The Short-run Impact on Total Factor Productivity Growth

of the Danish Innovation and Research Support System

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Foreword

As new initiative, the Danish Agency for Science, Technology and Innovation has initiated a comprehensive impact study of the Danish system of innovation and support systems. This is possible because of the Innovation Danmark database which has a comprehensive amount of information about the innovation and support programs. With this new information available, we have an obligation to make use of the new opportunities that is provided to us for creating new knowledge; not only about the innovation system itself, but about the way we assess the system.

The comprehensive information from the Innovation Danmark database makes it possible to assess the innovation system, which is a rare opportunity. During the work with this report I have received very positive feedback from colleagues regarding the collection of information and the opportunities that this presents. Also when presenting drafts of this report I have received positive and impressed comments regarding the level at which we assess the Danish system of innovation and support systems.

This report is first and foremost a methodology report on the edge of the research frontier of impact assessments. We have accepted the new possibilities of assessing the system, by trying to clear the impact effect from other sources. Therefore I advise the reader to be careful when interpreting the results of the report and for a deeper analysis of the individual innovation programs; I refer to the individual impact assessments of the innovation programs.

I hope the reader of this report will find it as enlightening and inspiring as we have and will use this as an inspiration for further studies of impact assessments.

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1. Introduction

This study performs the first joint estimation of the economic impact of innovation and research support programs. We focus solely on firms with less than 500 employees, and later restrict our analysis to firms with less than 100 employees.

This report features three important types of findings:

1) We quantify relative impact on productivity

2) We are the first who attempt to perform a causal study of multiple and simultaneous support programs[1]

3) We use the cleanest sample of participants and non-participants, to date, because for the first time we have access to extensive information about multiple program participation

We follow firms two years after participation, which is a short period. However, we have to make a compromise when aiming to cover as many programs as possible. This short window has two important downsides: 1) In programs, where we find higher productivity growth for participants, we cannot conclude on whether the effect on growth is a permanent effect, or 2) whether productivity growth rises in the short run because the participation effect induces a one-time lift to the productivity level.

Because we add strict criteria to avoid contaminated estimates, we perform our analyses on a sample of firms that most notably did not receive support two years before observed participation or two years following observed participation. These criteria apply to both participants and non-participants. We find that these criteria are necessary, as we wish to make causal inference on our estimates.

When estimating impact, we take into account the historical productivity performance of firms to rule out that firms participating were growing fast in the first place, and that we are simply picking a select group of firms that are growing faster.

Using our sample, we find that firms establishing contact with the support system, subsequently, on average, grow 2.5 percentage points faster annually the first two years, compared to non-participating firms. Behind this average estimate lies highly varying estimates for the individual programs.

Our main results (annual effects in percentage points) are that firms participating in *Innovation Network* (3.6), *Innovation Voucher* (3.6), and *Innovation Assistant* (2.9) tend to grow faster the first two years.[2] The qualitative results are robust to alternative specifications, however, when we limit our analysis to firms with less than 100 employees and control for firm individual productivity growth trends (depending on firms size), we find that effects are larger for some programs. While *Innovation Assistant* effects are robust to alternative specifications, *Innovation Networks* (4.3) and *Innovation Voucher* (4.1) effects are amplified, and *Innovation Consortia* (4.6) now enters significantly in the analysis. All of these programs are designed spur an increase of knowledge via the channels collaboration, *counseling or within-firm skill upgrading*.

We find no enhanced productivity growth following participation in *Industrial PhD* (negative but insignificant impact), which is in line

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[1] *Impact of several of the programs have been studied individually or grouped as for example "research projects". See e.g. CEBR (2009, 2011b, 2013a), DASTI (2011), DASTI & DAMVAD (2013), Kaiser & Kuhn (2012), and Chai & Shih (2013).*

[2] *Results are from the instrumental variable approach in TABLE 5.2. Consult the table for significance levels.*

with previous studies, and *Innovations Agents* (zero impact).3 The finding that Innovation Agents participation does not return differential growth is not surprising, but rather comforting. The *Innovation Agents* program is designed to give firms a "checkup" and then forward them to relevant private consulting or to other programs such as *Innovation Voucher*. One possible conclusion is that *Innovation Agents* check up on Danish firms with exhibiting productivity growth rates that are not different from that of the typical non-participating firm.

In the report we suggest other explanations for missing effects. One important circumstance is that this study does not look at productivity *levels*, only productivity *growth*. Thus, programs with no documented pro-

ductivity enhancing effects may still play an important role by, for example, helping highly productive firms to expand product markets (possibly export markets) and thereby grow. This is, however, not within the scope of this study, but we encourage further studies into other performance measures.

The report proceeds as follows: Section 2 describes the different innovation support programmes. Section 3 presents the data and how we construct the sample, while section 4 explains the estimation method. In section 5 we present the main results (section 5.1) of our analysis as well as results using alternative specifications for robustness check (section 5.2), before finally discussing of our results (5.3). We conclude in section 6.

3 *We have somewhat few observations on Industrial PhD to firmly conclude. We have enough observations to conclude on Innovation Agents. Consult sections 3 and 5.1 for further information on which programs we have too few observations to conclude upon.*

2. Description of innovation support programmes

The description of the programmes contained in this section was written by The Danish Agency for Science, Technology and Innovation (DASTI).

Danish Council for Strategic Research
The primary focus of the Danish Council for Strategic Research (CSR) is to promote excellent and relevant research that will be of benefit to future development and economic growth in Denmark. Hence, the research must be of high standard and lie within areas of research that is related to societal challenges. CSR offers a number of different support programmes (including SPIR) aimed at both private firms and research institutions.

EUopStart
Danish firms and research institutions may apply the EUopStart programme for a grant (up to 20,000 euros) when applying for participation in selected European and international research programmes. The grants cover different activities related to the application process such as salary, travel, conference and consultancy. The receiving firm or research institution has to put down 50 percent of the grant in self-financing.

Industrial PhD
The Industrial PhD programme aims at increasing knowledge sharing between universities and private sector firms, promoting research with commercial perspectives, and taking advantage of competences and research facilities in private firms to increase the number of PhDs with knowledge about industrially focused research and innovation. For this purpose, the Industrial PhD student is employed in a firm and enrolled at a university at the same time. The student spends all his or her time on the project both places and shares

his or her time equally between the firm and the university while taking the degree. The Danish Agency for Science, Technology and Innovation subsidises the Industrial PhD's salary with a fixed monthly amount and the expenses at the university with a fixed amount over the three years. A grant is approximately 134,000 euro divided between the firm and the university.

Eurostars
The Eurostars programme offers grants to small and medium sized firms (SME) and research institutions who participate in research and development programmes under the Eurostars programme. Hence, the Eurostars programme supports business-to-business cross border collaboration projects between enterprises from minimum two countries, and promotes market oriented R&D activities among research intensive SMEs. Grants amount to a maximum of 310,000 euros.

FP7
The Seventh Framework Programme is the European Union's chief instrument for public funding of research and for increasing private R&D. The Seventh Framework Programme is based on four principal programmes (Cooperation, Ideas, People and Capacities), with public sector bodies eligible to participate across all four. The major fields of research supported by the themes of the Cooperation programme are industry led and bring together public and private sector stakeholders to define research and development priorities, timeframes and action plans on a number of issues that are strategically important to achieving Europe's future growth, competitiveness and sustainability. The Marie-Curie actions funded under the People programme aims to increase mobility between public and

private sectors, as well as between countries. To this end they will support industry training, joint research partnerships and staff secondments between the two sectors. As well as specific actions to help SMEs, the Capacities programme aims to develop European research infrastructures, optimise their use and improve access for researchers, including from industry. It will also support regional research-driven clusters, involving enterprises as well as universities and local authorities.

Research Voucher

The Research Voucher scheme was offered in the period 2008-2009. It provided support for research based collaboration between SMEs and knowledge institutions (Universities, RTOs etc.). The purpose of the Research Voucher scheme was to enhance innovation in SMEs as well as to make public research more application-orientated. The financial support was solely for the activities in the knowledge institutions, and could be up to a maximum of 200,000 euros for projects with duration of up to 2 years. The financial support could not surpass 25 pct. of the total budget for the project. Support was granted at a first come, first served basis. A total of 17 projects were initiated under the Research Voucher scheme.

Gazelle Growth

The Gazelle Growth programme helped small firms achieving their growth potential on foreign markets – especially the US-market. Due to the size of the home market, especially small gazelle firms from small economies have to look at foreign markets sooner than small gazelle firms from big economies, if they want to grow. That can be at a time, where their network and knowledge of foreign market can be limited. With the Gazelle Growth programme small gazelle firms was advised and trained, so the entry on a foreign market can go faster and succeed then if they tried themselves. The Danish Gazelle Growth programme was terminated by the end of 2010.

