms are privately held. They were established in 1980 or later, were independent at founding time and have remained so up to the end of 2003 (i.e. they are not controlled by another business organization even though other organizations may hold minority shareholdings). They operate in the following high-tech sectors in manufacturing and services: computers, electronic components, telecommunication equipment, optical, medical and electronic instruments, biotechnology, pharmaceuticals and advanced materials, robotics and process automation equipment, multimedia content, software, Internet services (i.e. e-commerce, ISP, and web-related services), and telecommunication services.
The sample of NTBFs was drawn from the 2004 release of the RITA (Research on Entrepreneurship in Advanced Technologies) database. Developed at Politecnico di Milano, RITA presently is the most complete source of information on Italian NTBFs. It was created in 2000 and it was updated in 2002 and 2004. The development of the database went through a series of steps. First, Italian firms that complied with the above mentioned criteria relating to age and sector of operations were identified. For the construction of the target population a number of sources were used. These included lists provided by national industry associations and regional Chambers of Commerce, on-line and off-line commercial firm directories, lists of participants in industry trades and expositions, and information provided by the national financial press, specialized magazines, and other sector-based studies. Altogether, 1,974 firms were selected for inclusion in the database. For each firm, a contact person (i.e. one of the owner-managers) was also identified. Unfortunately, data provided by official national statistics do not allow to obtain a reliable description of the universe of Italian NTBFs.\(^2\) Second, a questionnaire was sent to the contact person of the target firms either by fax or by e-mail. The first section of the questionnaire provides detailed information on the human capital characteristics of firms’ founders. The second section comprises further questions concerning the characteristics of the firms including access to national public subsidies, the typology of subsidies, and the evolution over time of firms’ employees. Lastly, answers to the questionnaire were checked for internal coherence by educated personnel and were compared with information obtained from firms’ annual reports and other public sources. In several cases, phone or face-to-face follow-up interviews were made with firms’ owner-managers. This final step was crucial in order to obtain missing data and ensure that data were reliable.\(^3\)

The sample used in the present work consists of the 238 RITA firms that participated in the 2004 survey. As presented in Table 1 firms operate in three macro-industries (resulting from the aggregation of previously

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\(^2\) The main problem is that in Italy most individuals who are defined as “self-employed” by official statistics actually are salaried workers with atypical employment contracts. Unfortunately, on the basis of official data such individuals cannot be distinguished from entrepreneurs who created a new firm.

\(^3\) Note that for only 3 firms the set of owner-managers at survey date did not include at least one of the founders of the firm.
mentioned industries):\(^4\) manufacturing (39.02% of the observations), software (39.63%) and web services (21.35%). The sample is large and quite heterogeneous. Overall, government granted 84 subsidies to NTBFs: 33 (39.29%) were selective and 46 (54.76%) were R&D subsidies. More than half of our sample is composed by firms that operate in the north-west part of Italy. These NTBFs receive 35 subsidies (41.67% of the total number of grants provided by national authorities): 11 out are selective (31.43%) and 22 are R&D subsidies (62.86%). Two \(\chi^2\) tests show that there are no statistically significant differences between the distributions of sample firms across industries and regions and the corresponding distribution of the population of 1,974 RITA firms from which the sample was obtained \(\chi^2(3)=13.53\) and \(\chi^2(3)=6.116\), respectively.

Note however that there is no presumption here to have a random sample. First, in this domain representativeness is a slippery notion as new ventures may be defined in different ways (Birley 1984, Aldrich et al. 1989, Gimeno et al. 1997). Second, as was mentioned above, absent reliable official statistics, it is very difficult to identify unambiguously the universe of Italian NTBFs. Therefore, one cannot check ex post whether the sample used in this work is representative of the universe or not. Third, as in most previous studies based on survey data, only firms having survived up to the survey date could be included in the sample. In so far as failure rates of new firms decrease when firms manage to obtain public financing, our data might overestimate NTBFs’ access to national support schemes. This notwithstanding, the sample is sufficiently large and it exhibits considerable heterogeneity as to variables of our interest.

