Do Companies Benefit from Public Research Organizations? The Impact of the Fraunhofer Society in Germany

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Keywords: Innovation; R&D; diffusion; applied research; Fraunhofer

JEL: O33; O38

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The Impact of the Fraunhofer Society in Germany

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Abstract

Among available policy levers to boost innovation, investment in applied research organisations has received little empirical attention. In this paper, we analyse the case of the Fraunhofer Society, the largest public applied research organization in Germany. We analyse whether project interaction with Fraunhofer affects the performance and strategic orientation of firms. To that end, we assemble a unique dataset based on the confidential Fraunhofer-internal project management system and merge it with the German contribution to the Community Innovation Survey (CIS), which contains panel information on firm performance. Using instrumental variables that exploit the scale heteroscedasticity of the independent variable (Lewbel, 2012), we identify the causal effects of Fraunhofer interactions on firm performance and strategies. We find a strong, positive effect of project interaction on growth in turnover and productivity. In particular, we find that a one percent increase in the size of the contracts with FhG leads to an increase in growth rate of sales by 1.3 percentage points, and to an increase in the growth rate of productivity by 0.8 percentage points in the short-run. We also provide evidence of considerable long-run effects accumulating to 18% growth in sales and 12% growth in productivity over the course of 15 years. More detailed analyses reveal, amongst others, that the performance effects become stronger the more often firms interact with Fraunhofer and that interactions aiming at generation of technology have a stronger effect than interactions aiming merely at the implementation of existing technologies. Finally, we provide evidence on the macroeconomic productivity effects of Fraunhofer interactions on the German economy. Our results indicate that doubling Fraunhofer revenues from industry (+€ 0.68 bn.) would increase overall productivity in the German economy by 0.55%.

Key words: Innovation, R&D, diffusion, applied research, Fraunhofer

JEL codes: O33, O38

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1 Introduction

Innovation is the key driver of sustained economic growth in advanced countries. Given its importance, policies that foster and increase the effectiveness of innovation activities should be a top priority for governments. Yet, in reality, only a small fraction of the human and financial resources of governments are devoted to innovation policy. One reason for the relatively small efforts devoted to the design of innovation policies by governments may be the limited knowledge we have about the foundations and effects of innovation policies.

Researchers that study the effects of specific innovation policies have confronted two key issues. The first issue is to find a source of exogenous variation in the treatment provided by the government. Coming up with a valid identification strategy is particularly challenging in this context because companies can typically self-select into the treatment. The second issue is the difficulty to assemble datasets that contain measures of the policy treatment received by companies and the company-level outcome that we are interested in. The severity of these challenges may explain why much of the existing work in the literature focuses on treatments that are economy-wide and outcomes that are covered in pre-existing company-level datasets. For example, the majority of the empirical work has focused on the effect of financial incentives and intellectual property (IP) protection on private R&D expenditures and patenting activity.[1] In contrast, we know much less about the foundations and actual impact of other policy levers such as, for example, having the public sector directly involved in the innovation process rather than just its financing or regulation. Similarly, there are relatively few studies that have shed light on the impact of innovation policies on other variables such as productivity, employment and sales growth or relevant dimensions of the company' strategy such as its human resource or product commercialization decisions.

This paper differs from much of the innovation policy literature along several dimensions. The first difference is that the policies we study do not affect the financial cost of innovating for the treated companies, or the protection of the intellectual property rights of their innovations. Instead, the aim of the policies is to facilitate the access to key inputs in the innovation process for which markets may be imperfect or altogether missing. The second difference is that the goal of the innovation policies we focus on is not the development of new patents. More specifically, the institutions we study intend to solve specific technological problems faced by individual companies. The solutions to these problems sometimes may require the invention of a new technology, but in most cases it just involves applying

[1] Papers that estimate the effects of fiscal incentives on private R&D spending and or patenting include Berger (1993), Hall (1993), Bloom et al. (2002), Bronzini and Piselli (2016), Cappelen et al. (2012), Knoll et al. (2014), Cowling (2016), Dechezleprêtre et al. (2016), Montmartin and Herrera (2015), Castellacci and Lie (2015), Guceri and Liu (2017), Rao (2016), Cerulli and Poti (2012), and Czarnitzki et al. (2011). Papers that study the effect of IP protection on innovation include Murray and Stern (2007), Williams (2013), Sampat and Williams (2019), Galasso and Schankerman (2014), Galasso and Schankerman (2018).

existing technological knowledge to the specific circumstances of the company. This observation highlights a third difference of our study with the bulk of the innovation literature. Namely, that the policies and institutions we study may impact welfare not only by fostering innovation but, possibly more importantly, by facilitating the diffusion of technological knowledge from those that have it to those that need it. These three differences suggest that our analysis has the potential to shed light on policies, channels and aspects of the innovation process that differ markedly from those studied in the literature.

To be precise, we study the effects for a German company of engaging in a research contract with the Fraunhofer society on the companies' performance and strategy. The Fraunhofer society (FhG) is a public applied research organization established after WWII and that currently employs over 24,000 people, most of them scientists from engineering and natural sciences, to work on R&D projects. It produces around 500 patents per year and launches around 10 start-ups. However, the key activity of FhG we study is the approximately 8000 research contracts that FhG signs per year with German companies. The scope of research contracts varies greatly but, in general, they intend to provide some technological service to the company that typically cannot be obtained in the market. These services allow the companies to improve on their production processes, products or services. In general, the contracts aim at making the companies more innovative, though research contracts do not necessarily increase the technological frontier in Germany.

To investigate the effects of research contracts on company performance it is necessary to assemble a firm-level data set that contains information on the contracts and on the firm performance. The first contribution of this paper consists in constructing such a dataset. For the first time in history, we have gained access to the population of confidential FhG research contracts. For each of the 130,000 contracts signed between 1997 and 2013, we have information on the companies involved, the duration, payments, the research institutes that participated and a short description of the tasks it involved. We have merged these data with the German contribution to the Community Innovation Survey (CIS), which contains information on the performance and innovation activities of a large panel of companies in Germany. After merging these two datasets, we have assembled a panel that covers a representative sample of German companies and that contains information of over 109,000 contracts signed by 3.4% of the companies in the Community Innovation Survey.

A key challenge to identifying the causal effect of FhG on firm performance is that firms may self-select into contracting with FhG. If firms that are more able are more likely to engage with FhG, standard econometric techniques may result in biased estimates of the effect of research contracts on company's performance. To deal with the potential endogeneity of the firms' interactions with FhG, we follow a long tradition in applied econometrics that has taken advantage of the presence of heteroscedasticity in the selection equation. King et al. (1994), Sentana and Fiorentini (2001), Rigobon (2003) and Rigobon and Sack (2004), for example, have used heteroscedasticity over time as a source of exogenous variation.

Building on insights from Wright (1928), Lewbel (2012) has recently shown how to generate valid instrumental variables also in the presence of purely cross-sectional scale-heteroscedasticity.

Like in the case of standard IV-methods, for Lewbel-instruments to be valid they must be relevant and exogenous. The relevance requirement is met, if there is scale-heteroscedasticity in the treatment. In our data, we uncover strong (positive) scale-heteroscedasticity of the FhG treatment both with respect to the size of the firm and its own lagged value. The exogeneity assumption is equivalent to the standard requirement that the instruments and the second stage-error term are uncorrelated. A sufficient condition is the standard assumption of homoscedasticity in the unobserved variable. In the standard unobserved variable model, this assumption is usually implied. However, in overidentified models, this exogeneity assumption can be tested empirically as well. Our test results indicate that the Lewbel instruments also meet the exogeneity assumption. Additionally, we test the validity of the instrumentation strategy by conducting a placebo test by which we estimate the (instrumented) effect of future expenditures on research contracts on lagged firm performance measures. The estimated coefficient is small and insignificant.

In a first step we implement purely static models, which take into account only short-term effects of Fraunhofer interactions on firm performance. The static models show significant and positive effects on firm growth, productivity, the share of turnover due to new products, and the share of employees with tertiary education. Based on the static models, we investigate whether the impact varies along different observable characteristics of the companies, and research projects. We find significant heterogeneity in the effects of research contracts. For example, we estimate a greater effect on (i) the growth of sales and the share of sales from new products in younger firms; (ii) the impact tends to be larger and more significant on medium and (especially) large companies; and (iii) we find stronger effects on companies that already engage in some R&D expenditures but those tend to be larger if the expenditures are below the sample average. We also estimate significant heterogeneity in the effects based on project characteristics. Projects that involve the generation of technologies tend to have greater effect on firm sales and on the share of college educated workers than those that involve technology implementation. Larger projects tend to have greater effects on sales growth but not necessarily on the composition of the labour force and on the share of sales from innovative products and services. Finally, we document that the effect of research contracts is higher when the company has previously interacted with FhG.

The observation that Fraunhofer expenditures are strongly autocorrelated, however, suggests that there are long-term effects on Fraunhofer performance. In order to estimate the long-run effects, we therefore devise dynamic models, which control for the autocorrelation in the Fraunhofer expenditures in a first step. Indeed, controlling for dynamics seems essential as indicated by a series of placebo-tests. The results on the dynamic models in particular show that only the effects on firm growth and productivity remain significant. Specifically, we find that a one percent increase in the size of the contracts with FhG leads to an increase in growth rate of sales by 1.3 percentage points, and to an increase in the growth rate of productivity by 0.8 percentage points. These effects are economically significant, and amount, respectively, to 21% and 11% of the average growth rates observed for turnover and productivity in our sample. Furthermore, autocorrelation structure of the Fraunhofer expenditures allows estimating the long-run effects on firm performance by analysing how the effects of a shock to Fraunhofer expenditures propagate over time. We find that entering into a research contract of the median size (€ 22,762), induces cumulative growth over the next fifteen years of 18% in company sales and 12% in productivity.

We conclude our analysis by calculating the aggregate effects of FhG research contracts on German productivity. Basing our results on our dynamic models, the figures suggest a doubling of FhG revenues from industry in total would increase the productivity in the total German economy by 0.55%. FhG's productivity leverage with respect to the German economy is therefore considerable given that a hypothetical doubling of industry revenues corresponds only to an additional amount of € 0.68 bn. p.a.

Related literature

In addition to the papers cited above, our work is related to another important strand in the literature dealing with the econometric analysis of the university-industry interactions on firm performance. The analyses in this field have to a large extent focused on the role of universities as providers of basic knowledge (Lööf & Broström 2008, Maietta 2015, Robin and Schubert 2013). However, basic knowledge may often be too distant from the market and very difficult for the firms to absorb (Toole et al. 2014). That is why a number of countries have established (partly) publicly funded applied research organizations, whose goal is to help firms to integrate complex scientific knowledge into their innovation processes. Among these countries are Germany with the Fraunhofer Gesellschaft, Sweden with the RISE institutes, and the Netherlands with TNO. Yet, despite the great importance for the local research landscape, to date little research is available focusing on extra-university public research organizations explicitly. One exception is Giannapolou et al. (2019) who analyse inasmuch firms cooperating with universities and firms cooperating with extra-university public research organizations differ. Because of data limitations, it is however questionable whether the observed differences may be interpreted as causal effects. Identifying causal effects is at the centre of our interest in this paper.

The rest of the article is organized as follows. Section 2 describes the related literature, presents a brief description of the Fraunhofer Gesellschaft and introduces the datasets used in the analysis. Section 3 presents the identification strategy. Section 4 presents the empirical results. Section 5 concludes.