The Danish National Advanced Technology Foundation

The Danish National Advanced Technology Foundation offers private firms and universities the funds and the framework for developing new and important technologies. The general objectives of the Danish National Advanced Technology Foundation is to enhance growth and strengthen employment by supporting strategic and advanced technological priorities within the fields of research and innovation. Up to this day the Foundation has invested in 273 advanced technology projects with a total budget exceeding 700 million euros. Half of the finance comes from firms and research institutions themselves. Average support per project is approximately 1.5 million euros with a support range of each project from 0.5 to 12 million euros.

Innovation Agents

The aim of the Innovation Agents is to create innovation in small and medium-sized firms. Innovation Agents are public funded consultants that help firms identify barriers to innovation by performing an "innovation check". The consultants identify the most important development opportunities for the firms and work closely together with regional growth houses and business advice offices to provide firms with one access point to the public innovation system.

Innovation Consortia

Innovation Consortia subsidies and facilitate collaboration projects between firms, research institutions and non-profit advisory and knowledge dissemination parties. The purpose of the programme is that the parties jointly develop knowledge or technologies that benefit not only individual firms but entire industries within the Danish business community. The joint projects should result in the completion of high-quality research relevant to Danish firms. Furthermore, the project should ensure that the new knowledge is converted into competences and services specifically aimed at firms, and that the acquired knowledge is subsequently spread widely to the Danish business community – including in particular

SMEs. A consortium can apply for financial grants at the Danish Agency for Science, Technology and Innovation, and the grants subsequently finance the expenses incurred by the research and knowledge institutions whilst undertaking the cooperative project. Typically grants amount to approximately 1-2 million euros.

Innovation Incubators
The objective of the innovation incubator programme is to promote commercialisation of new innovative ideas, inventions and research in particular through the creation of new knowledge based start-ups. The innovation incubators provide professional counselling and early stage gap funding (pre-seed and seed capital) for entrepreneurs and new innovative enterprises. The innovation incubators operate at the very early stage of the investment chain, where venture capitalists and other private investors are reluctant to engage. The innovation incubators funds 50 – 60 new knowledge based firms per year, and has a total budget of approximately 30 million euros.

Innovation Network Denmark (The National Danish Cluster Programme)
The Innovation Network Denmark programme supports the establishment of network and cluster organizations. An Innovation Network is a cluster organization with participation of all relevant Danish universities and technology institutes within a specific technological area, a business sector or a cross-disciplinary theme. Today a total of 22 innovation networks are scattered all over Denmark. Each network has pools for innovation projects where firms and researchers work together to solve concrete challenges. The innovation networks also carry out idea generation processes and matchmaking activities, and they hold theme meetings and specialist events. Hence, the overall objective for the innovation networks is to facilitate and encourage knowledge exchange between SMEs and knowledge institutions.

SPIR – Strategic Platforms for Innovation and Research
SPIR funds initiatives which seek to strengthen the link between strategic research and innovation and thereby promoting efficient knowledge dissemination and possibilities for fast application of new knowledge in connection with innovation in the private and public sectors. Typically grants amount to approximately 8 - 10 million euros.

Innovation Voucher
The Innovation Voucher scheme supports collaborative projects between a small or medium sized firm and a knowledge institution. The objective of the Innovation Voucher scheme is to encourage more SMEs to collaborate with universities, research and technology institutes and education institutions. The maximum amount of public support is 13,500 euro. The public support must not exceed 40 pct. of the total innovation project.

Innovation Assistant
The Innovation Assistant program provides an incentive for small and medium-sized firms to hire a highly educated person. The rationale is that highly educated people working on an innovative project promotes growth in the SMEs. The firm must have between 2 and 100 employees in order to receive subsidy (up to one year) to employ the highly educated person. Also the firm must pay at least half of the Innovation Assistants wages. Each grant is approximately 20,100 euro.

Open Funds
Open Funds where earmarked for innovative collaboration projects between firm and public knowledge institutions. The objective was to ensure that innovation projects that would benefit entire industries did not fall flat because they did not fit into the innovation system. Open Funds could finance up to 50 percent of a project. The programme was terminated in 2012.

3 Data

We use data from two different sources:

- The *Innovation Danmark* database created by the Danish Agency for Science, Technology and Innovation (DASTI) containing a list of firms that have received support (hereafter *participants*)
- Worker-firm matched registry data from Statistics Denmark

The databases have a common firm identifier that allows us to match the list of program participants with firm information. Firm information is crucial to performing impact assessment. We utilize information on value added, capital, number of employees, full-time employment, skills of employees, and industry (using the NACE3-classifiction)[4].

We have tried to combine the Innovation Danmark database with a different firm panel of annual reports data (Experian data, formerly also known as KOB-data). However, we are effectively able to match fewer participants using Experian data than through Statistics Denmark. Searching for missing matches after matching on firm identifier and year, is a much too comprehensive and ad hoc task for this project, as it involves searching through firm names in the panel data, or parts of names, from an extensive list of firm names that were not matched (either due to missing firm identifier (cvr-number) or, likely, mistyping in the Innovation Danmark database).[5] Why we find more mechanical matches using Statistics Denmark registry data, we cannot tell, because we do not control the data matching process (restricted for regulatory reasons to enforce anonymity of the firms in the registry data).

One advantage of Experian data over Statistics Denmark data is that it has one more year of observations (2012 over 2011). Some programs were introduced in later years, whereby adding one more year of observations would be very important to the analysis. However, due to the poor mechanical data match result, it does not add crucial information to the analysis.

For this analysis, we generally prefer data from Statistics Denmark to Experian data, because we can control for the skill of employees and use the effective size (full-time employment) of the firm level workforce instead of the number of employees. The skill level at participating firms is, on average, different from that of non-participants. Not controlling for the skill level introduces an upward bias on the impact assessment of productivity growth. Using the number of employees (the only available option in Experian data) instead of the fulltime equivalent number of employees (available in Statistics Denmark registry data) also creates a possible bias, because participating firms may differ from other firms in terms of the share of full time workers. Thus, we must compare firms using effective unit input of labor.

The Estimation Sample

Measuring productivity growth impact is not straightforward, because several circumstances affect firm performance. For instance, a natural bias of this sample is that we observe only firms that are neither bankrupt, bought up, nor reconstructed. We enforce strict criteria to isolate potential effects, implying that our sample shrinks from information of about 3,000 participation activities to about 1,100.

In this section we describe the process of creating the estimation sample(s). We illustrate the process in FIGURE 3.1 and TABLE 3.1, respectively.

4. *The NACE-classification (Nomenclature statistique des activités économiques dans la Communauté européenne) is the EU stan-dard industry classification.*

5. *CEBR (2011b) focused on the Industrial PhD program and were able to recover a substantive number of missing observations.*

We measure the impact of a particular program on firm performance relative to non-participating firms. We adjust the raw sample of firms from a set of criteria that are intended to center on capturing *participation effects*. Our point of reference is the *Raw Sample*, which is simply the result of matching the complete worker-firm panel of private Danish firms with the Innovation Danmark database. The raw sample spans from 2000-2011.

Using the full sample to measure these *participation effects* delivers an average firm performance difference between non-participants and participants. We control for a range of differences between firms based on statistical facts about the firms, and we leave out firms in industries where no participants are found. For an observation to be included we need a full set of information on each observation. The observations that fulfill the requirement of a full set of information make up the Estimation Sample.

We foremost use *Estimation Sample 1*, including all firms that have less than 500 employees and can be observed in a four year window.

The estimation samples are not just the result of mechanical changes to the data butalso the result of the chosen estimation strategy. The strategy imposes certain requirements to the data. We formally walk through the estimation strategy in section 4, but some of the criteria mentioned in this section are the result of the estimation strategy.

Using the same criteria as for *Estimation Sample 1*, we create *Estimation sample 2*, where the only altered criteria is that firm employment must be less than 100. We want to rule out as many biases as possible, i.e. in this case that firm size band is too wide. With so many programs and also repeated firm appearances in the support system we have to drop firm observations associated with participation before and after observed participation status in a given year.

TABLE 3.1 demonstrates how almost 11,000 observations of contact with the system in the Innovation Danmark database become about 1,100 observed participations in *Estimation Sample 1*.[6] We begin with the full Innovation Danmark database spanning from 2002 to 2012, imposing no criteria.[7] Here we have almost 11,000 observed participation activities from 8,300 firms. When we matched this data with the firm panel spanning from 2002 to 2011 (step 1 in TABLE 3.1), we drop more than 4,000 observations, most of which are from 2012.

We observe productivity growth development for two years. Thus, given that the last year of the sample is 2011, we can only measure impact on participation initiated no later than 2009. Therefore, we cut the number of observations in half to 3,100 by excluding information on support in 2010 and 2011 (step 2).

We limit our main analysis to firms with less than 500 employees, dropping more than 300 observations (step 3).

To measure productivity growth impact, we must observe productivity two years ahead and also other participation activity, dropping 800 observations (step 4).