4. Econometric specification

Our task is to estimate the impact of different subsidies on productivity; therefore, we specify the following equation:

\[
\text{logTFP}_{it} = \beta_0 + \beta_1 \text{Subsidy}_{i,t-1} + \beta_2 \text{Subsidy}_{i,t-2} + \beta_3 \text{Subsidy}_{i,t-3} + \\
+ \beta_4 \text{Age}_{i,t} + \beta_5 \text{LocDevelop}_{i} + \gamma_t + \epsilon_{it}
\]

where \(\text{logTFP}\) is firm’s total factor productivity; \(\text{Subsidy}\) is a vector of dummy variables representing different types of subsidies; \(\text{Age}_{i,t}\) is the age of the focal NTBF at \(t\); \(\text{LocDevelop}_i\) is a time-invariant variable that allows for the level of infrastructure development in the province of NTBF’s

\(^4\) Note that we aggregate the previously exposed sectors into three macro industries in order to have a sufficient number of observations in each industry.
location (source: Centro Studi Confindustria, 1991); \( \gamma \) is a full set of time
dummies and \( \varepsilon_t \) an error term.\(^5\)
Among covariates we do not insert the firm size because this variable
already enters in the construction of the dependent variable (see section 4.1).
This approach is well-known in the productivity literature (e.g. Javorcik,
2004; Castellani and Zanfei, 2006).
In Table 2 we describe in detail the variables entering in Eq. (1).
In order to calculate NTBFs’ TFP, we follow the semi-parametric approach
suggested by Olley and Pakes (1996).

4.1. The dependent variable
Profit maximizing firms respond to positive productivity shocks by
expanding output, which requires additional inputs. TFP reflects how
effectively the focal NTBF uses production inputs to produce output with
respect to other NTBFs that operate in the same industry. In other words,
NTBFs perform better if they produce the same output with fewer inputs or
if they produce more output from the same inputs than their counterparts.
NTBFs’ TFP is estimated through a now rather standard semi-parametric
estimation procedure originally proposed by Olley and Pakes (1996), which
allows for firm-specific productivity differences exhibiting idiosyncratic
changes over time.\(^6\) This semi-parametric approach, increasingly used in the
empirical industrial organization and applied econometrics literature (e.g.
Pavcnik, 2003; Cingano and Schivardi, 2004; Blalock and Gertler, 2007;
Girma et al., 2007), presents several advantages compared with other
methods in dealing effectively with the typical simultaneity problem in the
choice of inputs.\(^7\) In fact, ordinary least squares (OLS) estimates of

\[^{5}\] We do not insert industry dummies in the equation because the estimation of total factor
productivity has been separately conducted for each macro industry.

\[^{6}\] For a survey of the different estimation techniques of TFP and a more detailed description

\[^{7}\] Quoting Griliches and Mairesse (1998) also reported by Levinsohn and Petrin (2003, p.
321): “The major innovation of Olley and Pakes is to bring in a new equation, the
investment equation, as a proxy for \( \omega \) (i.e. the productivity shock), the unobserved
component of the error term. Trying to proxy for the unobserved \( \omega \) (if it can be done
correctly) has several advantages over the usual within estimators (or the more general
Chamberlain and GMM type estimators): it does not assume that \( \omega \) reduces to a “fixed”
(over time) firm effect; it leaves more identifying variance in \( l \) (labour) and \( k \) (capital), and
hence is a less costly solution to the omitted variable and/or simultaneity problem, and it
should also be substantively more informative.” Additionally, differently from other
alternative methods (e.g. the GMM instrumental variables approach by Blundell and Bond,
coefficients of production functions are biased and thus lead to biased estimates of productivity.
Specifically, the Olley and Pakes methodology\(^8\) assumes that at the beginning of every period a firm chooses variable production factors (e.g. labor) and the level of investments. The latter, together with the current value of the capital stock determines the capital stock at the beginning of the next period.\(^9\)

The production technology is assumed to be Cobb-Douglas:
\[
y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 t_{it} + \omega_{it} + \eta_{it}
\]
(2)

Where \(y_{it}\) is the logarithm of firm’s output, measured by firm’s value of production; \(l_{it}\) is the logarithm of labour input cost; \(k_{it}\) is the logarithm of the state variable capital and \(i_{it}\) is the logarithm of the proxy variable (e.g. investments);\(^10\) \(\omega_{it}\) is the transmitted productivity component and \(\eta_{it}\) is the classical error term, uncorrelated with input variables. \(\omega_{it}\) is a state variable and thus impacts firm’s way to allocate resources among inputs. As we know, it is not observed by the econometrician and leads to the well-known simultaneity problem.

Investments are assumed to depend on capital \(k_{it}\) and productivity \(\omega_{it}\):
\[
l_{it} = l_{it}(k_{it}; \omega_{it})
\]

Levinsohn and Petrin show that the above relation is monotonically increasing in \(\omega_{it}\) and thus the investment function can be inverted:\(^11\)
\[
\omega_{it} = \omega_{it}(k_{it}; t_{it})
\]
Now the unobserved productivity is expressed by a function of two observed variables.
This procedure introduces also an identification restriction: productivity follows a first order Markov process
\[
\omega_{it} = E[\omega_{it} | \omega_{it-1}] + \xi_{it}
\]

2000), it also easily allows to specify separate production functions across sectors, notably to distinguish manufacturing from services industries, which is particularly indicated for a sectoral heterogeneous sample like the one considered in the present study.