2 Institutional and data preliminaries

2.1 What is Fraunhofer?

The Fraunhofer Gesellschaft is a public non-profit organization focused on the advancement of applied research. Founded in 1949 with the strategic intent of fostering the rebuild of the German industrial sector after WWII, it fosters to bridge the gap between basic research and industrial applications. It took a while for FhG to reach its current size. In 1959, it consisted of 9 institutes with a budget of less than € 10 m. in today's value. Only in 1965, the Research Council (a semi-public advisory organization) proposed extending extra-university research. Following the advice of the Research Council, the German parliament officially accepted the so-called "Fraunhofer-model" forming the bases of the still continuing growth of the Fraunhofer Society in 1973.

Today, FhG is the biggest non-profit organization for applied sciences in the world, with a budget of € 2.1bn. FhG is organized as a private registered association ("eingetragener Verein, e.V.") and receives public funding amounting to roughly 25% of its total budget (90% from the federal government and 10% from regional government where the respective institute is located). The Fraunhofer Society comprises 72 research institutes located all over Germany. The institutes focus on different topics mostly in the field of engineering and natural sciences, though a few institutes exist which are more related to social sciences and economics.

FhG's mission makes it the natural organization to study the magnitude of scientific knowledge transfer to private firms. Of the total budget of € 2.1bn. in 2016 almost 30% came from industry funds, which is by far the largest share compared to other extra-university research organizations (Table 1).[2] Likewise, the share in universities in Germany was with approximately 11% much smaller.

Table 1: Fraunhofer key-figures[3]

	2005	2010	2014	2015	2016
Budget (mln. €)	1,252	1,657	2,060	2,115	2,081
Employees	12,400	18,130	23,786	24,984	24,485
Project funds (mln. €)	826	1,173	1,272	1,305	1,386
Budget share industry funds (%)	40	34	30	29	32
Budget share public funds (%)	26	38	32	31	34
Budget share base funds (%)	29	22	22	25	24

Overall, the Fraunhofer society organizes its core research within seven broad clusters presented in Table 2, where some institutes belong to more than one cluster.

[2] It is noteworthy that the share of industry funding declined over time. The reason is, however, more related to the fact that the Fraunhofer budget was considerably extended by the government over the last years. In absolute terms the industry funds rose but not at the same pace as the overall budget.
[3] Budget shares do not add to 100%, because the total budget includes also project returns from defense, about which information is classified.

Table 2: Activity areas

Cluster	Member institutes	Research topics
ICT	16	Digital media, E-business, E-government, ICT technologies, energy and sustainability, medicine production, security, financial services, automotive
Life sciences	7	Medical translation research and biomedicine, regenerative medicine, healthy food, biotechnology, safety of chemicals
Light and surfaces	6	Surface technologies, radiation sources, micro and nanotechnology, materials, optical measurement
Microelectronics	11	Smart and healthy living, energy efficient systems, mobility and urbanization, industrial automation
Production	12	Product development, production technologies, production systems, production processes, production organization, logistics
Defence and security	10	Security research, defence and effect, intelligence and surveillance, explosives, decision support for the governments and firms, localization and communication, image processing
Materials	16	Health, energy and environment, mobility, construction and living, mechanical engineering, microsystems technology, safety
Innovation	5	Digitalization, Industry 4.0; Mobility, Technology evaluation, Road mapping, Scenarios

Source: Fraunhofer (2017).

2.2 Database construction

The empirical analysis is based on two main data sources. The first is the project database provided by the Fraunhofer Gesellschaft, which covers all projects started between 1997 and 2014, excluding contracts related to defence and security. The database contains information on the FhG institute and department involved, the client, the title, short description and time span of the project, and any payments related to the project. In total, the database includes records on 131,158 projects. The detailed nature of this unique database provides an exceptional opportunity to open the black box of public knowledge dissemination by public research institutes.

We merged the FhG data to waves of the German contribution to the Community Innovation Survey (CIS). The German CIS provides a representative annual sample of German firms with five or more employees (See Aschhoff et al. 2013 for further details) and follows the methodology outlined in the Oslo Manual (OECD & Eurostat 2005). The present analysis makes use of a panel of the 1996 to 2013 waves of the German CIS. Excluding firms which were observed less than three times, the German CIS covers 198,385 observations on 30,125 firms between 1996 and 2013. Of the 131,158 projects in the FhG project database, we were able to match 46,651 projects to 7,781 distinct firms, which were surveyed at least once in the CIS survey. Due to nonresponse and the condition of observing a firm at least three times, 32,568 projects, representing 4,495 firms in the CIS panel, were used in the final analysis.

There are several reasons for not matching projects. First, 17% of projects relate to clients outside of Germany and, thus, naturally were not part of our sample. Second, any public clients (such as universities, research centres, and government institutes) are not covered by the German CIS and hence remain unmatched. Third, the German CIS only presents a representative sample of German firms of roughly 10% of the population (Aschhoff et al. 2013), which does not capture all firms potentially entering contractual relationships with FhG. Fourth, we assigned projects to firms conservatively, requiring a match in both name and address. While this avoids errors based on namesakes, it might also imply that actual relationships remain unidentified.

2.3 Interactions with FhG

This section presents an overview of FhG's interactions with firms. Figure 1 shows that between 1997 and 2014 approximately 6,500 projects were started per year. The number of initiated projects was especially high in 2009, when about 8,800 projects started.

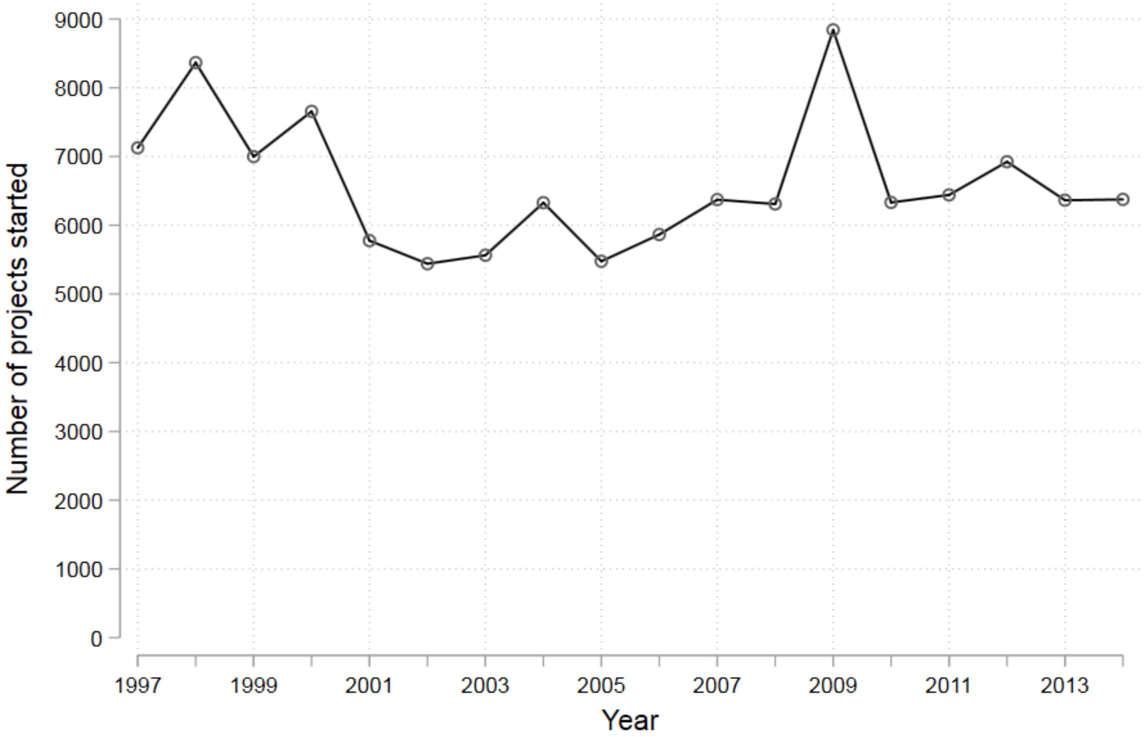

Figure 1: Projects started by year

The average project in our sample is relatively small-scaled, taking one year and eight months to complete and generating approximately € 37,000 in FhG revenue (all amounts refer to € real 2010) Figure 2 shows the distribution of project revenue. A sizeable share (26.55%) of projects have no registered revenue. Most firms in the data set collaborate with FhG once (42%), but 31% return for more than three projects. 90% of projects involve less than € 100,000 in revenue.

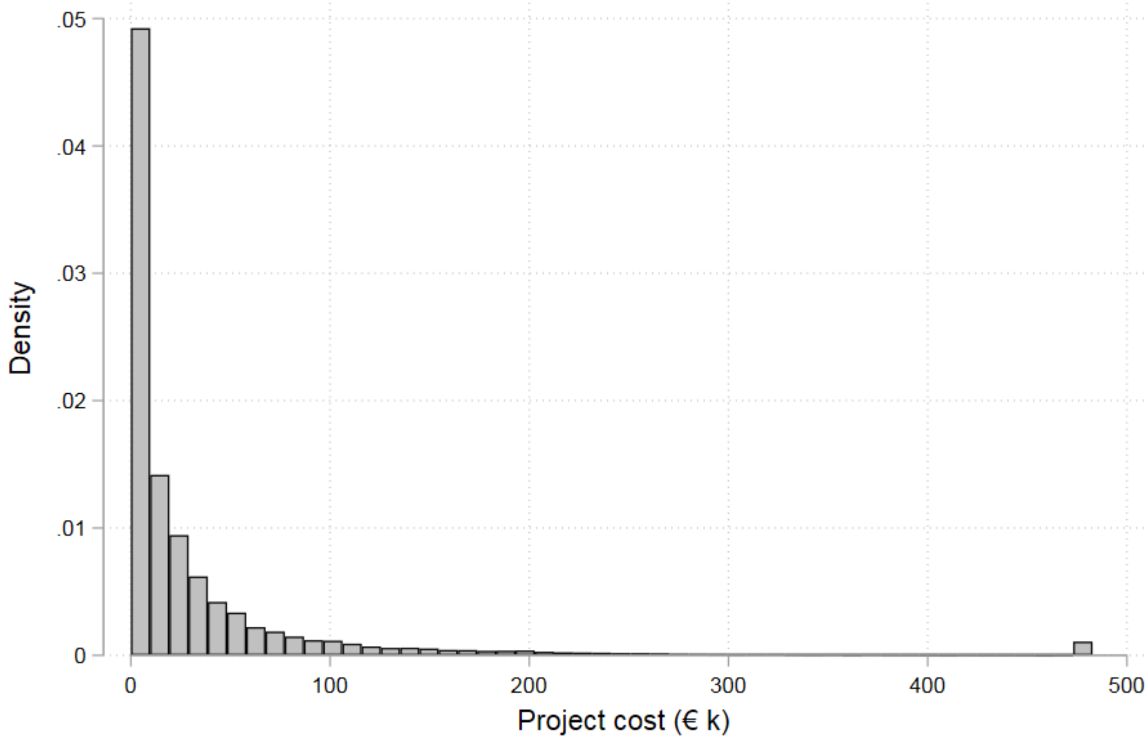

Figure 2: Distribution of project costs

Notes: Data have been censored at the 99th percentile (482 €k). The true maximum is higher than 150 €m. 0.98% of projects report negative revenue, these have been set at 0. 26.55% of projects report no revenue.