Figure 3.1
Procedure to narrow the sample
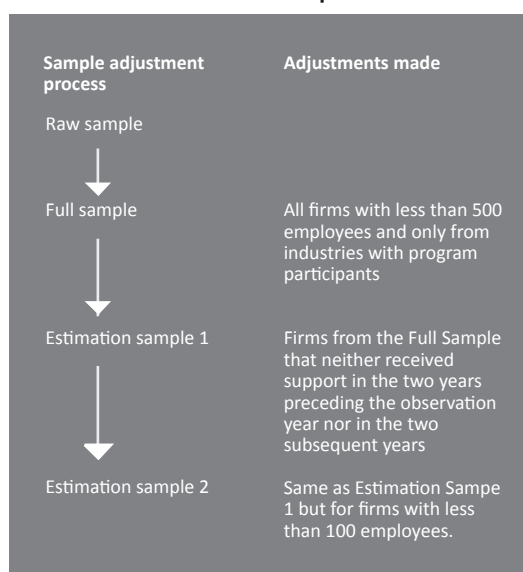
Sample adjustment process	Adjustments made
Raw sample	
Full sample	All firms with less than 500 employees and only from industries with program participants
Estimation sample 1	Firms from the Full Sample that neither received support in the two years preceding the observation year nor in the two subsequent years
Estimation sample 2	Same as Estimation Sampe 1 but for firms with less than 100 employees.

Notes: The figure shows the narrowing of the full sample of firms to comprise only relevant firms under stricter criteria.

Table 3.1

The effective number of participation observations in *estimation sample 1*

Steps	Criteria	First year	Last year	# obs.	# firms	# obs. /#firms	Revenue	Value added	Full-Time empl.
	None	2002	2012	10887	8307	1,310581	-	-	-
1	Matched with registry data	2002	2011	6409	4840	1,324174	449,0	149,0	249,4
2	Effective event window	2002	2009	3152	2488	1,266881	495,0	177,0	323,6
3	Firms with less than 500	2002	2009	2815	2357	1,194315	92,7	29,5	48,3
4	Observations required (forward-looking)	2002	2009	2022	1720	1,175581	109,0	36,8	55,0
5	Observations about the firm historical growth	2002	2009	1665	1424	1,169242	117,0	40,0	59,2
6	Only firms not participating in two years before nor after observed participation status	2002	2009	1096	1071	1,023343	94,5	32,0	46,2

Notes: The table step by step demonstrates each of the added criteria resulting in the final Estimation Sample 1.
Source: CEBR calculations using Innovation Danmark Database and Statistics Denmark registry data.

To control for historical productivity growth and participation activity adds further restrictions to the information criteria, dropping about 350 observations (step 5).

Finally, we restrict observations of participation to include only firm observations in those years where they did not receive support in the preceding two years and the following two years (step 6).

From TABLE 3.1 we observe that the number of observed participations across the 2002-2009 period is 1,096 split on 1,071 unique firms. Some few firms appear twice in the sample period. The 1,096 are indicative of activity.

Behind that aggregate number we find 1,140 individual program participation indications. These are shown in TABLE 3.2. Vertically the rows indicate the individual program. Horizontally, the columns indicate which types of programs fit into which group. We have seven groups but we include group 3 in group 2. Effectively, we can measure average group impact on group 2, 4, 6 and 7. Note that group 7 only comprises *Innovation Assistants*.

From TABLE 3.2, we see that the number of observed participations that fulfill all the necessary criteria to be included in *Estimation Sample 1* varies greatly from one program to another. For example, we have one observation of the *Danish Council for Strategic Research (DCSR),* but 327 on Innovation Networks. We are not able to make inference from the estimates of impact concerning participation in initiatives under *DCSR; SPIR, EUOpSTART and Eurostars* (all started recently); FP7 (started in 2007 and many applications made by large firms); *Research Voucher and Gazelle Growth* (few applicants, fewer observations); *The Danish National Advanced Technology Foundation* (effectively few observations).

Table 3.2

The effective number of observed program participations in *estimation sample 1*

Program	PROGRAMS GROUPS						
	1. Strategic research	2. Colla-boration	3. Intl. collaboration	4. Counceling and support	5. Financing	6. Industrial PhD	7. Skill enhancing employment
Danish Council for Strategic Research	1						
EUopSTART				0			
Industrial PhD						51	
Eurostars			0				
FP7			14				
Research Voucher		2					
Gazelle Growth				10			
The Danish National Advanced Technology Foundation		11					
Innovation Agents				252			
Innovation Consortia		91					
Innovation Incubators					2		
Innovation Networks				327			
SPIR		0					
Innovation Voucher Scheme		180					
Innovation Assistant							167
Open funds		32					
GROUP TOTALS	1	136	14	589	2	51	167

Notes: The table shows the effective number of observations found in Estimation Sample 1 and used for the main analysis (see construction procedure above). The horizontal grouping of the 16 individual programs has been determined in collaboration with the Danish Agency for Science, Technology and Innovation.
Source: CEBR work on Innovation Danmark Database and Statistics Denmark registry data.

Next, in section 4, we present the estimation strategy.

4 Method

In this chapter we discuss in general terms the estimation methods used. The estimation design must suit the impact measure, in our case: Productivity growth differences between participating firms and non-participants, ruling out as many other factors as possible that may also have an impact, but founded on a well-formulated production function. Productivity is directly related to the availability of technology to a firm and the firm's ability to utilize the available technology. This is referred to as total factor productivity (TFP). To measure TFP we must specify a production function. However, by the estimation method that we choose, we obtain productivity growth directly from a transformation of the production function.

A widely used method for estimating participation effects of a single program is a twin study using a matching estimator. In this type of study, we match participating firms with, statistically speaking, twin firms that do not participate. This estimation procedure has some advantages over, for example, linear regression models. Communicating the analysis is reasonably straightforward: 1) A clear-cut control group of non-participating firms similar to participants is constructed. Thus, we can argue that any found effects are likely the true isolated effects of participation. 2) Given certain assumptions, we can conclude that the effect found is causal.

Given these clearly attractive properties of matching methods, we still cannot rule out a well-specified regression model, which is more flexible. One important downside of matching is that we match on level variables, which are "snapshot" characteristics, because matching on growth patterns preceding participation is very complicated. Thus we may be

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BOX 4.1 PRODUCTIVITY GROWTH

When a firm uses inputs of production it incurs production costs. We can measure the total extra value created by the firm by subtracting production costs other than remuneration of capital and labor from revenue obtained from the sale of its production of goods or services. Economists refer to this extra value as value added. A firm can create more ***value added*** if it grows in size, for example by increasing capital use and/or hiring more labor. However, that does not per se imply increased production efficiency.

Often the public debate focuses on ***labor productivity***, which is simply valued added per employee. It is easy to calculate for descriptive purposes. However, labor productivity is indicative for comparing productivity differences across firms, industries (to some extent) etc. but does not take into account intensive use of capital. Thus, the productivity measure that we are interested in is one that takes into account the use of both labor and capital in production. Economists refer to this as ***total factor productivity***.

We measure ***total factor productivity growth*** as the growth in firm value added that cannot be attributed to increased use of capital or labor

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matching firms that at a snapshot in time have identical revenue, capital intensity, productivity level, workforce skill level, but actually follow two different dynamic paths. In such a case the firms are not suitable twin pairs to be compared.

The linear regression method (estimated using ordinary least squares, OLS) is still the best linear unbiased estimator available, and often we can justify that linearity of effects is a fair assumption. Measurement of growth differences is definitely such a case, and controlling for historical growth is uncomplicated, broadly used and well-described in the literature. Furthermore, we can specify our regression model and select our estimation sample such that any differences between a regression model and a matching procedure to assess impact of participation are, for practical purposes, eliminated.

4.1
Estimation

We rely on OLS estimation with fixed effects to estimate firm productivity growth from the firm level production function. Using this method, we can directly obtain a measure of participation effects from the estimates of productivity growth differences between participants and non-participants without having to estimate productivity separately for participants and non-participants in the first place.

We derive our estimating equation from a standard production function for firm i in year t:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\beta_1} L_{i,t}^{\beta_2}$$

(1)

Firm level value added, *Y*, is produced using capital *(K)* and labor *(L)* inputs, but also depends on firm level total factor productivity *(A)*. The total factor productivity level of a specific firm can be perceived as the result of available technology and its capabilities (e.g. strong management) to utilize labor and capital inputs. To see this, rewrite the production

function to include firm *i*'s individual productivity level component, c_i:'

$$Y_{i,t} = \left(c_i \widetilde{A_t} \right) K_{i,t}^{\beta_1} L_{i,t}^{\beta_2}$$

(2)

Hence, firm level total factor productivity, $A_{i,t}$, is the scale product of cross-firm common technology $\widetilde{A_t}$ and firm individual ability to take advantage of common technology, c_i (i.e. the firm fixed effect).