\(^8\) See Petrin, Poi and Levinsohn (2004) for a more technical description of the procedure.

\(^9\) As customary in this context, investments are calculated as the book value of tangible and intangible assets at time \(t\) minus the same value at time \(t-1\) plus depreciation at time \(t\).

\(^10\) In the econometric literature, Levinsohn & Petrin (2003) propose an extension of Olley & Pakes (1996) using intermediate inputs such as materials or energy, instead of investments. Unfortunately, we do not have this kind of data.

\(^11\) The tests verifying monotonicity between investments and estimated productivity for each macro industry have been conducted.
where ζ is an innovation to productivity that is uncorrelated with k, but not necessarily with l.

To estimate the production function we start from the following equation:

\[ y_{it} = \beta l_{it} + \phi(k_{it-1} l_{it}) + \eta_{it} \]  

(3)

where the expression of \( \phi \) is easily recovered by Eq. (1) and is approximated non parametrically by a third order polynomial. In this way we can consistently estimate parameters of Eq. (3) via OLS estimation.

In the second stage, starting from the estimated values of \( \phi \) for any candidate value \( \beta k \), we can compute a prediction for \( \omega_{it} \):

\[ \omega_{it} = \hat{\phi}(k_{it}) - \beta l_{it} - \beta l_{it} \]  

Using these predictions, we can do a non parametric approximation of \( E[\omega_{it}] \) using

\[ \hat{\omega}_{it} = \gamma_0 + \gamma_1 \omega_{it-1} + \gamma_2 \omega_{it-1}^2 + \gamma_3 \omega_{it-1}^3 + \eta_{it} \]  

Then the residual is expressed by

\[ \eta_{it} = \omega_{it} - \beta l_{it} - \beta l_{it} - \beta l_{it} - E[\omega_{it}] \]  

(4)

In order to estimate the coefficients of capital and proxy variable we need at least two moment conditions:

\[ E[\eta_{it} + \xi_{it} | k_{it}] = 0 \]

\[ E[\eta_{it} + \xi_{it} | l_{it-1}] = 0 \]

The first means that capital stock in period t does not respond to productivity shocks in the current period. The second condition represents the uncorrelation between past investments and current productivity shocks.

Thus Olley-Pakes estimator finds \( \beta^* \) and \( \beta^* \) that minimize the moment conditions via GMM minimization.

The covariance matrix of the final parameters must take into account of the sampling variation introduced in the two stages of the estimation. This procedure employs the bootstrap method to compute standard errors. This method is robust in the construction of standard errors because the sample moments calculated using the original dataset are subtracted from the bootstrapped sample’s moments (Horowitz, 2001).

In order to decide the exact number of replications we resort to the rule of thumb suggested by Efron and Tibshirani (1993).

This procedure is run separately for each industry.12

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12 Note that in order to have a sufficient number of observations in each industry we aggregate the previously exposed sectors into three macro industries: manufacturing, software and Internet services.
4.2. The estimation method

If we observe systematic differences between supported firms and non-supported firms, a pure comparison of the mean impact of the subsidies may lead to biased results due to selection bias. The problem is that the counterfactual situation (the firm’s productivity that we would have observed without government support) is not directly observable. Hence, in order to make a reliable guess regarding the programme’s impact we have to look for methods that facilitate the best possible inference of the counterfactual situation. Thus we must estimate the treatment effect in the case of a non-random selection of the group of treated firms. For this analysis we chose the GMM system estimator.

In this paper generalized method of moments for panel data is used for estimation in order to account for possible (time-invariant and time-varying) unobserved heterogeneity that if correlated with regressors, may lead to biased estimates of the parameters of interest.

In order to take account of this problem, following the recent literature on dynamic panel data models (Arellano & Bond, 1991; Arellano & Bover, 1995), we resort to the generalized method of moments procedure and estimate models by the GMM-system estimator. This approach, originally proposed by Blundell and Bond (1998), extend the GMM-Difference estimator (first differenced) in that additional moment conditions are used in order to obtain more efficient estimates. In particular, other than using lagged levels of the series as instruments for first differences (as in GMM-Difference), additional information is extracted using first differences as instruments for variables in levels.\(^\text{13}\) Moreover, it preserves information from the level equations enabling consistent identification of time-invariant covariates. As customary in this type of analysis (e.g. Girma et al., 2008) we formulate the weakest possible assumption: we consider the subsidies as potentially correlated with error terms, and treat them accordingly as endogenous. In our specification, we also use additional exogenous variables such as the sector-based percentage of firms that have received one or more subsidies since founding date, and the sector-based percentages of selective/automatic subsidies on the total number of received awards.\(^\text{14}\)

The validity of selected instruments can be verified using Hansen test. Many

\(^{13}\) In our case, pseudo-first stage regressions speak in favour of the goodness of GMM-SYS estimator: in fact, they highlight that lagged instruments in first differences are strongly correlated with Subsidy variables, pointing to the goodness other than the validity of the additional instruments.