The data also contains a short description of the project. Table 3 lists the 20 most common keywords in the project descriptions, translated from German and harmonized. They show that FhG projects cover the full spectrum of applied research, from (feasibility) studies and analysis to development, application, and implementation. To gain more insight into the nature of the projects which FhG engages in, we differentiated between projects based on the project descriptions into those involving genuine technology generation on the one hand and implementation of existing technologies on the other hand. The distinguishing feature is that most implementation projects, although potentially providing substantial benefits to the firm, are typically quite routine tasks for FhG and thus of limited technological complexity. As an example, many FhG institutes grant access to the technical infrastructure by offering measurement services. Another example is the installation of specialized machinery. Projects relating to technology generation instead involve a higher degree of novelty and technical complexity. To do this, we reviewed all major key-words and assigned them to the implementation class if they indicated a change or development. We then cross-checked the resulting classification of projects by reviewing the full descriptions to check whether the projects indeed could be interpreted to refer to implementation of technology. The final list of key-words includes terms such as ‘adapt’, ‘build’, ‘create’, ‘construct’, ‘develop’, ‘improve’, ‘innovate’, ‘integrate’, ‘intervene’, ‘install’, ‘manufacture’, ‘modify’, ‘realize’, ‘restructure’. One quarter of projects in the FhG database is classified as implementation (24.8%).

Table 3: Common project keywords

Rank	Term	Share projects	Rank	Term	Share Projects
1	Development	5.27%	11	Creation	1.04%
2	Analysis	4.08%	12	Feasibility	1.03%
3	Study	3.33%	13	Process	1.02%
4	System	1.89%	14	Application	1.00%
5	Manufacturing	1.35%	15	Technology	0.95%
6	Supply	1.33%	16	Structure	0.85%
7	Project	1.31%	17	Concept	0.82%
8	Optimization	1.29%	18	Simulation	0.81%
9	Evaluation	1.27%	19	Implementation	0.81%
10	Test	1.24%	20	Phase	0.79%

2.4 Variables

The goal of our analysis is to establish how interaction with FhG affects firm performance and strategy. We capture interaction through the amount spent on FhG’s services in each given year (FHG_{it}). About 3.44% of the firm-years in the panel show positive FhG expenditures, representing 2,181 of the 30,125 distinct firms included in the sample (7.2%).[4]

As firms might benefit in different ways from working with FhG, we consider four outcomes in the analysis. First, we analyse performance in terms of turnover (TR) and productivity ($PROD$). Separating between productivity and turnover is necessary because firms differ widely in their strategic goals. Some may primarily focus on growing fast, while others may focus on increasing their economic efficiency in terms of value added per employee. In particular, the latter variable can also be understood as measure of innovative achievement, since growth in productivity is typically related to increasing resource efficiency following process innovations or higher sales increases resulting from successful product innovation. We capture productivity through a measure of value added by worker.

Second, we analyse to which extent interactions with FhG have a systematic effect on firm’s innovation strategy. We consider two aspects. First, a reasonable expectation is that in order to reap the benefits of interactions with FhG, firms need to develop a sufficient absorptive capacity. A key mechanism to raise

[4] A small minority of projects involves negative payment flows. These are set to 0 for the purposes of this analysis. Likewise, approximately one third of projects in the FhG database do not involve payment. These might be parts of larger projects (meetings, maintenance contracts, etc.) or small services. Whatever the reason, for the purpose of this analysis we are interested in the impact of larger projects which lead to significant knowledge flows, and therefore disregard these smaller interactions. Payment data closely tracks the contractual start dates of FhG projects: for projects lasting two years or less, payment is typically made in within the first year of the project. For the minority of projects which last three years or longer, the average lag between the project’s start and payment increases by approximately 4 months per year increase in project duration. We can therefore utilize payment data as a close proxy for the timing and duration of FhG projects.

the absorptive capacity is to invest in the human capital stock. Consequently, we expect that firms will adjust their hiring strategy and increase the share of employees with tertiary education background ($TERT$). Second, we expect that firms engage with FhG as a means to achieving their innovative goals. If FhG interactions have a positive effect on the firms' innovative performance, we expect that, in particular, the share of turnover achieved through the sales of products or services which have been introduced or significantly improved in the last three years ($INNOSALES$) as a central success measure of innovation (compare Robin and Schubert 2013), will increase post interaction.

The CIS collects information on a wide range of factors that might confound the relation between FhG expenditures and firm performance. These include R&D expenditures, as share of turnover ($RDINT$), and the size of the firm, as measured through the number of employees (EMP). We include the firm's age (AGE), and whether the firm exports any goods or services to other countries ($EXPORT$). In addition, we control for whether firm is located in former Eastern Germany ($EAST$), which captures broad regional economic differences within Germany still pertinent even after almost 30 years after reunification. We further control for the economic activities of the firm through the inclusion of sector indicators and include year fixed effects to account for common macroeconomic trends.

Table A.1 in appendix contain summary statistics and variable definitions.

2.5 Exploratory analysis

We start the analysis with an exploratory regression of FhG expenditures on the outcomes, controlling for other firm attributes. We employ a simple OLS model in levels with explanatory variables lagged one year, and structure the variable of interest, interaction with FhG, in two parts: one variable taking value 1 if there were expenditures in the previous year ($I[FHG_{t-1} > 0]$), and the natural log of the level of FhG expenditures (plus 1; $\ln[FHG_{t-1}]$). This is particularly interesting as the previous literature has typically established the effect of the presence of an interaction, and much less related outcomes to its intensity. Our data allows us to contrast these.

The results are shown in Table 4. The effects differ by outcome: turnover (column 1) does not correlate, conditional on other firm attributes, with the presence of FhG expenditures, but the elasticity between the level of FhG expenditures and turnover is strong and significant at 0.09 ($p<0.01$). Productivity (column 2), on the other hand, does not correlate with the level of FhG expenditures, but firms with some interaction are 8.7% more productive, albeit at a low level of statistical significance ($p<0.10$). In the case of innovative sales (column 3), we find that both matter: firms with some level of FhG experience a 2.9% points higher share of sales of new or improved products or services ($p<0.05$), and a semi-elasticity of 1.4% points to the level of FhG expenditures. As for the firms workforce (column 4), the initial estimation shows no relation to the presence of FhG expenditures but a semi-elasticity to their level of 1.1% points.

Table 4: Exploratory analysis

	(1) $\ln(TR_t)$	(2) $\ln(PROD_t)$	(3) $INNOSALES_t$	(4) $TERT_t$
$ln(FHG_{t-1})$	0.090***	0.023	0.014***	0.011**
	(0.015)	(0.015)	(0.004)	(0.005)
$I(FHG_{t-1} > 0)$	0.010	0.087*	0.029**	0.026
	(0.051)	(0.051)	(0.014)	(0.016)
$ln(EMP_{t-1})$	0.886***	0.047***	-0.011***	0.006***
	(0.005)	(0.005)	(0.001)	(0.001)
$RDINT_{t-1}$	-0.461***	-0.422***	0.312***	0.533***
	(0.040)	(0.071)	(0.025)	(0.029)
$ln(AGE_{t-1})$	0.034***	0.019**	-0.014***	-0.010***
	(0.008)	(0.008)	(0.002)	(0.001)
$EXPORT_{t-1}$	0.179***	0.189***	0.035***	0.046***
	(0.014)	(0.016)	(0.004)	(0.003)
$GROUP_{t-1}$	0.053***	0.053***	0.007*	0.009***
	(0.013)	(0.015)	(0.004)	(0.002)
$EAST_{t-1}$	-0.216***	-0.275***	0.043***	0.010***
	(0.014)	(0.016)	(0.004)	(0.003)
CONSTANT	-1.486***	3.589***	0.315***	-0.018
	(0.175)	(0.166)	(0.019)	(0.022)
Industry F.E. joint significance	F(25,14788)= 70.898***	F(25,9807)= 42.081***	F(25,13641)= 147.719***	F(25,14962)= 32.367***
Time F.E. joint significance	F(16,14788)= 10.009***	F(15,9807)= 5.608***	F(16,13641)= 17.499***	F(16,14962)= 90.671***
N	48268	27279	40784	42364
R^2	0.834	0.229	0.434	0.247

Notes: OLS regression. Standard errors clustered by firms in parentheses.
* p <0.10, ** p<0.05, *** p<0.01

Naturally, this regression is only descriptive and subject to the issue of selection bias: FhG expenditures are not allocated to firms randomly, but firms rather choose FhG as a cooperation partner when they expect to gain from the interaction. At the same time, the selection is typically mutual in the sense that FhG institutes will choose more innovative firms too. In the remainder of the analysis, we will make use of heteroscedasticity in the selection process as a source of exogenous variation to identify the true causal relation between FhG expenditures and firm outcomes.

3 Methodology

3.1 Identification strategy

Identification of the key effects of FhG interactions on firm performance through regression techniques faces the issue that FhG interactions are not random but rather results from selection. This section describes our empirical strategy to deal with the mutual selection issues.

To fix ideas, consider the following simple model of the relationship between the firm performance y_{it} and the cooperation variable FHG_{it}:

$$y_{it} = x_{it}\beta + FHG_{it}\delta + u_{it} \quad (1)$$

where x_{it} is a vector of control variables and u_{it} is a structural error term. δ is the central parameter of interest and measures how the interaction variable affects firm performance. If the time-varying factors governing the selection process can be sufficiently controlled for in x_{it} we can estimate Eq. (1) by regular Pooled OLS (POLS) and obtain consistent estimates of δ. If we assumed that any unobserved heterogeneity in u_{it} is time-constant we could also use Fixed Effects (FE). Time constant unobserved heterogeneity is, however, a problematic assumption, which is quite unlikely to hold. If selection is also a function of the firms' innovative capabilities, assuming constant unobserved heterogeneity would imply to assume away process of capability or skill accumulation inside the firm. This assumption seems particularly unreasonable since our dataset covers a long period, implying that neither FE-regression will lead to consistent estimates of δ.