Under the assumption that the above specification holds, each firm has an intrinsic productivity growth potential, because the individual component acts as a scale factor on firm productivity growth from changes in $\widetilde{A_t}$. This intrinsic ability of a firm to utilize available technology is unobservable. For shorter time periods we assume that this unobservable characteristic of the firm remains constant. Consequently, we focus on fixed effects estimation, which deals with time-constant unobservable characteristics. We therefore do not worry about the firm individual component c_i.

Taking logs of the production function (represented below by small letters) we can write up a basic estimating equation (leaving out potential control variables) for the production function:

$$y_{i,t} = c_i + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \varepsilon_{i,t}$$

(3)

Note the unobserved fixed effect of firm (*i*). We can remove the unobserved individual fixed effect by taking first differences (Δ), and when we then add some control variables and a participation indicator variable we arrive at our core estimating equation:

$$\Delta y_{i,t} = \alpha + \beta_1 \Delta k_{i,t} + \beta_2 \Delta l_{i,t} + \beta_3 education_{i,t} + \sum_{s=1}^{N} \gamma_s participation_{i,s,t} + \delta_j + \eta_t + \Delta \varepsilon_{i,t}$$

(4)

We estimate the linear regression model above using pooled OLS.

8 *Unless we specify another forward year, we always consider two-year forward differences.*

Our dependent variable is Δy_t measured in log points between time t and $t+2$.[8] This gives us the percentage point growth in firm total value added. We account for the growth contribution to value added from increasing use of capital and labor resources.

We choose a two-year lead period for two reasons. First, we find one year to be too short, and second, we lose too many observations if we use longer lead periods.

An observable variable, which is an indicator for a firm's ability to absorb new technology, is whether the firm a priori is skill intensive. Our fulltime equivalent labor stock variable cannot be divided into different skill types of labor. Thus, to account for the fact that labor is a heterogeneous input, we introduce a variable accounting for the initial share of workers that hold at least a bachelor degree. Furthermore, we account for industry specific trends in productivity growth (δ_j), and time varying trends in productivity affecting all firms (η_t).

Apart from accounting for the initial relative skill level of firm labor stock, we do not add further level variables (such as size or productivity level) to our estimating equation, because we stick to our model specification, i.e. the production function. Adding further variables on an ad hoc basis distorts the theoretically motivated estimation strategy. As explained above, the share of high skill workers is justified from the criteria of acting as a proxy for labor quality. In section 5.2 we perform robustness checks, adding level control variables.

We measure whether an average trend difference in Δy_t exists between firms receiving support and firms not participating. Thus, we obtain an estimate of potential participation effects from the coefficient(s) γ_s on the participation indicator variable(s) ($participation_{i,s,t}$).[9] The subscript s indexes the number of up to N different programs (or groups of programs) in question.[10]

By using first differences estimation, we eliminate unobserved time-invariant firm fixed effects that may drive firm-specific productivity growth effects. In the longer run, this may turn out to be a strict assumption. If firms enter an innovation support program that initiates a new firm specific growth trend, then we are dealing with time-varying firm effects. However, in the short event windows that we measure impact, we do not consider this to be a likely source of inconsistency.

We effectively measure annual productivity growth rates over two years for all firms that received support in any given year from 2002 to 2009 and compare them with non-participating firms.

FIGURE 4.1 illustrates the principle of measuring participation. Participation can happen in any year, but we only include an observation if a firm has no participation activity before nor after the observation year – in this case the observation year is 2005. From 2003 to 2005 neither firm participates. In 2005 some firms participate and some do not. We effectively compare firm productivity growth rates between 2005 and 2007, taking into account a range of other sources of productivity growth. Thus we can isolate the potential participation effect.

What happens after two years? We do not know. Will the firm remain on a higher productivity growth path? Intuitively that seems unlikely that entering a program suddenly transforms how a firm runs its business in any situation. We find it reasonable to assume that a firm temporarily grows faster than it would have and that the observed increased productivity growth rate is a combination of the normal, underlying growth rate and a one-time increase in productivity.

9 We do not consider dynamic additive effects between programs, e.g. that firms join one program in 2003 and another program in 2007. We showed in section 3, that very few firms are represented multiple times, across time, in our sample.

10 We also measure the overall impact of participating in any program. In this case we have just one indicator variable, participation$_{i,s,t}$, and the following estimating equation:

Figure 4.1

Assessment of impact on firm productivity growth from participating in a program
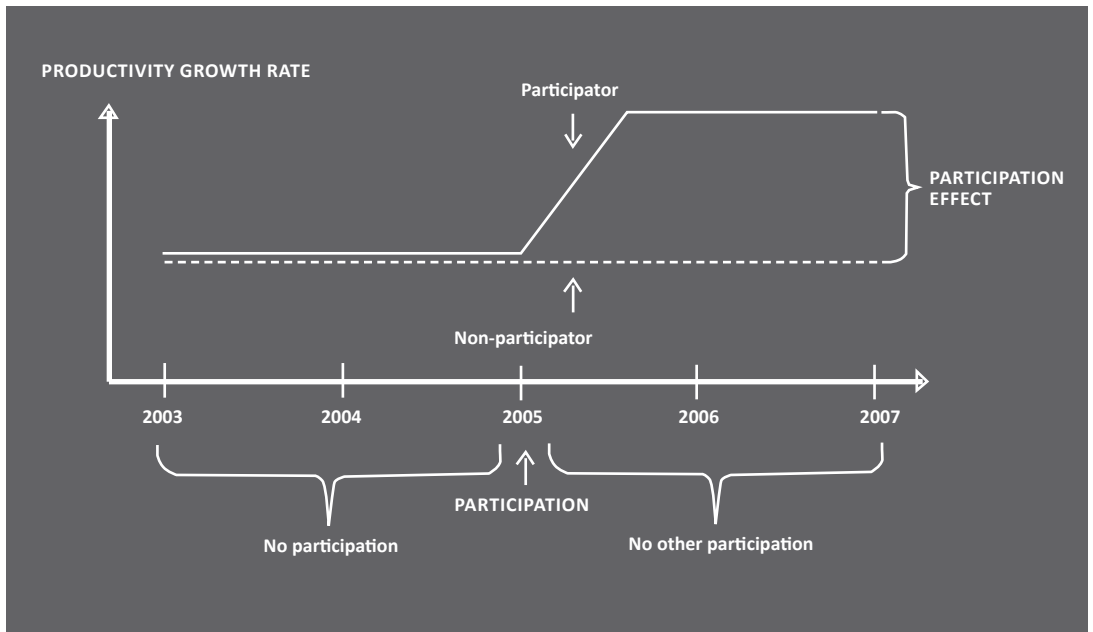
Notes: The figure shows the narrowing of the full sample of firms to comprise only relevant firms under stricter criteria.

Selection

A concern when performing impact assessment of programs that are designed to spur innovation and R&D activities is that the firms receiving support irrespective of participation or not have the potential to innovate and increase productivity growth, or plainly grow at a faster pace. One descriptive fact is that firms that innovate tend to employ more intensively highly educated workers (see CEBR 2013b). Our inclusion of the share of highly educated workers at the time program participation is initiated can account for this possible confounding effect. The inclusion of this information accounts for trend differences stemming from unleashed productivity potential of a highly educated workforce in participating firms that initially deliver relatively low productivity levels.[11]

However, participating firms could already be growing at a faster pace than non-participants. Clearly we must address this issue.

One way is to specify a lagged dependent variable model by adding lagged productivity to equation (3). This gives us the following fixed effect specification of a lagged dependent variable model (LDP) as an alternative to equation (4):

$$\Delta y_{i,t} = \ \alpha + \theta \Delta y_{i,t-2} + \beta_1 \Delta k_{i,t} + \beta_2 \Delta l_{i,t} + \beta_3 education_{i,t}$$

$$\sum_{s=1}^{N} \gamma_s participation_{i,s,t} + \delta_j + \eta_t + \Delta \varepsilon_{i,t}$$

$$(5)$$

We estimate the above equation using pooled OLS.

If the decision to participate in a program at time t is correlated with growth in productivity leading up to time *t, $\Delta y_{i,t-2}$*, then leaving out $\Delta y_{i,t-2}$ (as in equation 4) will bias the estimated coefficient of participation, γ_s. If θ<0, the estimate will be biased downward if we leave out $\Delta y_{i,t-2}$, and if θ>0, the

11 The underlying motivation for assuming productivity potential from highly educated workers comes from numerous correlation studies that document the relationship

estimate will be biased upwards if we leave out $\Delta y_{i,t-2}$. Note that, in general, we do not need $\Delta y_{i,t-2}$ but only $\Delta y_{i,t-1}$ (i.e. a one period difference from t-1 to t). We use two periods because 1) it is more stable to use annualized growth rate over two periods, and 2) we are looking back two periods anyway to observe prior participation activity.

The fixed effects specification of the LDP model suffers from $\Delta y_{i,t-2}$ and $\Delta \varepsilon_{i,t}$ being correlated by construction, making the OLS estimator never fully consistent.