\(^{14}\) Percentages are calculated on 16 industries (source: Rapporto RITA, 2005).
applied works (e.g. Leiponen, 2005; Benfratello and Sembenelli, 2006) show that external information, provided by a set of additional exogenous instruments, improve estimates consistency. This augmented GMM estimator requires the assumption of mean stationary of the series and is particularly appropriate where series are highly persistent.¹⁵

To evaluate the relevance of the econometric model different tests are applied. First, we implement the Arellano and Bond test for first- and second-order serial autocorrelation of residuals (AR(1), AR(2)). If \( \varepsilon_{it} \) is not serially correlated, the difference of residuals should be characterized by a negative first-order serial correlation and the absence of a second-order serial correlation. Then, the Hansen test for the validity of overidentifying restrictions is implemented. This statistics test the null hypothesis that the specified orthogonality conditions are equal to zero (Hansen, 1982). Failure to reject the null hypothesis indicates that the instruments are valid.

5. Econometric results

In Table 3 we show summary statistics of the average logarithm of TFP by typology of firms according to their status (awardees or not) and to the category of subsidies received. On average, subsidy recipients have higher total factor productivity than non recipients. Firms receiving subsidies with the scope to increase R&D investments appear more productive than other firms receiving awards with the scope to increase general investments or to support underdeveloped areas. Moreover, one finds that on average selective subsidy recipients have a higher TFP than automatic awards beneficiaries.

Using OLS and fixed effects within groups (WG) estimators to estimate Eq. (1) leads to inconsistent estimates of the parameters of interest \( (\beta_i) \) because of the presence of selection bias. In fact, a potential problem for the effectiveness of most public subsidy programs is that every firm has incentives to apply for financial support, including firms that do not need them. The difficulty of this kind of analysis coming from the public institutions that, on the basis of applying firms’ projects, decide the recipients of the public subsidy (Busom, 2000).

Our results are shown in Table 4, Table 5 and Table 6. First of all, we can see that the Hansen test statistics of over-identifying restrictions provide support for our use of instruments in all of our three

¹⁵ On this issue, see Bond (2002).
In addition, the autocorrelation tests are passed in all GMM-system regressions. In the first specification (Table 4), WG and GMM estimates show that subsidies lumped together do not have significant positive effect on total factor productivity of Italian NTBFs, while potential determinants of productivity are age and local development (the latter only for GMM estimation because WG estimation does not permit to identify the coefficients of time-unvarying covariates). Old firms are more likely to be more productive than young ones, while ventures located in more developed areas should benefit from positive externalities that may arise from external assets with public good nature (e.g., transport system, telecommunication infrastructure, efficient market for support services). Instead, in the OLS estimation we can see that Age and LocDevelop are still positive and statistically significant but also the average treatment effect of the subsidies on TFP (given by the sum of the three coefficients of subsidies) is positive and statistically significant at 99% significance level. This result is due to the important drawback of this estimation: in fact, OLS cannot prevent endogeneity and simultaneity problems due to the correlation between unobservable firm-specific effects and regressors. In WG estimation we can control only for the correlation between firm specific time-unvarying effects (in which way we can explain the positive ATE at 90% significance level). In the GMM estimation we can control also for time-varying firm specific unobservable components and thus we can have more robust results.

In the second specification (Table 5) we try to test if selective subsidies are more likely to be determinants of new technology-based firms’ productivity. As we can see, in the GMM estimation selective subsidies with a lag of one and two periods have a positive and statistically significant impact on productivity (at 90% significance level) respect to subsidies as a whole (in particular the coefficient of subsidies with two lags is negative at 95% significance level). If we look at the chi-squared test to verify if the three coefficients of selective subsidies are jointly null, we can see that the test rejects the null hypothesis at 90% significance level, but if we look at the ATE of selective subsidies on NTBFs’ TFP (given by the sum of the three coefficients of subsidies and the three coefficients of selective subsidies), we can see that this is positive but not statistically significant. In this specification the Hypothesis 1 concerning the differential positive impact of

16 The Hansen statistics test tests the null hypothesis of validity of the instruments.
17 As far as autocorrelation tests are concerned, AR(2) must be not significant in order to rule out the presence of a second-order serial correlation in the first difference residuals.
selective awards on firm’s productivity is not verified. Age and local development still show positive and significant coefficients; we could interpret them as positive backlashes on NTBFs’ performance. Instead, in the other two columns, OLS and WG estimates show a positive ATE at 99% significance level. This is due to their poor reliance in this context in which firm-specific time-varying effects are strong.