To prevent that, we need to identify δ from exogenous variation in the interaction with FhG induced by instrumental variables. Recently, Lewbel (2012) has demonstrated how scale heteroscedasticity can help to generate instrumental variables. Essentially, the method proposed by Lewbel (2012) builds on second moment restrictions, not unlike well-known dynamic panel data estimators (Arellano and Bond 1991, Arellano and Bover 1995). In fact, though not commonly known, the approach by Lewbel extends a literature with a long tradition. Other applications relying on time-dependent heteroscedasticity in longitudinal data can be found in King et al. (1994), Sentana and Fiorentini (2001), Rigobon (2003) and Rigobon and Sack (2004). Indeed not only time-dependent but also cross-sectional heteroscedasticity can lead to structural identification as indicated already by Wright (1928). In order to provide some intuition why heteroscedasticity can lead to structural parameter identification, we sketch the general idea. We based our presentation on simplified cross-sectional models. We note, however, the Lewbel (2012) approach is consistent also in a panel data setting. Assume a simplified model without control variables:[5]

$$y_i = FHG_i\delta + a_1 capabil_i + e_{1i},$$

$$FHG_i = a_2 capabil_i + e_{2i}. \quad (2a,b)$$

where we allow that e_{2i} is heteroscedastic, i.e. it may depend on some vector h_i. Estimating Eq. (2a) by OLS without taking the unobserved capability-term into account will result in a biased estimate $\hat{\delta}$. In particular, setting $X = (FHG_1, \dots, FHG_n)'$, $z = (capabil_1, \dots, capabil_n)'$ and $y = (y_1, \dots, y_n)'$, $\hat{\delta}$ can be written as:

$$\hat{\delta} = (X'X)^{-1}X'y$$

[5] Suppressing the control variables leads to a closed form expression of the bias without matrix algebra, but otherwise does not inhibit the generality of the illustration.

$$= (1/n \sum_{i=1}^{n} x_i' x_i)^{-1}\, 1/n \sum_{i=1}^{n} x_i' y_i = \delta + (1/n \sum_{i=1}^{n} x_i' x_i)^{-1}\, 1/n \sum_{i=1}^{n} x_i' (a_1 z_i + e_{1i}) \quad (3)$$

The probability limes of Eq. (3) is given by:

$$\hat{\delta} \overset{p}{\rightarrow}= \delta + a_1 \frac{E(FHG_{it} capabil_i)}{E(FHG_i^2)} = \delta + a_1 \frac{a_2 E(capabil_i^2)}{a_2^2 E(capabil_i^2) + E(e_{2i}^2)} \quad (4)$$

where the second equality follows from replacing $\mathrm{FHG_{it}}$ with Eq. (2b). Although the OLS estimate is generally biased, if $E\left(e_{2it}^2\right)$ is large, the bias will be small. Fisher (1976) calls the dependence of the bias on the first stage error variance near identifiability. We present a graphical representation in Figure 1, where we simulated the Eqs. (2a, b) using $\delta = \alpha_1 = \alpha_2 = 1, \mathrm{e_{1i}} \sim \mathrm{capabil_i} \sim N(0,1)$. The left panel is generated with $\mathrm{e_{2i}} \sim N(0,1^2)$ and the right panel is generated with $\mathrm{e_{2t}} \sim N(0,5^2)$. Obviously, the true parameter δ is 1. However, when running the regression $\mathrm{y_i}$ on $\mathrm{FHG_i}$ we obtain a biased estimate of about 1.5 in the left panel. If we increase the second stage error to variance to 25 (right panel), the estimated slope parameter drops to about 1.04 and is already very close to the true parameter. Intuitively, the increase in the variance of $\mathrm{e_{2i}}$ weakens the strength of the direct relationship between $\mathrm{FHG_i}$ and the omitted variable $\mathrm{capabil_i}$, which is defined by Eq. (2b), leading to a drop in the bias.

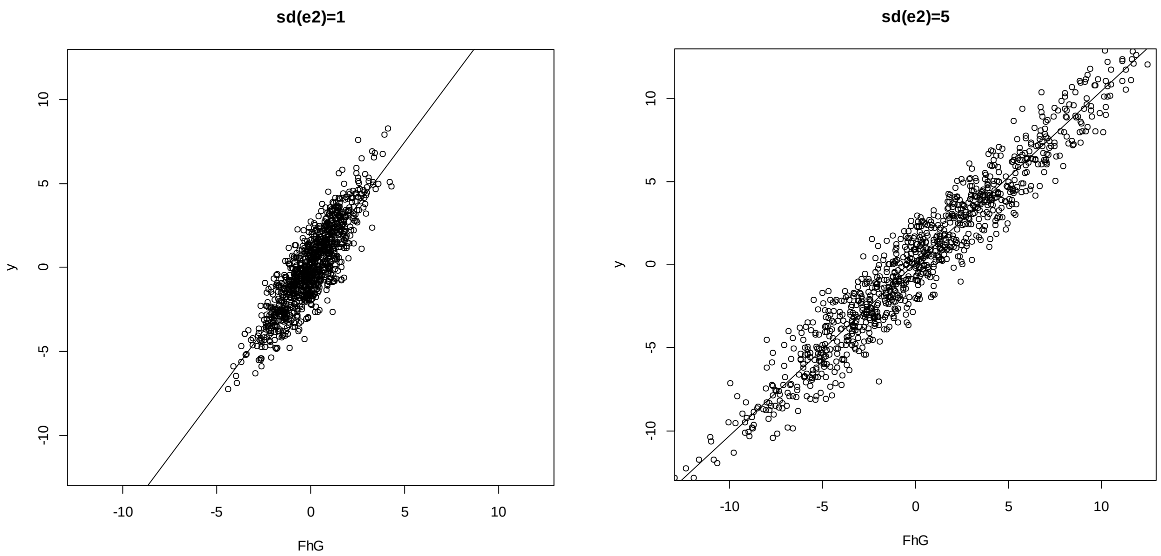

Figure 2: Higher degrees of heteroscedasticity lead to more accurate estimation of FHG

Two principal ways to exploit the dependence of the bias on the error variance have emerged in the literature. The first approach is the event-study design, which assumes that in specific events the error variance becomes so large that OLS leads to approximate identification. However, unless the variance becomes infinite, identification will never be exact. Under certain conditions it is however possible to use heteroscedasticity as a basis for defining instrumental variables, which can solve the identification problem even if the second stage error variance is finite. Eq. (4) gives an intuition: since the omitted variable bias is a function of the first stage error variance, heteroscedasticity implies that not only $E(e_{2i}^2)$ but also the bias in Eq. (4) is a function of the vector h_i. If for example we assume positive scale heteroscedasticity, the bias is smaller the larger the individual elements of h_i are. Moreover, since h_i appears nowhere else in the model, h_i induces exogenous variation in the model: it affects $\mathrm{FHG_i}$, more precisely its volatility, but it has no effect on $\mathrm{capabil_i}$ or its volatility. Indeed, we can define instruments, which use this exogenous information to identify the true regression parameters.

To illustrate that, we turn to more general version of Eqs. (2a, b) allowing for a vector of control variables $x_i \in \mathbb{R}^k$:

$$\mathrm{y_i} = \mathrm{x_i}\beta + FHG_i\delta + \mathrm{u_i}$$

$$FHG_i = \mathrm{x_i}\zeta + \mathrm{v_i} \qquad (5a,b)$$

with $\mathrm{u_{it}} = \mathrm{a_1 capabil_i} + \mathrm{e_{1i}}$, and $\mathrm{v_i} = \mathrm{a_2 capabil_i} + \mathrm{e_{2i}}$ and $E(e_{2i}^2)$ is allowed to depend on x_{it}. Again, we are not able to consistently estimate the model because of omitted variable bias induced by the unobserved variable $\mathrm{capabil_i}$.

To achieve identification by exploiting heteroscedasticity we make the usual minimal identification assumption that $\mathrm{x_i}$ is exogenous, i.e. $E(x_i u_i) = 0$ and $E(x_i v_i) = 0$. Lewbel (2012) shows that the variable $\mathrm{z_i}$ defined as $\mathrm{z_i} = (\mathrm{x_i} - \mathrm{E(x_i)})\mathrm{v_i}$ is a valid instrument for $\mathrm{FHG_{it}}$ if the following two conditions are met:

$$\mathrm{cov}(\mathrm{x_i} - \mathrm{E(x_{it})}, \mathrm{u_i v_i}) = 0$$

$$\mathrm{cov}\left(\mathrm{x_i} - \mathrm{E(x_i)}, v_i^2\right) \neq 0 \qquad (6a, b)$$

Because the proof is lengthy and somewhat tedious, we omit here. Yet, it is easy to create some intuition why these assumptions identify the parameters of interest. Eq. (6b), meaning heteroscedastic first stage errors, implies that the instrument $\mathrm{z_i}$ and the endogenous variable are correlated. Using Eq. (5a,b) we can write:

$$cov\left(x_i - \mathrm{E(x_i)}, \mathrm{v_i^2}\right) = E((x_i - \mathrm{E(x_i)})v_i(FHG_i - \mathrm{x_i}\zeta))$$

$$= E(z_i FHG_i) - \zeta\mathrm{E}(\mathrm{x}_i^2 v_i) + \zeta\mathrm{E(x_i)}\mathrm{E}(\mathrm{x_i} v_i) = \mathrm{E}(z_i FHG_i) \neq 0 \qquad (7)$$

On the other hand, Eq. (6a) guarantees that $\mathrm{x_i}$ does not simultaneously affect the variance of the unobserved variable. Assuming without loss of generality that the expectation of the unobserved variable is zero, note that:

$$\mathrm{cov}(\mathrm{x_i} - \mathrm{E(x_i)}, \mathrm{u_i v_i}) = E(z_i u_i)$$

$$= \mathrm{E}\left((x_i - \mathrm{E(x_i)})(\mathrm{a_1 a_2 capabil_i^2} + \mathrm{a_1 capabil_i e_{2i}} + \mathrm{a_2 capabil_i e_{1i}} + \mathrm{e_{1i} e_{2i}})\right) = 0 \qquad (8)$$

Thus, Eq. (6b) is similar to the regular rank condition in IV ensuring that the instruments are correlated with the endogenous variable. Eq. (6a) is equivalent to the exogeneity condition, because it requires that the instruments and the structural error term are uncorrelated. Furthermore, Eq. (8) illustrates the identification assumption: the variation in FHG_i induced by heteroscedastic first stage errors is exogenous only if it does not also affect the variance of the unobserved variable $\mathrm{capabil}_i$, which is a standard assumption in error component models (Lewbel 2012). We can easily implement the Lewbel estimator by constructing the sample equivalent of z_i:

$$\widehat{z_i} = (x_i - \overline{x})\widehat{v_i} \text{ (9)}$$

where $\widehat{v_i}$ is the residual from reduced form regression of FHG_i on the exogenous regressors x_i. $\widehat{v_i}$ is structurally identified because the parameters in the reduced form regression can always be consistently estimated (Wooldridge, 2002).[6]

For the purpose of our paper, the results by Lewbel (2012) imply that we are able to identify the causal effect of an interaction with FhG on firm performance, if and only if we detect a source of heteroscedasticity in the reduced form regression.

3.2 First-stage heteroscedasticity

We will now continue by providing evidence that in particular firm size induces positive scale heteroscedasticity, such that the variance of the FhG expenditures is a robust and positive function of firm size. The other control variables (e.g. age, exports, etc.) do not show any evidence of inducing heteroscedasticity, implying that we cannot fruitfully use them as a basis to identify the causal effect of FhG interaction on firm performance. Mathematically, the size variable meets the condition in Eq. (6b) while the other controls do not. An important implication is that the identification strategy based on heteroscedasticity leads in our application to an exactly (though not over) identified model.

[6] It should be noted that Lewbel-methodology works in broader settings than the omitted variable bias considered here. In specific, even full simultaneity in Eq. (2a) and Eq. (2b) is admissible.

Table 5: Regression for instrument calculation

	(1)
Dependent:	$\ln(FhG_{t-1})$
$RDINT_{t-1}$	0.629***
	(0.091)
$ln(AGE_{t-1})$	0.000
	(0.007)
$ln(EMP_{t-1})$	0.094***
	(0.007)
$EXPORT_{t-1}$	0.011
	(0.012)
$GROUP_{t-1}$	-0.011
	(0.010)
$EAST_{t-1}$	0.004
	(0.011)
CONSTANT	-0.282***
	(0.042)
Industry F.E. joint significance	F(25,17603)= 10.043***
Time F.E. joint significance	F(16,17603)= 20.671***
N	57301
R^2	0.090

Notes: OLS regression. Standard errors in parentheses.
Standard errors clustered by firm
* p<0.10, ** p<0.05, *** p<0.01.