Instead of accounting for the omitted variable bias using a fixed effects LDP model we can use a two-stage least squares (2SLS) approach, instrumenting lagged productivity growth with further lags of the productivity level.[12] This instrumental variable (IV) approach will account for selection of firms that were already growing at faster pace before participating in a program.

As we described in section 3, the estimation samples only include participating and non-participating firms that did neither receive support two years before the starting year of the observed difference or during the two subsequent years we observe firm performance.

Thus, using a clean sample of participation activity, accounting for lagged productivity growth both using the LDP approach and performing an IV estimation taking into account historical productivity growth, delivers a sound foundation for estimating participation effects.

In the next section we present the results of performing the simple pooled OLS fixed effects estimation not account for historical growth (equation 4), pooled OLS fixed effects estimation of the LDP model (equation 5), and the 2SLS IV approach.

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12 *Anderson & Hsiao (1981) suggested the idea of using productivity levels lagged two periods as an instrument for productivity growth lagged one period. See Verbeek (2008) for a discussion of the method and alternative specifications. See also Nickell (1981) and Angrist & Pischke (2009). Griffith, Redding & Van Reenen (2004) argue to use IV approach for robustness if TFP measurement error is a concern.*

5 Results

In this section we present the results from applying the methods we discussed in section 4. We present results based on *Estimation Sample 1* (firms with less than 500 employees) in section 5.1, while presenting results of alternative specifications for robustness checks in section 5.2.

We present the resulting estimates starting with the overall average effect of participation without distinguishing between the programs. From that general average estimate of contact with the support system, we search for individual participation effects of the 16 programs. However, we do have a sufficient number of observations for all programs to conclude upon, which is why we finally supplement with estimated participation effects based on groups of programs.

All estimations are carried out on a panel dataset of firms that received support within the period 2002-2009. We estimate participation effects with and without controlling for *historical productivity growth*, defined as the annualized growth rate in the two years leading up to participation. In order to avoid estimates contaminated by time-overlapping support, we effectively rule out observations from firms that also received support two years before or after observed participation. All these criteria are described in detail in section 3.

In section 5.1 we present the main results, and elaborate further in section 5.3, commenting on circumstances and how they relate to other papers and reports that have measured effects of individual programs. In section 5.2 we test the robustness of the estimates using alternative samples and adding more control variables.

5.1
Main results

A few general comments about all estimations in this section can be made: The models exhibit significant coefficients with an adjusted R2 of about 0.3. A high R2 with insignificant variables would be an indicator of multicollinearity issues among the explanatory variables and possibly with omitted variables. Multicollinearity inflates standard errors of explanatory variables and causes wide range of insignificant estimates. Thus, even if we, beforehand, checked the cross-correlations between the explanatory variables, we might mistakenly conclude that missing effects were the result of reality, but in fact influenced by multicollinearity with omitted variables

-       Firms in contact with the support system increased productivity growth by 2.5-2.9 percentage points, on average, following program participation.

TABLE 5.1 presents the results of simply estimating whether firms that entered any program subsequently had higher productivity growth than firms that did not have contact with the support system.

Column (1) shows the results of a pooled OLS estimation, where we do not take lagged productivity growth into account when estimating the effect of participation on subsequent productivity growth. The results suggest that participating firms on average grew 2.5 percentage points faster per year over two years following project initialization. Not controlling for former performance, however, unquestionably introduces a potential bias that we must account for.

When we account for historical productivity growth (a lag dependent OLS specification), defined as growth in the two years leading up to project initialization, we observe that serial correlation exists for the dependent variable in the estimation. The estimates suggest that participating firms grew 2.9 percentage points faster that non-participants. One concern in the literature when dealing with TFP measurement is measurement error. If measurement error is a risk, the OLS estimates in column (2) could be biased. One approach to correct this problem is to instrument historical growth. The results are shown in column (3). Using this approach, we observe that the participation effect is similar to the simple OLS estimate in column (1). However, we can then not conclude that the specification in column (1) is correct. We can conclude only on columns (2) and (3).

We also observe that the concern for not controlling for the share of high skilled workers is not, relatively speaking, a primary bias concern in this case. However, while it contributes to productivity with highly significant estimates, an estimated coefficient of 0.01 suggests that at the starting point for performance measurement, a firm with 10 percentage points higher skill share compared to another firm predicts 0.1 percentage points higher annual productivity.

The estimates in TABLE 5.1 are very generalizing, because participation covers 16 programs, some of which are very different programs. In TABLE 5.2 we present the resulting estimates from measuring participation effects from each of the 16 different programs.

- The detailed participation effects obtained from individual programs show evidence of variation ranging from no significant difference with non-participants to 4.1 percentage points higher productivity growth rates.

We described, earlier in section 3, that we do not have enough observations to conclude on some of the programs, and in general we only have a reasonable number of observed participations on a few programs. These programs include *Innovation Agents* (252), *Innovation Consortia* (91), *Innovation Networks* (327), *Innovation Voucher*, and *Innovation Assistant* (167). These programs and also Industrial PhD (51) and Open Funds (32) are presented in TABLE 5.2. The rest are left out of the tables as we have even fewer observations, however, they are included in the estimation.

As in TABLE 5.1, we refrain from concluding on the results from the model in column (1) that

Table 5.1

Average effect on annualized productivity growth from participation in any program

	1 OLS	2 OLS (LDP)	3 IV
Participation	0.0246*** (0.00720)	0.0293*** (0.00678)	0.0247*** (0.00718)
High skill share	0.0100*** (0.00327)	0.0134*** (0.00315)	0.0101*** (0.00326)
Historical productivity growth		-0.211*** (0.00277)	-0.00505 (0.00514)
Observations	350,429	350,429	350,429
Unique firms	87,719	87,719	87,719
Participations	1,140	1,140	1,140
Adjusted R2	0.284	0.332	0.286

Notes: All estimations are based on (first difference) fixed effects estimations and include controls for time variation and industry trends (NACE3) (see section 4.1). The dependent variable is firm valued added growth (log points) controlling for (log point) labor and capital growth (i.e. a proxy for productivity growth). Effects cover program participation observed from 2002 to 2009. Only firms that did not receive support two years before and after observed participation/non-participation are included. Historical productivity growth refers to twoyear lagged productivity growth. ***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively.
Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

does not take into account historical productivity growth. The results on *Industrial PhD* and *Innovation Agents* do not indicate any effects. Firms participating in *Innovation Consortia* are significant at the 10 percent level in the LDP specification but (borderline) insignificant in the IV specification, suggesting a weak tendency to higher average growth rates of 4.1 to 2.7 percentage points.

While observations on *Industrial PhD* and *Innovation Consortia* are somewhat few in numbers to firmly conclude on, we have enough observations to conclude that firms associated with *Innovation Agents* do not, on average, subsequently grow faster than firms not associated with participation. The estimated coefficient is close to zero and insignificant.

Innovation Networks, *Innovation Voucher*, and *Innovation Assistant* show evidence of participation effects.

Significant at the 1 and 5 percent level (LDP and IV respectively), the estimates of 4.0 and 3.6 percentage points for *Innovation Networks* clearly indicate that firms participating in *Innovation Networks* subsequently grow at a faster pace than other firms.

Firms active within the *Innovation Voucher* program show effects of around 3.5 percentage points at the 10 percent significance level. Firms that made use of the *Innovation Assistant* program to hire their first highly educated workers significantly (1 percent level) increased productivity up to 4.1 percent faster annually than other firms, according to the LPD specification. Using the IV specification, borderline significant at the 5 percent level, the average estimated effect was a little lower, 2.9 percentage points.

Table 5.2

Effect on annualized productivity growth from participation in a specific program

	1 OLS	2 OLS (LDP)	3 IV
Industrial PhD	-0.0127 (0.0394)	0.00173 (0.0361)	-0.0124 (0.0392)
Innovation Agents	-0.00273 (0.0144)	-0.000977 (0.0129)	-0.00269 (0.0144)
Innovation Consortia	0.0271 (0.0182)	0.0405* (0.0219)	0.0274 (0.0182)
Innovation Networks	0.0360** (0.0141)	0.0397*** (0.0134)	0.0361** (0.0140)
Innovation Voucher	0.0357* (0.0205)	0.0343* (0.0177)	0.0356* (0.0204)
Innovation Assistant	0.0289* (0.0150)	0.0407*** (0.0142)	0.0292* (0.0149)
Open funds	0.0348 (0.0246)	0.0380* (0.0224)	0.0349 (0.0245)
High skill share	0.0100*** (0.00327)	0.0134*** (0.00315)	0.0101*** (0.00326)
Historical productivity growth		-0.211*** (0.00277)	-0.00505 (0.00514)
Observations	350,429	350,429	350,429
Unique firms	87,719	87,719	87,719
Participations	1,140	1,140	1,140
Adjusted *R2*	0.284	0.332	0.286

Notes: All estimations are based on (first difference) fixed effects estimations and include controls for time variation and industry trends (NACE3) (see section 4.1). The dependent variable is firm valued added growth (log points) controlling for (log point) labor and capital growth (i.e. a proxy for productivity growth). Effects cover program participation observed from 2002 to 2009. Only firms that did not receive support two years before and after observed participation/non-participation are included. Historical productivity growth refers to twoyear lagged productivity growth ***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively. For presentation reasons, the table presents only programs with a minimum of 32 observations (Open funds). "Industrial PhD" (51) and "Innovation Consortia" (91) also have less than 100 observations (see TABLE 3.2).

Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

The final program estimate that we have not commented on is the Open funds program. Here we find rather weak evidence of growth effects. Whether this is a correct finding or not, regarding both the level and missing significance is unclear, as 32 observations are too few to conclude upon. If we want to somehow conclude indirectly on a program such as Open Funds, we must group the program with other similar programs.

As discussed earlier the programs can be grouped into broader categories of program types. In TABLE 5.3, we present results from grouping the individual programs. As in the previous table, we present only results for groups with a reasonably sufficient amount of observations. Of the four groups presented, *Industrial PhD, and Innovation Assistant* remain ungrouped. The two other groups are *Collaboration and Counseling and Support*.

- Grouping individual programs documents statistically significant and positive subsequent productivity growth for the three program groups Collaboration, Counseling and Support, and Skill enhancing employment (i.e. Innovation Assistant).

The resulting estimates from grouping the programs are influenced by the underlying individual program estimates presented earlier. 96 percent of the observations in *Collaboration cover Innovation Consortia, Innovation Voucher,* and *Open Funds*, all with positive individual coefficient estimates of 2.7-4 percentage points.

For *Counseling and Support*, however, 98 percent of the observations cover *Innovation Networks* (56 percent) and Innovation Agents (43 percent) with very different estimates (see TABLE 5.2). Therefore, not surprisingly, *Collaboration* programs come out with a higher average estimate of participation effects compared to *Counseling and Support* programs. With effectively so few individual programs behind the average estimate we find it hard to argue that Collaboration projects in general are more fruitful than *Counseling and Support* projects. We leave that discussion up to the reader.

5.2
Robustness

In this section we briefly present results from adding more control variables, and results

Table 5.3

Average effect on annualized productivity growth from participation in a program type

	1 OLS	2 OLS (LDP)	3 IV
Collaboration	0.0375** (0.0147)	0.0371*** (0.0137)	0.0375** (0.0147)
Counseling and support	0.0198* (0.0101)	0.0237** (0.00950)	0.0199** (0.0101)
Industrial PhD	-0.0130 (0.0394)	0.00170 (0.0361)	-0.0127 (0.0392)
Skill enhancing employment	0.0282* (0.0149)	0.0399*** (0.0142)	0.0285* (0.0149)
High skill share	0.0100*** (0.00327)	0.0135*** (0.00315)	0.0101*** (0.00326)
Historical productivity growth		-0.211*** (0.00277)	-0.00507 (0.00514)
Observations	350,429	350,429	350,429
Unique firms	87,719	87,719	87,719
Participations	1,140	1,140	1,140
Adjusted *R2*	0.284	0.332	0.286

Notes: All estimations are based on (first difference) fixed effects estimations and include controls for time variation and industry trends (NACE3) (see section 4.1). The dependent variable is firm valued added growth (log points) controlling for (log point) labor and capital growth (i.e. a proxy for productivity growth). Effects cover program participation observed from 2002 to 2009. Only firms that did not receive support two years before and after observed participation/non-participation are included. Historical productivity growth refers to two-year lagged productivity growth. ***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively. For presentation reasons, the table presents only groups with a minimum of 50 observations (see TABLE 3.2). "Collaboration" covers both national and international collaboration (see TABLE 3.2).

Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

using *Estimation Sample* 2 that is identical with Estimation Sample 1 except for covering only firms with less than 100 employees.

Adding size control to the main estimations

We have already argued why we use the specified models (i.e. LDP and IV models with fixed effects). Thus, we are confident in using these models to measure productivity effects. For the main estimation results we have included central variables that influence firm trend productivity growth. Only one of these is a level variable specific to the firm. Thus, one can argue that firm trend growth may be heterogeneously influenced at the firm level: Large firms may increase productivity at a slower pace than smaller low-productive firms catching up, or large firms may increase productivity faster because they are well-established and ready to embrace new technology or knowledge. Thus, we add level variables indicating firm size before observed productivity growth (i.e. at year t before observing productivity growth from year t to year t+2).

TABLE 5.4 shows the results of adding labor stock (columns 1 and 4) and revenue (column 2 and 5), separately and jointly (columns 3 and 6), to account for the possibility that historical productivity growth does not capture trends of firms of certain size in terms of number of employees or revenue. Columns 1 and 2 show the results of adding labor stock and revenue separately for the LDP model specification, while columns 3 and 4 show the results of adding labor stock and revenue separately for the IV model specification.

Recall that we are already controlling for industry effects. Thus, when controlling for any size effects that may be attributed industry (and also other controls), firm size in terms of revenue is associated with below average subsequent productivity growth (-0.8 to -0.4 percentage points). Labor stock, on the other hand, is positively associated with subsequent productivity growth (0.6 to 1.1 percentage points).

Table 5.4

Robustness: adding more control variables to the LDP and IV models

	1 OLS (LDP)	2 OLS (LDP)	3 OLS (LDP)	4 IV	5 IV	6 IV
Industrial PhD	-0.0195 (0.0362)	0.00986 (0.0361)	-0.0105 (0.0362)	-0.0284 (0.0403)	0.00880 (0.0379)	-0.0141 (0.0388)
Innovation Agents	-0.00753 (0.0128)	0.00157 (0.0129)	-0.00520 (0.0127)	-0.0069 (0.0149)	0.00278 (0.0137)	-0.0043 (0.0139)
Innovation Consortia	0.0270 (0.0225)	0.0469** (0.0218)	0.0457** (0.0226)	0.0161 (0.0184)	0.0448** (0.0189)	0.0427** (0.0193)
Innovation Networks	0.0278** (0.0135)	0.0447*** (0.0134)	0.0368*** (0.0132)	0.0283** (0.0144)	0.0470*** (0.0137)	0.0390*** (0.0137)
Innovation Voucher	0.0260 (0.0179)	0.0377** (0.0177)	0.0306* (0.0175)	0.0312 (0.0213)	0.0415** (0.0191)	0.0349* (0.0196)
Innovation Assistant	0.0358** (0.0142)	0.0424*** (0.0142)	0.0352** (0.0140)	0.0232 (0.0154)	0.0370** (0.0144)	0.0270* (0.0145)
Open funds	0.0222 (0.0227)	0.0445** (0.0225)	0.0312 (0.0245)	0.0249 (0.0257)	0.0483** (0.0236)	0.0349 (0.0267)
Labor stock (log)	0.0111*** (0.0004)		0.0525*** (0.0009)	0.0064*** (0.00042)		0.0583*** (0.00093)
Revenue (log)		-0.0044*** (0.00041)	-0.0461*** (0.0009)		-0.0083*** (0.0004)	-0.060*** (0.001)
High skill share	0.0159*** (0.0031)	0.0136*** (0.0032)	0.0262*** (0.0031)	0.0106*** (0.0033)	0.0116*** (0.00320)	0.0250*** (0.0032)
Historical productivity growth	-0.213*** (0.0028)	-0.209*** (0.0028)	-0.202*** (0.0027)	0.0496*** (0.0032)	-0.0828*** (0.0027)	-0.031*** (0.0026)
Observations	350,429	350,380	350,380	350,429	350,380	350,380
Participators	1,140	1,140	1,140	1,140	1,140	1,140
Adjusted *R2*	0.334	0.332	0.344	0.259	0.316	0.313

Notes: The table shows re-specifications of columns (2) and (3) in TABLE 5.2. For technical notes, consult the notes in TABLE 5.2.***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively.
Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

We see that the two added controls affect the estimates and standard errors differently, and they affect different programs differently:

-   Conclusions on the estimates for *Industrial PhD* and *Innovation Agents* remain unchanged.
-   Estimates for *Innovation Consortia* turn insignificant and become smaller when controlling for labor stock (column 1 and 4), but turn significant at the 5 percent level and larger when controlling for revenue instead (Column 2 and 5).When adding both controls simultaneously the estimates are significant at the 5 percent level and higher than the main results estimates.
-   Estimates for *Innovation Networks* are robust to adding controls though the size of the estimates change somewhat
-   Estimates for *Innovation Assistant* changes are not notably affected by the joint adding of the two controls.
-   Conclusions on *Open Funds* (few observations) are unchanged, as estimates are not considerably influenced, and standard errors tend to become somewhat larger.