In the third specification (Table 6) we classify subsidies on two dimensions: selective versus automatic and R&D purpose versus other than R&D purpose. We could see that our hypotheses are proved to be true. In fact, selective subsidies have a positive impact on productivity (ATE is positive at 90% significance level), with a stronger effect if their goal is to increase R&D investments (ATE statistically positive at 95% significance level). To verify this statement, the reader can also look at the chi-squared test to verify if the six coefficients of selective subsidies are jointly null: as we can see, the test rejects the null hypothesis at 99% significance level. We also conduct two chi-squared tests separately on the three coefficients of R&D selective subsidies and of the three coefficients of other than R&D selective ones in order to verify if they are jointly null. We find that the first test rejects the null hypothesis (at 99% significance level) while the second accepts $H_0$ in the GMM estimation. We thus state that all selective subsidies impact positively and significantly on NTBFs’ productivity. Moreover, if we divide selective subsidies in R&D-supporting and other than R&D supporting only the former enhance productivity. In this model, age is still significantly positive while local development has a positive but not significant impact on productivity. Concerning OLS and WG estimates, we can see that also the chi-squared test on the three coefficients of other than R&D selective subsidies rejects the null hypothesis. This can be due to their backlashes, already mentioned.

6. Conclusions
This paper evaluates the effectiveness of public financing on Italian NTBFs’ total factor productivity. In particular, we question whether direct general-purpose policy measures have been effective in supporting NTBFs. Italy, in fact, has never had any national support scheme exclusively targeted to new high-tech firms, but these firms have benefited from public assistance through measures that were also available to broader typologies of firms. In particular we address the question, almost neglected by the literature, of the efficacy of policy measures characterized by different evaluation methods and we also investigate whether the effectiveness of public subsidies depends on the goal of the subsidy. In fact, the preceding sections
investigate whether governmental support stimulates firms’ total factor productivity measured semi-parametric estimation. The econometric analyses reveal positive treatment effects only in presence of selective subsidies (that is, selective subsidies are more effective than automatic ones); treatment effects are more pronounced if selective subsidies are targeted to enhance R&D investments. Our findings shed a positive light on the role of public subsidies and, in particular, on the government build efficiency function.

The fact that the most effective public subsidies are the selective ones enhancing R&D investments, together with the observation that this very rarely happens in the Italian context is worth of some reflections by Italian policy makers.

Of course, our study has a number of caveats that remain for further research. First, we only consider Italy and it is questionable whether our results hold for other countries. Second, it would be interesting to use Levinsohn-Petrin estimator as a robustness check for our results. In fact, it turns out that the investment proxy is only valid for firms reporting non zero investments. Using intermediate inputs proxies instead of investments avoid truncating all zero investment firms. Furthermore, intermediate inputs may respond in a better way to productivity shocks than investments, due to less adjustment costs and because intermediate inputs are not typically state variables. Third, in our database we have only dummy variables taking value equal to one if the focal NTBF had received a subsidy. It would be interesting to test if our hypotheses hold by using not only these dummy variables but also the amount of different subsidies. That way, we can test if there would be a non linear relation between the amount of the subsidy and NTBFs’ productivity.
References