Table 5 presents an OLS regression of FhG expenditures on firm characteristics, representing the first stage in Eq. 5. The main observable factors driving FhG expenditures are R&D intensity and size: other factors equal, a one percentage point increase in R&D intensity coincides with a 0.63% increase in FhG expenditures, and a one percent increase in size leads to a 0.094% increase in expenditures. Likewise, the sector and time fixed effects are statistically jointly significant at p<0.01.

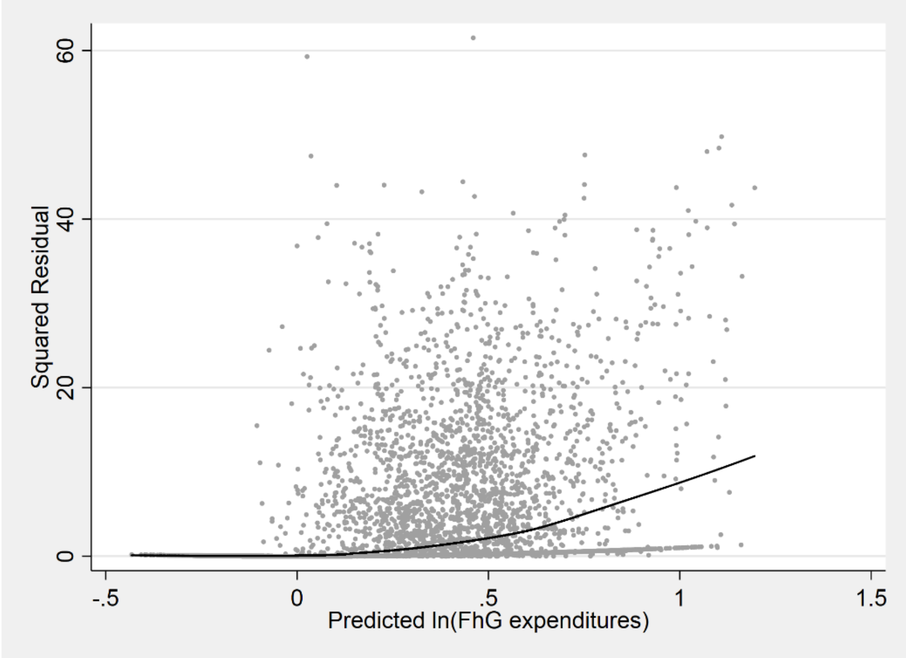

Figure 3: First stage heteroscedasticity
Notes: Lowess smoother. Bandwidth = 0.8.

As Figure 3 shows, FhG expenditures exhibit strong scale heteroscedasticity. The presence of heteroscedasticity is confirmed by Koenker's (1981) NR^2 test statistic ($LM(47) = 5470.244$, $p<0.01$) as well as White's (1980) NR^2 test ($LM(652) =2142.160$, $p<0.01$). Both strongly reject homoscedasticity.

As argued above, this scale heteroscedasticity appears to be solely driven by firm size. We see that explicitly in figure 4, where the results of linear partial regressions of the explanatory variables on the squared error are shown.[7] This result is intuitive: as firm size increases, the variation in R&D budget, and hence expected FhG expenditures, increases as well. In the empirical analysis, we make use of the scale heteroscedasticity in FhG expenditures driven by firm size in order to instrument FhG expenditures and identify a causal relationship between collaboration with FhG and firm outcomes.

[7] Each panel shows the outcome for one regression, where the other covariates are controlled and the variable of interest is estimated through a Lowess smoother. The last three panels (Exporter, Group, East German) present the outcome of a t-test where the residual of a regression of the squared error on the other covariates is compared across the (binary) variable of interest.

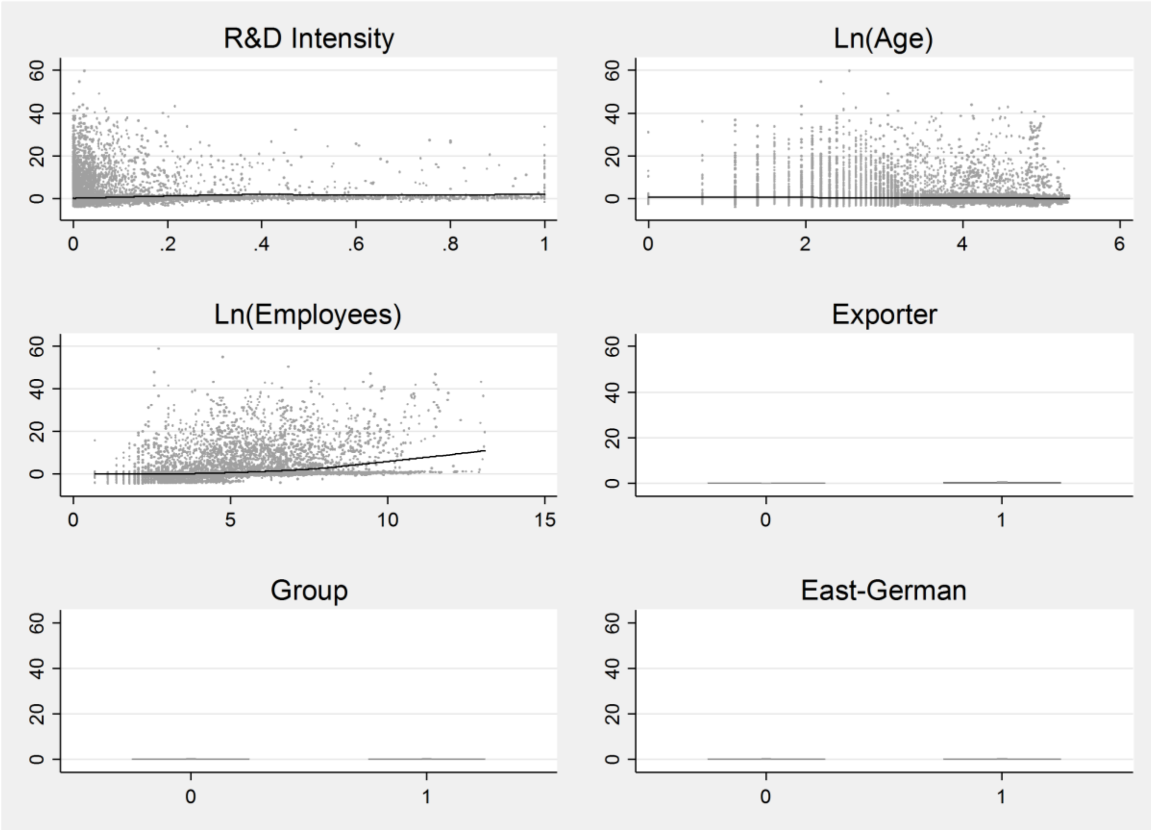

Figure 4: Linear partial regression of heteroscedasticity in first stage on firm characteristics
Notes: Y axis: squared residual of regression of FhG expenditures on controls. Line: Lowess smoother. Bandwidth = 0.8.

3.3 Econometric specification

We make additional changes to the main specification in addition to using heteroscedasticity in FhG expenditures to identify their effect. To further eliminate unobserved heterogeneity between firms, we use year-on-year growth rates (for turnover and productivity) and differences (workforce education and innovative sales) as outcomes, rather than their levels. This correction removes variation due to common factors among firm-year combinations from the data (compare Imbens and Wooldridge, 2008). In the case of turnover and productivity growth, we can write the baseline model as follows:[8]

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha + \ln(\mathrm{y}_{it-1})\,\gamma + \ln(FhG_{it-1})\delta + X_{it-1}\beta + T_t\zeta + I_{it-1}\eta + \varepsilon_{it} \quad (7)$$

The left hand side of the equation, $\ln\left(\frac{y_{it}}{y_{it-1}}\right)$, represents the logged growth factor of respectively turnover and productivity. Both the outcome and FhG expenditures, $\ln(FhG_{it-1})$, are estimated in logs.

[8] Table A-2 additionally reports results for a level specification estimated with OLS and Fixed Effects. The results reported below are robust to the OLS level model, and hold for turnover and productivity in the Fixed Effects model. However, as we explain in the methodology, neither model solves the endogeneity issue of nonrandom selection into FhG expenditures.

Because $\ln\left(\frac{y_{it}}{y_{it-1}}\right) \approx g_y$, with g_y being the growth rate of y, our specification allows us to interpret the coefficient of $\ln(FhG_{it-1})$ as a semi-elasticity on the growth rate. As suggested by Imbens and Wooldridge (2008), we include the log of the lagged outcome, $\ln(y_{it-1})$, in the estimation in order to account for any systematic relationship between the average growth rates and the level of the outcome variable. We furthermore control for other observable firm characteristics captured in X_{it-1}, including lagged R&D intensity, firm age and size[9], and whether the firm exports, is part of a group, and is situated in former Eastern Germany. We also include a set of year and industry dummies to account for generic time and sector effects.

In the case of the share of employees with tertiary education and the share innovative sales, we adapt Eq. 7 to take into account the fact that the outcome is a share and hence bounded between 0 and 1. Because the outcome already represents shares, using a growth rate would make the results hard to interpret intuitively. As a more convenient alternative, we difference the outcome variable, which allows us to interpret the coefficient of $\ln(FhG_{it-1})$ as an effect on the outcome variable in percentage points.

$$y_{it} - y_{it-1} = \alpha + y_{it-1}\gamma + \ln(FhG_{it-1})\delta + X_{it-1}\beta + \varepsilon_{it} \quad (8)$$

We estimate the models with OLS and with 2SLS. In the latter, we instrument $\ln(FhG_{it-1})$ through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$, where $\hat{v}$ is the estimated first-stage error term, as described in the previous section. In all models, we account for cross-sectional dependence by calculating standard errors clustered by firm.

4 Results

4.1 Turnover growth and productivity growth

Table 6 presents OLS and 2SLS estimates of the relation between FhG expenditures, $ln(FHG_{t-1})$, on the right hand side, and turnover and productivity growth factors ($\ln(TR_{GRt})$ and $\ln(PROD_{GRt})$ on the left-hand side. Column 1 shows the OLS estimates for turnover growth. A one percent increase in a firm’s FhG expenditures relates to a large 1.0 percentage point increase in the firms' annual growth rate ($p<0.01$). The 2SLS estimates (column 2) yields a slightly higher effect of 1.1 percentage points. The model shows a strong first stage with Cragg-Donald Wald F-statistic far exceeding Stock-Yogo critical values (Stock & Yogo, 2005). If we compare the latter to the average growth in the sample, which is 6.7% (Table A-1), the FhG effect is substantial. It amounts to approximately 16% of the total average growth in the sample.

[9] We omit the latter from the specification focusing on turnover growth, as lagged turnover and number of employees are highly correlated (0.89). However, the coefficient of Fraunhofer expenditures does not change significantly if this variable is included.