Some concerns when adding further controls are that these controls introduced are correlated with other control variables (e.g. if size is largely determined by industry), and that using the first difference method to eliminate fixed effects also removes variation in the first place. Thus, it can be hard to argue why some estimates turn insignificant. Is it caused by better controls or lost variation? The overall impression, though, is that adding the controls proves robustness of the estimation strategy, because the main results, in general, are confirmed. In some cases the estimates (e.g. Innovation Consortia) increase more than the standard errors are inflated, thus turning more significant. It is tempting to conclude, that the added controls result in a more well specified model. However, we stick to our initial specification, because we argue from a well-known theoretical setup, where we have not modeled size heterogeneity.

Results for smaller firms

Now we focus on estimations using *Estimation Sample 2*, i.e. the sample that uses the same criteria as *Estimation Sample 1*, except for limiting the analysis to firms with less than 100 employees.

TABLE 5.5

Robustness: average effect on productivity growth from participation in any program - firms with less than 100 employees

	1 OLS (LDP)	2 OLS (LDP)	3 OLS (LDP)
Participation	0.0266*** (0.00819)	0.0323*** (0.00767)	0.0266*** (0.00820)
High skill share	0.00950*** (0.00330)	0.0131*** (0.00317)	0.00949*** (0.00329)
Historical productivity growth		-0.211*** (0.00277)	0.000825 (0.00500)
Observations	342,255	342,255	342,255
Unique firms	86,510	86,510	86,510
Participations	942	942	942
Adjusted *R2*	0.282	0.330	0.281

Notes: All estimations are based on (first difference) fixed effects estimations and include controls for time variation and industry trends (NACE3) (see section 4.1). The dependent variable is firm valued added growth (log points) controlling for (log point) labor and capital growth (i.e. a proxy for productivity growth). Effects cover program participation observed from 2002 to 2009. Only firms that did not receive support two years before and after observed participation/non-participation are included. Historical productivity growth refers to two-year lagged productivity growth. ***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively.
Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

Although limiting the analysis in the first place to firms with less than 500 employees removes the concern of inherent differences between small firms and very large firms, we still have to address the concern that the firm size band is still too large, and that relatively small initiatives cannot be interpreted as firm productivity growth improvements. The *Innovation Assistant* program, for example, supports firms with less than 100 employees, but in the main analysis, we compare these firms with firms that have more than 100 employees. A criticism to the analysis can be therefore that, despite adding size controls in the robustness check, we are comparing with firms that never could apply or take advantage of this program. Limiting the analysis to firms with less than 100 employees addresses such an issue for this particular program.

For some programs, the number of observations drops in relatively large numbers. For others, the number remains relatively large. The overall number of observed participations drops from 1,140 to 942. Thus, we keep 82 percent of the observations from *Estimation Sample 1*, while *Industrial PhD* falls from 59 to 31, *Innovation Consortia* from 91 to 59, and *Open Funds* from 32 to 24. The rest of the programs presented earlier are still relatively well-represented compared to *Estimation Sample 1* (firms with less than 500 employees): *Innovation Assistant* (unaffected, program criteria), *Innovation Voucher* and *Innovation Agents* (93 percent), and *Innovation Networks* (81 percent).

TABLE 5.5 presents the average participation estimate from having contact with the innovation and research support system. The results show, that the estimates increase slightly from a span of 2.5-2.9 percentage points extra productivity growth to 2.7-3.2 percentage points.

TABLE 5.6

Robustness: effect on productivity growth from participation in a specific program - firms with less than 100 employees

	1 OLS	2 OLS (LDP)	3 IV
Industrial PhD	-0.0409 (0.0614)	-0.0184 (0.0562)	-0.0410 (0.0614)
Innovation Agents	-0.00381 (0.0153)	-0.00293 (0.0136)	-0.00382 (0.0153)
Innovation Consortia	0.0268 (0.0252)	0.0518* (0.0311)	0.0267 (0.0252)
Innovation Networks	0.0406** (0.0168)	0.0449*** (0.0159)	0.0406** (0.0168)
Innovation Voucher	0.0413* (0.0218)	0.0396** (0.0189)	0.0413* (0.0218)
Innovation Assistant	0.0294* (0.0152)	0.0415*** (0.0144)	0.0294* (0.0152)
Open funds	0.0399 (0.0299)	0.0438 (0.0269)	0.0398 (0.0299)
High skill share	0.00953*** (0.00330)	0.0131*** (0.00317)	0.00952*** (0.00329)
Historical productivity growth		-0.211*** (0.00277)	0.000842 (0.00500)
Observations	342,255	342,255	342,255
Unique firms	86,510	86,510	86,510
Participators	942	942	942
Adjusted *R2*	0.282	0.330	0.281

Notes: The table follows the setup in TABLE 5.2.***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively.
Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

Turning to the individual programs, in TABLE 5.6, we see that inference made from *Innovation Consortia, Innovation Networks, Innovation Voucher*, and *Innovation Assistant* remain unchanged. Some estimates have increased by a minor factor of about 1/10.

Finally, we add revenue and labor stock as size controls in TABLE 5.7, (presenting only the results on joint inclusion of the variables, which can be compared with columns 3 and 6 in TABLE 5.4).

From TABLE 5.7 we note that the estimate for *Innovation Consortia* turns significant at the 10 percent level.

Changing the control group to firms with less than 100 employees has no effect on the *Innovation Assistant* estimate. Adding size controls lowers the LDP estimate, but the IV estimate hardly changes, both compared to the main results in TABLE 5.2 (firms with less than 500 employees) and the results in TABLE 5.6 (equivalent estimations for firms with less than 100 employees).

Table 5.7

Robustness: effect on productivity growth from participation in a specific program - firms with less than 100 employees and further controls added

	OLS (LDP)	IV
Industrial PhD	-0.0335 (0.0560)	-0.0470 (0.0598)
Innovation Agents	-0.00736 (0.0135)	-0.00542 (0.0147)
Innovation Consortia	0.0603* (0.0322)	0.0458* (0.0272)
Innovation Networks	0.0422*** (0.0155)	0.0431*** (0.0162)
Innovation Voucher	0.0361* (0.0187)	0.0413** (0.0208)
Innovation Assistant	0.0355** (0.0141)	0.0280* (0.0147)
Open funds	0.0365 (0.0298)	0.0386 (0.0329)
Labor stock (log)	0.0533*** (0.000905)	0.0588*** (0.000948)
Revenue (log)	-0.0469*** (0.000935)	-0.0571*** (0.00100)
High skill share	0.0256*** (0.00314)	0.0240*** (0.00321)
Historical productivity growth	-0.201*** (0.00273)	-0.0317*** (0.00260)
Observations	342,255	342,255
Unique firms	86,510	86,510
Participators	942	942
Adjusted *R2*	0.342	0.311

Notes: The table shows re-specifications of columns (2) and (3) in TABLE 5.2 using Estimation Sample 2 (less than 100 firms). For technical information, consult the notes in TABLE 5.2. ***, **, and * refer to statistical significance at 1, 5, and 10 percent level, respectively.
Source: CEBR calculations using Statistics Denmark registry data and DASTI's Innovation Danmark database.

5.3
Discussion

Our point of reference is that firms make decisions and initiate projects that potentially enhance their performance and probability of survival, and we know that firms use incentives for employees in order to perform better. Search for innovative business solutions (from process innovation to marketing innovation), and research into better or new products include possible actions for investing in future firm performance.

Public research and innovation support programs aim to support firms with external knowledge from specialists (e.g. *Innovation Voucher*) or connect researchers and firms via research networks *(e.g. Innovation Consortia)*. Other programs aiming to increase firm skills, involve skill upgrading (*Innovation Assistant). The Industrial PhD* program potentially combines skill upgrading with collaboration between industry and research institutions.

If all of the above mentioned activities can be associated with company strategies that we expect can increase firm performance, we are able to measure potential effects. Performance can be measured in many ways, but one objective measure of firm performance is productivity improvement. We measure *productivity growth enhancing effects*, i.e. we measure whether firm total factor productivity of participating firms subsequently grow faster than non-participating firms, while taking into account historical productivity growth performance.

Some challenges exist in effect measurement at the firm level. First of all, are observed support activity a minor spin-off of other firm projects? If this is the case we are not measuring firm performance related, first and foremost, to program grants. We cannot infer from the data if this is the case. However, by ruling out participation activity in preceding and subsequent years, we can at least say that we observe only firms that are actively partici-

13 See Chai & Shih (2013) for an impact assessment of DNATF, although it considers other performance measures than productivity growth.

pating that one year in a four year period. If participation activity for some firms is a by-product of other primary initiatives that firms would have initiated regardless of support options, we can expect to see them repeatedly in the data. These firm observations are thus not included in our sample.

No effect, why?
For some programs in section 5.1 (main results) we do not find any effects. The question arises, why? The general answer is that we cannot say why, but we can list some possible explanations:

Explanation 1:
There is no effect of the initiatives associated with the program in question.