Tables

Table 1 – Descriptive statistics

<table>
<thead>
<tr>
<th>Industry</th>
<th>Total sample firms</th>
<th>Subsidies</th>
<th>Selective subsidies</th>
<th>R&amp;D subsidies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N.</td>
<td>%</td>
<td>N.</td>
<td>%</td>
</tr>
<tr>
<td>Web services</td>
<td>51 21.35</td>
<td>14 16.67</td>
<td>4 12.12</td>
<td>6 13.04</td>
</tr>
<tr>
<td>Software</td>
<td>94 39.63</td>
<td>36 42.86</td>
<td>11 33.33</td>
<td>19 41.30</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>93 39.02</td>
<td>34 40.48</td>
<td>18 54.55</td>
<td>21 45.65</td>
</tr>
<tr>
<td>Total</td>
<td>238 100.00</td>
<td>84 100.00</td>
<td>33 100.00</td>
<td>46 100.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geographical area</th>
<th>Total sample firms</th>
<th>Subsidies</th>
<th>Selective subsidies</th>
<th>R&amp;D subsidies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N.</td>
<td>%</td>
<td>N.</td>
<td>%</td>
</tr>
<tr>
<td>Northwest</td>
<td>122 51.13</td>
<td>35 41.67</td>
<td>11 33.33</td>
<td>22 47.83</td>
</tr>
<tr>
<td>Northeast</td>
<td>52 21.85</td>
<td>16 19.05</td>
<td>8 24.24</td>
<td>12 26.09</td>
</tr>
<tr>
<td>Centre</td>
<td>40 16.89</td>
<td>17 20.24</td>
<td>5 15.15</td>
<td>9 19.56</td>
</tr>
<tr>
<td>South&amp;Isles</td>
<td>24 10.13</td>
<td>16 19.05</td>
<td>9 27.27</td>
<td>3 6.52</td>
</tr>
<tr>
<td>Total</td>
<td>238 100.00</td>
<td>84 100.00</td>
<td>33 100.00</td>
<td>46 100.00</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>logTFP</td>
<td>Logarithm of firm’s total factor productivity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LocDevelop</td>
<td>Value of the index measuring regional infrastructures in 1989 (mean value among Italian regions=100; source: Centro Studi Confindustria 1991)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Number of years since firm’s foundation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AllSubs</td>
<td>Time varying dummy variable that equal unity if firm received a subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SelSubs</td>
<td>Time varying dummy variable that equal unity if firm received a selective subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;DSelSubs</td>
<td>Time varying dummy variable that equal unity if firm received an enhancing R&amp;D selective subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;DAutSubs</td>
<td>Time varying dummy variable that equal unity if firm received an enhancing R&amp;D automatic subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NoR&amp;DSelSubs</td>
<td>Time varying dummy variable that equal unity if firm received an other than enhancing R&amp;D selective subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NoR&amp;DAutSubs</td>
<td>Time varying dummy variable that equal unity if firm received an other than enhancing R&amp;D automatic subsidy</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Legend:** LogTFP is estimated via Olley-Pakes methodology. LocDevelop is calculated as the average of the following indexes: per capita value added, share of manufacturing out of total value added, employment index, per capita bank deposits, automobile-population ratio, and consumption of electric power per head. The Italian benchmark value is 100.

---

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogTFP</td>
<td>Non recepients</td>
</tr>
<tr>
<td>All subsidy</td>
<td>All subsidy recipients</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>R&amp;D recipients</td>
</tr>
<tr>
<td>No R&amp;D</td>
<td>No R&amp;D recipients</td>
</tr>
<tr>
<td>Selective</td>
<td>Selective recipients</td>
</tr>
<tr>
<td>Automatic</td>
<td>Automatic recipients</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Non recipients</th>
<th>All subsidy recipients</th>
<th>R&amp;D recipients</th>
<th>No R&amp;D recipients</th>
<th>Selective recipients</th>
<th>Automatic recipients</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>8.122</td>
<td>8.175</td>
<td>8.390</td>
<td>7.885</td>
<td>8.354</td>
<td>8.098</td>
</tr>
<tr>
<td><strong>St. Dev.</strong></td>
<td>0.907</td>
<td>0.881</td>
<td>0.873</td>
<td>0.815</td>
<td>0.726</td>
<td>1.000</td>
</tr>
</tbody>
</table>

**Legend:** LogTFP is estimated via Olley-Pakes methodology. The first column represents non awardees while the other columns represent different types of awardees.
<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>WG</th>
<th>GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log TFP_{it} )</td>
<td>0.127 (0.094)</td>
<td>0.027 (0.049)</td>
<td>0.615 (0.551)</td>
</tr>
<tr>
<td>( L1.Sub_{it} )</td>
<td>0.238 (0.110)**</td>
<td>0.065 (0.043)</td>
<td>0.045 (0.144)</td>
</tr>
<tr>
<td>( L2.Sub_{it} )</td>
<td>0.320 (0.110)***</td>
<td>0.068 (0.047)</td>
<td>0.052 (0.108)</td>
</tr>
<tr>
<td>( Age_{it} )</td>
<td>0.050 (0.010)***</td>
<td>0.015 (0.007)**</td>
<td>0.050 (0.012)***</td>
</tr>
<tr>
<td>( LocDevelop_{it} )</td>
<td>0.007 (0.002)***</td>
<td>-</td>
<td>0.007 (0.002)***</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Obs.</td>
<td>1064</td>
<td>1064</td>
<td>1064</td>
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<tr>
<td>Groups</td>
<td>238</td>
<td>238</td>
<td>238</td>
</tr>
<tr>
<td>Hansen Test</td>
<td>-</td>
<td>-</td>
<td>Chi2[16]=16.20</td>
</tr>
<tr>
<td>AR(1) Test</td>
<td>-</td>
<td>-</td>
<td>-1.88*</td>
</tr>
<tr>
<td>AR(2) Test</td>
<td>-</td>
<td>-</td>
<td>-1.03</td>
</tr>
</tbody>
</table>

\( \chi^2 \) Tests on groups of variables

\( L1.Sub_{it}=0 \) \( \chi[3,237]=3.19** \) \( \chi[3,817]=1.13 \) \( \chi2[3]=2.32 \)