With respect to the control variables, the model show the expected relations. Turnover growth rates increase in R&D intensity ($RDINT_{t-1}$), and decrease in size (ln[TR_{t-1}]) and age (ln[AGE_{t-1}]). Exporting firms ($EXPORT_{t-1}$) and firms which are part of groups ($GROUP_{t-1}$) experience higher turnover growth, and firms from former Eastern Germany ($EAST_{t-1}$) tend to grow more slowly. The sector and year dummies are each jointly significant at p<0.01. [10]

Columns 3 and 4 present the result for productivity growth. The results support that engaging with FhG increase also the firms' productivity growth, with both the OLS and 2SLS estimates situated around an effect at 0.7 percentage points. The IV estimations are however less precise than the OLS estimates (OLS: p<0.01, 2SLS: p<0.05). Productivity growth also correlates positively with R&D intensity (albeit at weak statistical significance) and the size of the firm (ln[EMP_{t-1}]). Exporting and firms which are part of groups also show higher productivity growth. Firms situated in former Eastern Germany instead have a lower productivity growth. In addition, productivity growth also drops more quickly at higher productivity levels than turnover growth (estimated elasticity of $PROD_{t-1}$ to $PROD_{GRt}$: -0.155%, compared to -0.009% for TR_{t-1} and $\mathrm{TR}_{\mathrm{GRt}}$).

[10] The results presented in these columns are robust to including $ln(EMP_{t-1})$ as additional covariate. We however do not include it to avoid issues of multicollinearity.

Table 6: FhG expenditures and firm performance

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	$\ln(TR_{GRt})$		$\ln(PROD_{GRt})$	
$ln(FHG_{t-1})$	0.010***	0.011***	0.007***	0.007**
	(0.002)	(0.003)	(0.002)	(0.003)
$ln(TR_{t-1})$	-0.009***	-0.008***		
	(0.001)	(0.001)		
$ln(PROD_{t-1})$			-0.155***	-0.155***
			(0.005)	(0.005)
$ln(EMP_{t-1})$			0.013***	0.013***
			(0.001)	(0.001)
$RDINT_{t-1}$	0.154***	0.151***	0.055*	0.055*
	(0.024)	(0.024)	(0.029)	(0.029)
$ln(AGE_{t-1})$	-0.009***	-0.009***	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
$EXPORT_{t-1}$	0.013***	0.013***	0.028***	0.028***
	(0.003)	(0.003)	(0.005)	(0.005)
$GROUP_{t-1}$	0.014***	0.014***	0.011***	0.011***
	(0.003)	(0.003)	(0.004)	(0.004)
$EAST_{t-1}$	-0.012***	-0.012***	-0.043***	-0.043***
	(0.003)	(0.003)	(0.005)	(0.005)
CONSTANT	0.054*	0.006	0.494***	0.633***
	(0.028)	(0.013)	(0.051)	(0.031)
Industry F.E. joint significance	F(25,14836)= 5.160***	Chi²(25)= 128.781***	F(25,9480)= 13.378***	Chi²(25)= 335.120***
Time F.E. joint significance	F(16,14836)= 58.905***	Chi²(16)= 946.268***	F(15,9480)= 11.716***	Chi²(15)= 176.093***
N	48268	48268	25468	25468
R^2	0.031	0.031	0.100	0.100
Cragg-Donald Wald F-statistic		49150.140		25552.642

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$, where $\hat{v}$ is the estimated first-stage error term. Specifications 1-2: $ln(EMP_{t-1})$ omitted to avoid multicollinearity with $ln(TR_{t-1})$. The results do not change substantially when $ln(EMP_{t-1})$ is included.
* p <0.10, ** p<0.05, *** p<0.01

4.2 Human capital and innovation success

We now turn to innovation as a potential driver of the positive effects in terms turnover and productivity growth. If interacting with FhG affects firms' innovation strategy, as we have argued, this may be reflected in the firm's hiring strategy or innovative success. Table 7 presents the impact of FhG expenditures on the change in the share of employees with tertiary education ($\Delta TERT_{t,t-1}$, column 1 and 2) and on the change in the share of innovative products and services in turnover ($\Delta INNOSALES_{t,t-1}$, column 3 and 4).

As shown in column 1, the OLS coefficient of $ln(FHG_{t-1})$ is positive and statistically highly significant ($p<0.01$). A one percent increase in FhG expenditures relates to a 0.3 percentage point increase in the share of employees with tertiary education. This supports the intuition that FhG expenditures lead to a shift in the firm's hiring strategy towards the recruitment of more qualified personnel. The effect however turns insignificant in the 2SLS specification (column 2), indicating that the observed correlation is most likely due to selection. The regressions also show expected negative relations between the lagged share of employees with tertiary education ($TERT_{t-1}$), firm age, and size. We find stronger increases among exporting firms, more R&D intense firms, and firms in former Eastern Germany.

Columns 3 and 4 present the relation between FhG expenditures and the change in the share of sales due to innovative products and services. The OLS and 2SLS estimations indicate that a one percent increase in FhG expenditures leads to an increase in the share of innovative sales enjoyed by the firm of respectively 0.7 and 0.5 % points. Comparing that increase to the average share of turnover with due to new products of 6.7% (Table A-1), we find an economically sizeable effect of 7.5% of the overall average.

Table 7: FhG expenditures and firm strategy

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	$\Delta TERT_{t,t-1}$		$\Delta INNOSALES_{t,t-1}$	
$ln(FHG_{t-1})$	0.003***	0.001	0.007***	0.005**
	(0.001)	(0.001)	(0.002)	(0.002)
$TERT_{t-1}$	-0.143***	-0.143***		
	(0.004)	(0.004)		
$INNOSALES_{t-1}$			-0.425***	-0.424***
			(0.008)	(0.008)
$ln(EMP_{t-1})$	-0.001***	-0.001***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
$RDINT_{t-1}$	0.042***	0.043***	0.212***	0.213***
	(0.007)	(0.007)	(0.017)	(0.017)
$ln(AGE_{t-1})$	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
$EXPORT_{t-1}$	0.004***	0.004***	0.018***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
$GROUP_{t-1}$	0.001	0.001	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
$EAST_{t-1}$	0.006***	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
CONSTANT	0.005	0.057***	-0.011	-0.002
	(0.009)	(0.006)	(0.013)	(0.006)
Industry F.E. joint significance	F(25,13258)= 21.893***	Chi2(25)= 548.819***	F(25,12884)= 13.925***	Chi2(25)= 347.213***
Time F.E. joint significance	F(16,13258)= 7.345***	Chi2(16)= 120.670***	F(16,12884)= 39.329***	Chi2(16)= 627.508***
N	39019	39019	35019	35019
R^2	0.083	0.081	0.288	0.313
Cragg-Donald Wald F-statistic		35194.618		32009.447

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$, where $\hat{v}$ is the estimated first-stage error term.
* p <0.10, ** p<0.05, *** p<0.01

4.3 Result heterogeneity

This section presents heterogeneous results along project and firm characteristics. In order to obtain results differentiated by type of project and firms, we interact $\ln(FhG_{it-1})$ with dummies representing certain cut-off points (e.g. small in contrast to large firms).

In terms of project characteristics, we first consider whether the effects differ between projects relating to technology implementation or generation. Second, we test whether the effects differ for firms with a longer history of FhG interactions. Third, we analyse whether FhG expenditures are subject to diminishing returns. On the firm side, we study variation among the effect along R&D intensity, sector of operations, size, and age.

Because IV methods typically become instable when the number of endogenous variables increases, all results are based on OLS estimates where the differentiating factor in question is interacted with $\ln(FhG_{it-1})$. We believe that using OLS results is justifiable, since the IV and the OLS-results did not differ tremendously in the baseline regressions in Table 6 and Table 7.

4.3.1 Project characteristics

Table 8 compares projects aimed at technology implementation and projects focused on technology generation. For this we make use of the keyword-based definition outlined in Table 3. We define implementation projects as those relating to concrete changes in the firm, such as the installation of new equipment, the introduction of a new product, etc. Technology generation relates more to upstream activities such as performing scientific studies. Whereas both bring valuable knowledge to the firm, generation projects deliver more abstract knowledge which might have a different effect on performance and strategy.

The difference is reflected in the results: only expenditures for technology generation show a strong and significant relation to all types of firm-level outcomes, whereas implementation projects only lead to increases in productivity growth and innovative sales. Technology generation projects instead also lead to higher turnover growth and more personnel with tertiary education. The stronger effect on turnover growth and a change towards use of higher qualified personnel indicate that a substantial part of the value generated by FhG is in the form of enabling firms to make us of abstract scientific knowledge, which might otherwise be unattainable.

Table 8: Impact of FhG expenditures by project focus

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
Technology implementation	0.002	0.010***	0.002	0.006**
	(0.003)	(0.004)	(0.001)	(0.002)
Technology generation	0.011***	0.010***	0.003***	0.006***
	(0.003)	(0.003)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

Table 9 shows how the impact of FhG expenditures evolves along firm's experiences with FhG, as proxied by the number of years in which payments were made to FhG. The dynamics are different for the different outcomes. Turnover growth effects do not materialize after the first payment, but later payments show positive effects. In other words, an additional FhG -related project interaction – as proxied by a payment - consistently relates to increases in growth, even when the firm already interacted with FhG in the years before. The estimates concerning productivity growth paint a partially different picture: some productivity growth shows after the first FhG payment, but the effect of the second is much higher. However, later payments, with the exception of the final group which groups together five and more, do not result in additional efficiency gains.

These patterns are also reflected in the innovation and human capital related outcome measures: additional payments to FhG consistently result in gains in the increase in the share of innovative sales, but further increases in the share of employees with tertiary education taper off after the 3rd. Our results therefore show that interacting with FhG does not lead to immediate positive effects. Instead, firms need to engage in multiple projects with FhG before benefits peak, suggesting that firms probably need to make adjustments to their processes and their internal capability base in order to reap the full benefits of FhG interactions.

Table 9: Impact of FhG expenditures by interaction number

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
1st	0.006	0.011*	0.002	0.004
	(0.004)	(0.007)	(0.002)	(0.003)
2nd	0.012***	0.021***	0.002**	0.008**
	(0.004)	(0.006)	(0.001)	(0.003)
3rd	0.010**	0.010	0.005**	0.008**
	(0.004)	(0.006)	(0.002)	(0.004)
4th	0.009*	0.008	0.002	0.012***
	(0.005)	(0.007)	(0.002)	(0.004)
5th+	0.010**	0.010***	0.002*	0.007***
	(0.004)	(0.003)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

Table 10 explores the returns to scale associated with FhG expenditures. To that end, differential effects are estimated for each quartile of the distribution of FhG expenditures. Again, the results differ by outcome. The smallest volumes of expenditures realize neither turnover growth nor productivity gains. Expenditures in the 2nd to 4th quartile do result in turnover growth, but at comparable marginal effects across the level of expenditures. Productivity gains are only realized among firms which show relatively high levels of FhG expenditures, that is, in the upper half of the distribution. Growth in the share of employees with tertiary education is only found at high levels of statistical significance ($p<0.01$) for the largest category of FhG expenditures. In contrast, increased innovative sales show up significant at most ranges. However, the estimated coefficient is highest at the lower end of the FhG expenditures distribution.

Table 10: Impact of FhG expenditures by expenditures level

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
1st Quartile	0.004	0.013	0.006*	0.019**
	(0.010)	(0.012)	(0.003)	(0.008)
2nd Quartile	0.013***	0.008	0.00006	0.009**
	(0.005)	(0.006)	(0.002)	(0.004)
3rd Quartile	0.013***	0.019***	0.002*	0.005*
	(0.003)	(0.004)	(0.001)	(0.002)
4th Quartile	0.009***	0.011***	0.003***	0.008***
	(0.002)	(0.003)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. 1st Quartile: up to 6,203 EUR. Second quartile: 6,204 EUR up to 22,762 EUR. Third quartile: 22,763 EUR up to 72,306 EUR. Fourth quartile: more than 72,306 EUR. Other controls included. * $p<0.10$, ** $p<0.05$, *** $p<0.01$ Standard errors in parentheses. Standard errors clustered by firm.