Explanation 2:
We measure effects on firms that exist two years after participation. Some firms may close down due to financial restraints or bankruptcy. (Successful) firms may also have been bought up. However, a program may still have had a positive, or negative, impact that we will never be able to measure.

Explanation 3:
Data availability complicates impact assessment.

Explanation 4:
Firm productivity growth is not a suitable measure for all programs.

Explanation 1 is plain and simple. To take *Innovations Agents* as an example, we find no enhanced productivity growth following participation. The finding that *Innovation Agents* participation does not return differential growth is not surprising, but rather comforting. The *Innovation Agents* program is designed to give firms a "checkup" and then forward them to relevant private consulting or to other programs such as *Innovation Voucher*. One possible conclusion is that *Innovation Agents* check up on Danish firms

exhibiting productivity growth rates that are not different from that of the typical non-participating firm.

Explanation 2 tells us that we can only measure effect on survivors and firms that remain independent. Some programs in particular may in practice engage participation by firms that are more likely to be bought up than other firms. What effects would be in these firms, we cannot infer, as is the case for firms closing down or restructuring into a new firm.

Explanation 3 covers the Mother of all data analysis problems. One of the initiatives, that we cannot measure an effect for, concerns projects under *Danish National Advanced Technology Foundation* (*DNATF*). When imposing our criteria we end up with just 11 observations. However, as evident in the robustness results, there is apparently a tendency to find effects for smaller firms (i.e. estimates are larger for most programs when analyzing on firms with less than 100 employees, compared to analyzing on firms with less than 500 employees). Thus, one could imagine that the effect of larger scale research projects dominate impact on performance, compared to other programs such as the innovation voucher, that typically awards DKK 100.000-500.000 for knowledge assistance at a recognized knowledge institution. Thus, it might be reasonable to allow for other minor participation activities when evaluating the impact of, for example, *DNATF* projects.[13]

Another clear issue is that measuring performance of projects, two years into a research project, lasting up to five years, is a strict and possibly unrealistic criterion. Even if we could measure performance for a longer term, we might never observe the productivity effects. If a firm, for example, is bought before its new innovative products or business methods start generating revenue, the productivity effects generated are hidden in the value of the firm. Furthermore, the longer the observation period, the more likely it

will be that other projects or circumstances influence the performance measure.

Explanation 4 suggests that certain programs could practically target firms that are relatively productive and well-established. These firms may be past revolutionary productivity changes. For these firms, steadily increasing, or just maintaining, productivity may be the realistic short run target. If this argument is correct, the research support system may be an endogenous part of an already integrated private-public (or private-private) research collaboration environment. Furthermore, using other performance measures may reveal that highly productive firms expand following participation. CEBR (2011b) finds that firm workforce of firms hiring *Industrial PhD's* (partially supported) grow faster following the decision and action to hire *Industrial PhD's*.

A program such as the Industrial PhD hosts the potential to increase macro-level productivity, because the program allows talented industrial researchers to obtain a PhD while working in the industry, bringing with them fundamental research knowledge from academic institutions. Thus, one can imagine that such a flexible option in the statutory educational system can facilitate labor shifting from low-productive firms to high-productive firms, improving macro level productivity because talented researchers instead work and contribute to firm value added more efficiently. Such macro level productivity effects would never show up in a micro level study such as ours.

Comparison to other impact evaluations

In this section we compare some of our estimates to previous reports and articles that have tried to measure the impact of a particular program or initiative on productivity. We focus on the programs that we have highlighted in section 5.1 (main results), because these are the programs where we have enough observations to, at least, make careful inference. Comparing estimates and methods directly

is difficult, because the underlying data approaches are, in general, different from ours. We also use a different productivity measure, which we also point out below. This project is the first project to take all other known innovation and research support programs into account, ruling out simultaneous or short run overlapping participation effects.

We cannot conclude on *Danish Council for Strategic Research* projects and *DNATF* projects. An impact assessment of *DNATF* has been completed by Chai and Shih (2013) focusing not on productivity growth but on other measures such a patent activity (a likely indicator of future value creation), firm survival, and employment growth.

Another study of research activities includes DASTI & DAMVAD (2013), which, among other things, estimates production functions with R&D capital inputs. The study finds, across firms, a significant and increasing productivity level for firms that have built up more R&D capital stock.[14]

We find that *Industrial PhD* is not associated with significantly higher productivity growth following participation. This finding is consistent with CEBR (2011b). Though (TFP) productivity growth is not higher for participants, as in this study, CEBR (2011b) also investigates individual wages and proposes that the higher wages found for PhD candidates suggests high individual productivity. Furthermore, as we have noted earlier, productivity potential may be hidden in long product introduction time paths. One potential indication of this is patent seeking activity, and CEBR (2011b) does find that employing *Industrial PhD's* is associated with subsequent increased patent activity.

We do not find solid proof of effects of productivity gains for *Innovation Consortia*. However, adding size controls, the estimate increases and turns significant. Kaiser and Kuhn (2012) and CEBR (2010) have also evaluated productivity but using labor productivity instead of TFP. They find no effects on labor productivity. We cannot directly compare these two results, because the productivity measures are different. Using labor productivity does not account for changes in capital use. The TFP-growth estimation takes account of this. Thus, our results suggest that accounting for capital changes in productivity effects matters.

The *Innovation Assistant* program has been evaluated by CEBR (2013a). In a detailed study Kuhn follows workers wage histories and firm performance, finding no effect on labor productivity. As we explained above, we cannot directly compare results from Kuhn with our results, because we use a different setup that measures TFP growth.

6 Conclusion

The innovation and research support system includes programs that are associated with enhanced (possibly only short run) productivity growth of 2.5 percentage points annually the first two years following participation.

We find that (all effects are measured by annualized added growth measured in percentage points):

-   Following participation in *Innovation Network* (with an effect of 3.6 percentage points), *Innovation Voucher* (3.6), and *Innovation Assistant* (2.9) participating firms grow faster than non-participating firms.[15]

-   When limiting the analysis to firms with less than 100 employees and accounting for heterogeneous productivity growth trends depending on firm size, the effects are amplified and become more firmly significant.

-   For firms with less than 100 employees participation in *Innovation Consortia* is associated with enhanced growth performance (4.6).

-   Firms participating in *Industrial PhD*, *Innovation Agents*, or *Open Funds* do not grow significantly faster than other similar firms. The result for *Industrial PhD*, though based on somewhat few observations, is in line with previous studies. *Open Funds*, though positive, is insignificant, but based on just 32 observations.

15 All effects are annualized added growth measured in percentage points.

In our analysis we control for past productivity growth performance and exclude other observations of firms with other participation activity in the years preceding and following the observation of participation, adding a particular feature to our sampled firms. These criteria allow us not to worry about contaminated program effects from other programs and that we are not picking up that firms that participate simply grew faster in the first place.

The identification of program participation effects relies on the assumption that we can fully attribute the knowledge transferred via these programs to firm performance. We set up an analytical framework that allows causal inference on productivity growth performance following participation. However, we currently have no possibilities of revealing, or accounting for, whether particular types of firm innovative or knowledge enhancing activities would have generated the same result had the programs not existed, and that firm contact with the support system is simply correlated with these particular firm activities. We rely on the assumption that firms seeking support initiate activities based on grants and benefit first and foremost from having established contact with the support system.

The performance measure in this report is productivity growth enhancing effects. We recommend that our conclusions are used under the recognition that we do not consider other, possibly more likely, performance measures that may induce macro level productivity effects. Programs can help highly productive firms to expand. Such help to high-productive firms can improve macro level productivity (by shifting workers from

lower productive jobs in low-productive firms) but those productivity effects would never show up in our type of micro level study of firm productivity growth. We encourage further program comparison studies such as this study into other performance measures.

Some programs suffer from few observations, partly because we impose the aforementioned criteria. These programs include *The Danish Council for Strategic Research, EUopSTART, Eurostars, FP7, Research Voucher, Gazelle* Growth, The Danish National Advanced Technology Foundation, Innovation Incubators, and SPIR.

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About the project

This project was prepared for The Danish Agency for Science, Technology and Innovation (DASTI) under The Ministry of Science, Innovation and Higher Education.

The scope of the project was to conduct the first comprehensive productivity impact assessment of the Danish system of innovation and support system. This is the first time that effect studies include comprehensive information about many programs, ruling out latent connected effects of other programs.

To assure quality we consulted two highly qualified professors, Professor Søren Bo Nielsen and Associate Professor Battista Severgnini, who possess vast knowledge within the fields of public policy on science, research and innovation, and empirical productivity studies. We thank them for helpful and constructive comments. The authors, alone bear the responsibility of the entity of report.

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Centre for Economic and Business Research (CEBR) at Copenhagen Business School is an independent research and analysis centre.

Located at the Department of Economics, our analysts have close ties to leading researchers. Project managers all hold a doctoral degree in Economics, assuring that our analyses use proper techniques founded on high-level research.

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