\( L2.Sub_{it}=0 \) \( \chi[3,237]=3.19** \) \( \chi[3,817]=1.13 \) \( \chi2[3]=2.32 \)

\( L3.Sub_{it}=0 \) \( \chi[3,237]=3.19** \) \( \chi[3,817]=1.13 \) \( \chi2[3]=2.32 \)

\( \Delta T E(Sub) \) \( 0.685 (0.239)*** \) \( 0.160 (0.097)* \) \( 0.712 (0.670) \)

**Legend:** * p< .10; ** p< .05; *** p< .01. Estimates are obtained through a two-step GMM System model with finite sample correction. Std. Dev in round brackets, degrees of freedom in square brackets. All explanatory variables but Age and LocDevelop are treated as potentially endogenous and appropriately instrumented (3rd and 4th lags).
<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>WG</th>
<th>GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L1.\text{SelSub}_it$</td>
<td>-0.025 (0.168)</td>
<td>0.102 (0.085)</td>
<td>0.794 (0.454)*</td>
</tr>
<tr>
<td>$L2.\text{SelSub}_it$</td>
<td>0.551 (0.209)***</td>
<td>0.248 (0.079)***</td>
<td>0.528 (0.303)*</td>
</tr>
<tr>
<td>$L3.\text{SelSub}_it$</td>
<td>0.152 (0.219)</td>
<td>0.201 (0.073)***</td>
<td>0.307 (0.225)</td>
</tr>
<tr>
<td>$L1.\text{Sub}_it$</td>
<td>0.145 (0.120)</td>
<td>-0.014 (0.062)</td>
<td>-0.161 (0.410)</td>
</tr>
<tr>
<td>$L2.\text{Sub}_it$</td>
<td>-0.065 (0.146)</td>
<td>-0.069 (0.066)</td>
<td>-0.291 (0.134)**</td>
</tr>
<tr>
<td>$L3.\text{Sub}_it$</td>
<td>0.228 (0.159)</td>
<td>-0.050 (0.043)</td>
<td>-0.127 (0.108)</td>
</tr>
<tr>
<td>Age$_it$</td>
<td>0.049 (0.010)***</td>
<td>0.016 (0.007)**</td>
<td>0.043 (0.012)***</td>
</tr>
<tr>
<td>$\text{LocDevelop}_it$</td>
<td>0.007 (0.002)***</td>
<td>-</td>
<td>0.007 (0.002)***</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>6.997 (0.270)***</td>
<td>7.948 (0.076)***</td>
<td>6.734 (0.305)***</td>
</tr>
<tr>
<td>Obs.</td>
<td>1064</td>
<td>1064</td>
<td>1064</td>
</tr>
<tr>
<td>Groups</td>
<td>238</td>
<td>238</td>
<td>238</td>
</tr>
<tr>
<td>Hansen Test</td>
<td>-</td>
<td>-</td>
<td>Chi$^2[27]=29.54$</td>
</tr>
<tr>
<td>AR(1) Test</td>
<td>-</td>
<td>-</td>
<td>-2.16**</td>
</tr>
<tr>
<td>AR(2) Test</td>
<td>-</td>
<td>-</td>
<td>-1.61</td>
</tr>
</tbody>
</table>

**Chi² Tests on groups of variables**

$L1.\text{SelSub}_it=0$, $L2.\text{SelSub}_it=0$, $L3.\text{SelSub}_it=0$

<table>
<thead>
<tr>
<th></th>
<th>F(3,237)=3.43**</th>
<th>F(3,814)=4.58***</th>
<th>Chi$^2[3]=7.35$*</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L1.\text{Sub}+L1.\text{SelSub}=0$</td>
<td>0.120 (0.134)</td>
<td>0.088 (0.068)</td>
<td>0.633 (0.455)</td>
</tr>
<tr>
<td>$L2.\text{Sub}+L2.\text{SelSub}=0$</td>
<td>0.486 (0.146)***</td>
<td>0.179 (0.048)***</td>
<td>0.238 (0.230)</td>
</tr>
<tr>
<td>$L3.\text{Sub}+L3.\text{SelSub}=0$</td>
<td>0.380 (0.148)***</td>
<td>0.151 (0.066)**</td>
<td>0.180 (0.185)</td>
</tr>
<tr>
<td>ATE(Sub)</td>
<td>0.309 (0.344)</td>
<td>-0.132 (0.110)</td>
<td>-0.579 (0.391)</td>
</tr>
<tr>
<td>ATE(SelSub)</td>
<td>0.986 (0.323)***</td>
<td>0.418 (0.135)***</td>
<td>1.050 (0.764)</td>
</tr>
</tbody>
</table>