Taken as a whole, this exploration of the effects of FhG expenditures along the nature of the project shows that projects seem to either result in innovative success and growth, or in efficiency gains. When the goal is to increase innovative success and growth, projects focusing on technology generation, repeated interactions, and relatively lower levels of expenditures appear to be more effective. Efficiency gains are realized when projects are more strongly related to implementation tasks, do not yield additional benefits along further interactions, and are comparably large in terms of project volume.

4.3.2 Firm characteristics

Table 11 shows the impact of FhG for firms with different R&D intensities. Economic theory predicts that firms require certain levels of internal knowledge in order to optimally internalize and apply external knowledge (Cohen and Levinthal, 1989). It is therefore worthwhile to consider to which extent without high R&D expenditures can benefit from FhG's mission of knowledge transfer.

Table 11 shows that some level of R&D expenditures is a precondition for internalizing FhG expenditures into productivity and innovation, but even firms without any R&D expenditures in a year enjoy higher turnover growth in the wake of interacting with FhG. Even though the estimated coefficient is statistically only weakly significant, it is similar to the estimates for firms with either below or above average R&D intensity. The effect of FhG expenditures on productivity growth is only significant and large for firms with R&D expenditures, where both comparatively high and low R&D spenders benefit similarly. This is also the case for increases in innovative success.

Table 11: Impact of FhG expenditures by R&D intensity

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
No R&D expenditures	0.010*	0.001	0.001	-0.001
	(0.005)	(0.005)	(0.002)	(0.003)
Below average	0.010**	0.017***	0.007***	0.010***
	(0.004)	(0.005)	(0.001)	(0.003)
Above average	0.011***	0.013***	0.001	0.008***
	(0.002)	(0.003)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

Another relevant question is how much SMEs benefit from interacting with FhG. Table 12 shows differential effects for small firms (with less than 50 employees), medium-sized firms (50-249 employees), and large firms. Small firms only benefit weakly from interacting with FhG, with just a statistically weakly significant increase in the share of employees with tertiary education. This might to some extent be the result of a lower number of small firms interacting with FhG, as the point estimates are quite comparable to those of medium-sized and large firms.

Large firms, on the other side, show significant effects across the board. Medium sized firms experience no significant growth after interacting with FhG, but do show similar increases in productivity growth and innovative sales as large firms. The effect on highly educated personnel is larger for medium-sized firms than for large firms.

Table 12: Impact of FhG expenditures by firm size

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
Small (< 50 empl.)	0.010	0.007	0.004*	0.006
	(0.007)	(0.008)	(0.002)	(0.004)
Medium (50-249 empl.)	0.004	0.017***	0.005***	0.008**
	(0.003)	(0.005)	(0.001)	(0.003)
Large (≥ 250 empl.)	0.012***	0.012***	0.001**	0.008***
	(0.002)	(0.002)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

Interacting with FhG might also have a different impact on incumbent firms and start-ups. Start-ups are especially interesting, as they might be in higher need of short-term knowledge support to develop production and innovation lines, but at the same time likely have fewer resources with which to fund external research expenses such as FhG. They also might especially benefit from knowledge transfer early on, when they are better able to react to opportunities brought by it.

To assess this possibility, table 13 compares effects of FhG expenditures on young firms, which are seven years old or younger, and older firms. The results show that young firms seem to benefit more from FhG expenditures in terms if firm growth and increases in the share of innovative sales (even though the difference is smaller in this case). Both groups show equal elasticities between FhG expenditures and productivity growth. Only older firms seem to see shifts in the share of employees with tertiary education as a result of FhG expenditures.

Table 13: Impact of FhG expenditures by firm age

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
≤ 7 years	0.022***	0.013**	0.002	0.011**
	(0.006)	(0.006)	(0.002)	(0.005)
> 7 years	0.008***	0.013***	0.003***	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

Table 14 differentiates between firms in manufacturing and service sectors. It is ex ante unclear whether service firms also benefit from interacting with FhG to the same degree as firms in manufacturing sectors considering that the technologies FhG focuses on are to large extent situated in manufacturing industries. The results show that firms in both sectors show increases in performance, human capital composition, and innovation success in the wake of FhG expenditures, albeit in slightly different ways. The coefficient of FhG expenditures in turnover growth is only statistically significant for manufacturing firms. Service firms, however, seem to benefit slightly more in terms of productivity, and in terms of increases in the share of innovative sales. Both groups show similar effects of FhG expenditures on the share of employees with tertiary education.

Table 14: Impact of FhG expenditures by manufacturing versus services firms

	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
Manufacturing	0.011***	0.012***	0.002***	0.007***
	(0.002)	(0.002)	(0.001)	(0.002)
Services	0.007	0.017**	0.004***	0.011***
	(0.005)	(0.007)	(0.002)	(0.004)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Standard errors in parentheses. Standard errors clustered by firm.

The above analysis sheds more light on which firms are best suited to profit from knowledge translation in the form of interactions with FhG. Some level of R&D expenditures, i.e. absorptive capacity, on the firm's side seems essential for the translation of FhG expenditures in gains. Furthermore, the smallest firms only seem to benefit from FhG to a limited extent; medium-sized and larger firms show much stronger benefits. Firm age matters too: young firms show much higher increases in growth as a result of FhG expenditures than older firms. Lastly, the main beneficiaries of FhG interactions in terms of turnover growth seem to be manufacturing, as opposed to services, firms. At the same time, firms in service industries still benefit in terms of productivity growth, changes in the labour force, and innovation success.

4.4 Robustness check: controlling for other science cooperation

A potential limitation of our approach is that we did not control for the full range of cooperation involving the firm. If interaction with FhG is correlated with cooperation with other research institutions or universities, and if both are subject to similar selection processes, the results we documented until now might be contaminated by unobserved cooperation.

While we cannot formally control for all other potential cooperation, some waves of the German CIS register which innovation-active firms cooperate with higher education institutes ($COOPUNI$) and other public research institutions ($COOPINST$). Hence, we can test whether our results are robust to controlling for cooperation for this subsample and the years 2002-2004 and 2006-2013. There are two limitations to this approach: the estimations samples are markedly smaller, and the selection of innovation-active firms might introduce further distortions. Nevertheless, we can take these results are at least indicative.

These data confirm that interacting with FhG indeed correlates with cooperation with universities (correlation coefficient: 0.26) and research institutions (correlation coefficient: 0.29). Table 15 shows the results while controlling for $COOPUNI$ and $COOPINST$. Even though $COOPUNI_{t-1}$ correlates positively with TR_{GRt}, the elasticity to FHG_{t-1} remains robust at 0.012 in the 2SLS specification. The relation to $PROD_{GR}$ becomes weaker (0.004 instead of 0.007) and turns insignificant. This is also the case for $\Delta INNOSALES$, even though the estimated coefficient is much closer to the previous one (0.004 instead of 0.005).

Table 15: Controlling for other science cooperation

Panel A: firm performance	OLS	2SLS	OLS	2SLS
	$\ln(TR_{GRt})$		$\ln(PROD_{GRt})$	
$ln(FHG_{t-1})$	0.005*	0.012***	0.007*	0.004
	(0.003)	(0.004)	(0.004)	(0.006)
$COOPUNI_{t-1}$	0.021***	0.020***	0.012	0.012
	(0.007)	(0.007)	(0.010)	(0.010)
$COOPINST_{t-1}$	0.010	0.006	0.014	0.016
	(0.009)	(0.010)	(0.012)	(0.012)
Controls	YES	YES	YES	YES
N	13498	13410	9272	9272
R²	0.038	0.039	0.111	0.111
Cragg-Donald Wald F-statistic		6887.613		4164.942
Panel B: Innovation	OLS	2SLS	OLS	2SLS
	$\Delta TERT_{t,t-1}$		$\Delta INNOSALES_{t,t-1}$	
$ln(FHG_{t-1})$	0.002**	-0.001	0.002	0.004
	(0.001)	(0.002)	(0.002)	(0.003)
$COOPUNI_{t-1}$	0.011***	0.012***	0.041***	0.041***
	(0.003)	(0.003)	(0.005)	(0.005)
$COOPINST_{t-1}$	0.007*	0.008**	0.017***	0.016**
	(0.004)	(0.004)	(0.006)	(0.006)
Controls	YES	YES	YES	YES
N	11789	11789	11866	11866
R²	0.089	0.089	0.253	0.253
Cragg-Donald Wald F-statistic		5470.869		5740.132

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$, where $\hat{v}$ is the estimated first-stage error term. $\ln(TR_{GRt})$: $ln(EMP_{t-1})$ omitted to avoid multicollinearity with $ln(TR_{t-1})$. The results do not change substantially when $ln(EMP_{t-1})$ is included. Cooperation data is available for 2002-2004 and, 2006-2013. Sample only includes innovation active firms, for which cooperation variables are observed. Full results reported in Table A-3.
* p <0.10, ** p<0.05, *** p<0.01

4.5 Placebo tests and dynamics in the performance relationship

As a way of testing the validity of our approach to identification, we conducted the following logic. If our specification is correctly specified, a future increase in FhG expenditures, at, say, $t + 3$, should not show a causal relationship with past firm outcomes. A regression of $ln(FHG_{t+3})$ on outcomes should therefore yield an insignificant coefficient. As this experiment could be understood as a general test of misspecification, a significant coefficient would mean that at least one of the model assumptions fails. Such failures could include endogenous IVs, functional form misspecification or non-accounted sources of endogeneity. A further source of failure, which could be particularly relevant in this case, is autocorrelation in FhG expenditures due to persistence in interacting with FhG over time. This mechanism may give rise to dynamic interdependence, leading to failure of the placebo test operating on a static model.

Panel A of Table 16 shows the results of this specification (the full results are shown in Table A-4). In all specifications but the one estimating turnover growth, lead FhG expenditures are not statistically significant. We suspect that the significant coefficient for turnover growth is driven by unaccounted serial correlation in engagement with FhG. That means that the positive coefficient of $ln(FHG_{t+3})$ might represent a residual effect, where FhG expenditures in period $t-1$ correlate positively with FhG expenditures afterwards. To check our suspicion, we re-estimated these models with lagged FhG expenditures term in the first stage (Panel B). The positive coefficient of turnover growth indeed vanishes when this correlation is accounted for.

Table 16: Placebo test

Panel A: Placebo test	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta INNOSALES_{t,t-1}$	$\Delta TERT_{t,t-1}$
$ln(FHG_{t+3})$	0.007**	0.005	0.004	0.001
	(0.003)	(0.004)	(0.002)	(0.001)
Controls	YES	YES	YES	YES
N	22395	14113	14485	19494
R^2	0.041	0.093	0.260	0.078
Cragg-Donald Wald F-statistic	25400.589	17871.980	15329.832	19951.995
Panel B: Placebo test with dynamic first stage				
$ln(FHG_{t+3})$	0.006	0.004	0.0004	0.003**
	(0.004)	(0.006)	(0.003)	(0.001)
Controls	YES	YES	YES	YES
N	20357	12970	13405	17843
R^2	0.041	0.094	0.258	0.080
Cragg-Donald Wald F-statistic	6398.739	4237.055	3958.610	5164.762

Notes: Standard errors clustered by firms in parentheses. Panel B: include $ln(FHG_{t-1})$ in first stage. Full results reported in Table A-4.
* p <0.10, ** p<0.05, *** p<0.01

As a dynamic specification of the first stage seems to correct for at least one kind of misspecification, we re-estimate the main results instrumenting $ln(FHG_{t-1})$ through the scale heteroscedasticity instruments generated by firm size and the dynamic term. This yields the additional advantage that we can conduct a Hansen J-test for validity of the models over-identifying restrictions. Table 17 reports the results (the full regression tables are reported in Table A-5 in appendix). As the sample composition changes with the inclusion of a lag in the first term, we report again the OLS results. The first column of Panel A reports the regression used to calculate the instruments. The dynamic term, $\ln(FHG_{t-2})$, is indeed significant with an elasticity of 0.752 (p<0.01).