**Legend:** * p < .10; ** p < .05; *** p < .01. Estimates are obtained through a two-step GMM System model with finite sample correction. Std. Dev in round brackets, degrees of freedom in square brackets. All explanatory variables but Age and LocDevelop are treated as potentially endogenous and appropriately instrumented (3rd and 4th lags).
Table 6 – Third specification results

<table>
<thead>
<tr>
<th>LogTFP&lt;sub&gt;n&lt;/sub&gt;</th>
<th>OLS</th>
<th>WG</th>
<th>GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1.R&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.194 (0.203)</td>
<td>0.078 (0.110)</td>
<td>0.547 (0.560)</td>
</tr>
<tr>
<td>L2.R&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.495 (0.217)**</td>
<td>0.148 (0.072)**</td>
<td>0.508 (0.217)**</td>
</tr>
<tr>
<td>L3.R&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.654 (0.188)**</td>
<td>0.266 (0.107)**</td>
<td>0.550 (0.173)**</td>
</tr>
<tr>
<td>L1.R&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.193 (0.162)</td>
<td>-0.010 (0.060)</td>
<td>-0.221 (0.510)</td>
</tr>
<tr>
<td>L2.R&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.115 (0.203)</td>
<td>-0.106 (0.067)</td>
<td>-0.198 (0.164)</td>
</tr>
<tr>
<td>L3.R&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.414 (0.179)**</td>
<td>-0.013 (0.036)</td>
<td>0.062 (0.114)</td>
</tr>
<tr>
<td>L1.NoR&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.001 (0.174)</td>
<td>0.083 (0.081)</td>
<td>1.702 (1.830)</td>
</tr>
<tr>
<td>L2.NoR&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.452 (0.196)**</td>
<td>0.204 (0.061)**</td>
<td>0.269 (0.198)</td>
</tr>
<tr>
<td>L3.NoR&amp;DSel&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.210 (0.174)</td>
<td>0.105 (0.076)</td>
<td>0.127 (0.101)</td>
</tr>
<tr>
<td>L1.NoR&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.004 (0.173)</td>
<td>-0.024 (0.141)</td>
<td>-0.991 (3.027)</td>
</tr>
<tr>
<td>L2.NoR&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.237 (0.190)</td>
<td>0.019 (0.146)</td>
<td>-0.543 (0.369)</td>
</tr>
<tr>
<td>L3.NoR&amp;DAut&lt;sub&gt;i&lt;/sub&gt;</td>
<td>-0.186 (0.202)</td>
<td>-0.200 (0.149)</td>
<td>-0.930 (0.603)</td>
</tr>
<tr>
<td>Age&lt;sub&gt;n&lt;/sub&gt;</td>
<td>0.048 (0.010)**</td>
<td>0.016 (0.007)**</td>
<td>0.040 (0.015)**</td>
</tr>
<tr>
<td>LocDevelop&lt;sub&gt;n&lt;/sub&gt;</td>
<td>0.007 (0.002)**</td>
<td>-</td>
<td>0.005 (0.003)</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>7.037 (0.274)**</td>
<td>7.951 (0.076)**</td>
<td>7.062 (0.515)**</td>
</tr>
<tr>
<td>Obs.</td>
<td>1064</td>
<td>1064</td>
<td>1064</td>
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<tr>
<td>Groups</td>
<td>238</td>
<td>238</td>
<td>238</td>
</tr>
<tr>
<td>Hansen Test</td>
<td>-</td>
<td>-</td>
<td>Chi2[36]=34.27</td>
</tr>
<tr>
<td>AR(1) Test</td>
<td>-</td>
<td>-</td>
<td>-0.97</td>
</tr>
<tr>
<td>AR(2) Test</td>
<td>-</td>
<td>-</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Chi<sup>2</sup> Tests on groups of variables

- L1.R&DSel<sub>i</sub>=0
  - F(3,237)=6.92***
  - F(3,808)=2.56*
  - Chi2[3]=14.78***
- L2.R&DSel<sub>i</sub>=0
  - F(3,237)=2.90**
  - F(3,808)=3.88***
  - Chi2[3]=2.77
- L3.R&DSel<sub>i</sub>=0
  - F(3,237)=4.60***
  - F(6,808)=2.87***
  - Chi2[6]=21.50***

ATE(SelSub) 2.006 (0.652)***, 0.884 (0.276)***, 3.704 (2.094)*
ATE(R&DSel) 1.342 (0.462)***, 0.492 (0.207)**, 1.606 (0.729)**

Legend: * p< .10; ** p< .05; *** p< .01. Estimates are obtained through a two-step GMM System model with finite sample correction. Std. Dev in round brackets, degrees of freedom in square brackets. All explanatory variables but Age and LocDevelop are treated as potentially endogenous and appropriately instrumented (3rd and 4th lags).