The remaining results in Panel A and B depict the outcome of the resulting estimations. Note that in all specifications, both instruments are strong as indicted by the first stage t-statistics, and the Hansen J-statistic does not reject the null hypothesis that the over-identifying restrictions are valid. Compared to the results generated by a static first stage, the results are stronger in a dynamic specification, with a semi-elasticity of turnover growth (TR_{GRt}) to FhG expenditures of 1.3 % points (p<0.01; compared to 1.1 in the static model) and that of productivity growth ($PROD_{GRt}$) of 0.8 % points (p<0.05; compared to 0.7). The results concerning the qualification of the workforce ($\Delta TERT_{t,t-1}$) and the sale of new and improved products and services $\Delta INNOSALES_{t,t-1}$ turn insignificant in this specification, further confirming that their correlation with FhG expenditures is driven by selection bias.

Table 17: 2SLS with dynamic first stage

Panel A: Instrument calc. And firm performance	OLS Instrument calculation	OLS	2SLS	OLS	2SLS
	$\ln(FHG_{t-1})$	$\ln(TR_{GRt})$		$\ln(PROD_{GRt})$	
$\ln(FHG_{t-2})$	0.752***				
	(0.014)				
$ln(FHG_{t-1})$		0.010***	0.013***	0.008***	0.008**
		(0.002)	(0.003)	(0.002)	(0.004)
Controls	YES	YES	YES	YES	YES
N	51878	43848	43848	23949	23949
R²	0.572	0.033	0.033	0.100	0.100
Cragg-Donald Wald F-statistic			11129.816		5884.586
Hansen J Statistic (p-value)			Chi²(1)=0.000 (0.986)		Chi²(1)=0.085 (0.771)
First stage t-statistic of z_{emp}			21.224		16.163
First stage t-statistic of $z_{fhg_{t-2}}$			8.072		6.503

Panel B: Innovation	OLS	2SLS	OLS	2SLS
	$\Delta TERT_{t,t-1}$		$\Delta INNOSALES_{t,t-1}$	
$ln(FHG_{t-1})$	0.003***	0.001	0.0006***	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Controls	YES	YES	YES	YES
N	36076	36076	33679	33679
R²	0.081	0.081	0.287	0.287
Cragg-Donald Wald F-statistic		8355.850		7342.186
Hansen J Statistic (p-value)		Chi²(1)=1.066 (0.302)		Chi²(1)=0.164 (0.686)
First stage t-statistic of z_{emp}		17.814		14.852
First stage t-statistic of $z_{fhg_{t-2}}$		6.798		6.169

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $z_{emp} = \hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$ and $z_{fhg_{t-2}} = \hat{v}_{i,t-1} * [\ln(FhG_{i,t-2}) - \overline{\ln(FhG)}]$, where $\hat{v}$ is the estimated first-stage error term. $\ln(TR_{GRt})$: $ln(EMP_{t-1})$ omitted to avoid multicollinearity with $ln(TR_{t-1})$. The results do not change substantially when $ln(EMP_{t-1})$ is included. Full results reported in Table A-5.
* p <0.10, ** p<0.05, *** p<0.01

4.6 Further analysis

4.6.1 Long-term effects

Up to now, the analysis has focused on estimating the immediate effect of interacting with FhG. While valuable for establishing a causal effect, this approach does not quantify long-term effects, which result from the fact that Fraunhofer expenditures are serially correlated. To quantify long-term effects, we simulate the impact of an exogenous shock in FhG expenditures on firm growth and innovativeness using the IV regression models presented in Table 17 as input. We allow FhG expenditures to serially correlate along the model estimated in Panel A of Table 17.

We then apply the following procedure. In period one, growth, productivity, and innovativeness are set to the sample median and FhG expenditures are equal to the median expenditures level of firms with FhG expenditures (€ 22,762). From period 2 onwards, FhG expenditures are predicted using the coefficient of the dynamic model. Then, the expected level of growth and innovativeness is predicted for each period, taking as input the 2SLS regression coefficients in Table 17. Note that we abstract from any dynamic between growth and level of the outcomes, in order to show the full effect persistence of FhG expenditures.

Figure 5 plots the resulting evolution in FhG expenditures and outcomes. The initial level of FhG expenditures generates a long chain of expenditures, cumulating to € 60,917 after 15 years. The long residual in FhG expenditures drives long-lasting growth in the outcomes. The different in short-term and long-term effects is indeed significant. After 15 years, firms gain € 750,000 in turnover, an increase of 18% compared to the sample median. Value added per employee increases by € 6,639 per employee (10%). As a point of reference we also plot the effects on the share of turnover with new products and share of employees with tertiary education. These variables were however not significant in the 2SLS regressions, implying that we refrain from interpreting the results. This descriptive analysis therefore hints that the immediate effects of FhG documented above form only a small part of the total, long-term, impact.

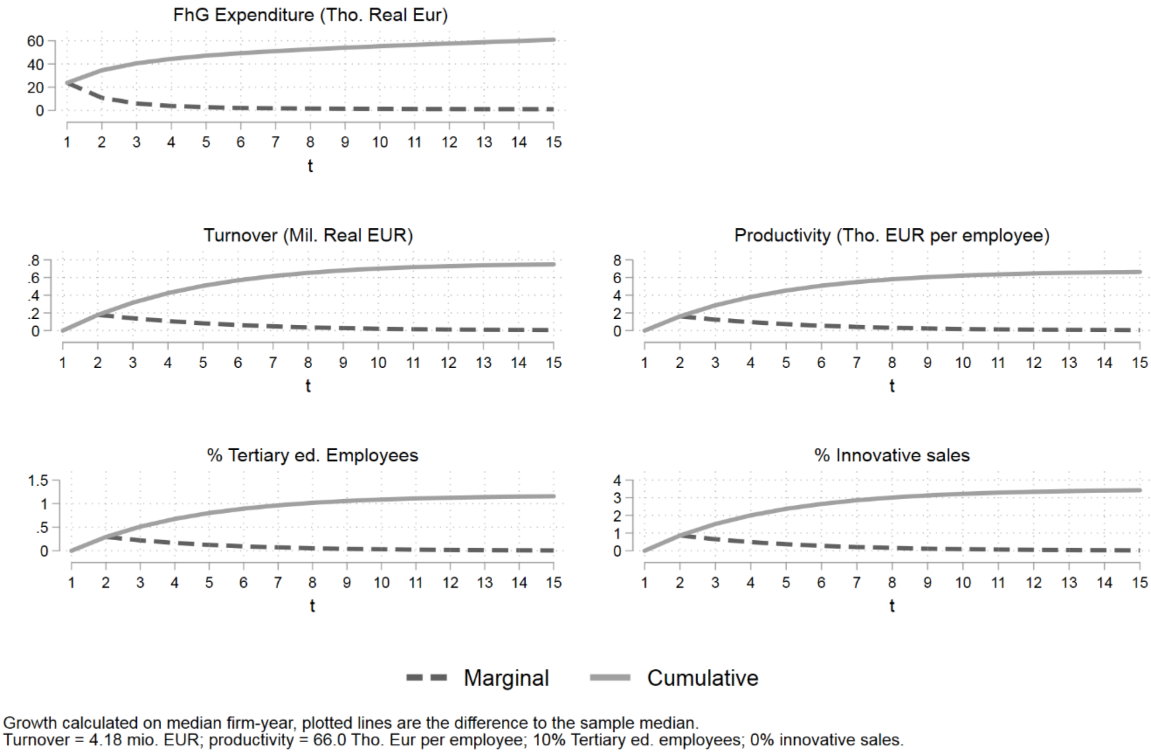

Figure 5: Long-term impacts

4.6.2 Macroeconomic productivity effects

In this section, we intend to estimate the long-term dynamic productivity effect of a hypothetical doubling of FhG revenue coming from industry funds on the German economy. To this end, we extrapolate the dynamic results in Section 4.5 to the German economy represented by the CIS. We assume that additional revenues come exclusively from firms that initially did not cooperate and now start one project with a median volume of 22,762€.

We assume that there are two periods, *0* and *1*, and three types firms. In period 0, the baseline period, non-cooperating firms ($nonc$) do not cooperate with FhG. Cooperating (c) firms already cooperate with FhG in period 0. In period 1, there are a number of firms that initially did not cooperate with FhG in period 0, but start cooperating as a response to the presumed increase in FhG budgets as outline above ($newc$). We assume further that productivities may differ between groups but not over time. Thus, all changes in productivity occur because some initially non-cooperating firms become co-operators in period 1. In each period, the total productivity can thus be written as the weighted average of the productivities of group i weighted by the respective employment shares of the groups:

$$totprod_t = \sum_{i\in I} \overline{prod_i} w_{it}, \quad with\ I = \{nonc, newc, c\}$$

$$w_{jt} = \frac{\overline{empl_j} n_{jt}}{\sum_{i\in I} \overline{empl_i} n_{it}} \quad (9)$$

where w_j are the employment shares and n_{jt} is the number of firms in group j. Note that $w_{newc,0} = 0$ by assumption. Thus, because productivities do not change over time, we can write the productivity change induced by some initial non-co-operators becoming new co-operators as follows:

$$\Delta totprod = \overline{prod_{nonc}}(w_{nonc,1} - w_{nonc,0}) + \overline{prod_{newc}} w_{newc,1} \quad (10)$$

All terms in Eq. (10) can be estimated either from the sample or from the assumptions about the hypothetical increase in industry revenues. The $\overline{prod_\iota}$ and $\overline{empl_\jmath}$ terms are sample averages. The number of firms not cooperating with FhG can be calculated as $n_{nonc,0} = (1 - p_c)pop$, where pop is the population size, i.e. the number of firms in the population covered by the CIS. p_c is the relative frequency of firms cooperating with FhG. It follows that $n_{c,0} = pop - n_{nonc,0}$.

We assume that all co-operators in period 0 remain active in period 1 ($n_{c,1} = n_{c,0}$). As FhG revenue increases in period 1, we will have $n_{new,1}$ new cooperators in period 1 that were in $n_{nonc,0}$ in period 0. If these funds result from each firm having one median project, we have $n_{new,1} = \Delta rev/mps$, where Δrev is the increase in revenue and mps is the median project size. We summarize all statistics and the resulting calculation of Eq. (9) in Table 18.

Table 18: Macroeconomic productivity effects

Parameter	Value		
p_c			3.44%
Δrev			€ 680,000,000.00
pop			277,296
mps			€ 22,762.00
Group	c	$nonc$	$newc$
$\overline{empl_\iota}$	4,415	392	392
n_{j0}	9,537	267,759	0
n_{j1}	9,537	237,885	29,874
$\overline{prod_\iota}$	€ 114,091.50	€ 90,095.01	€ 96,734.55
w_{j0}	28.63%	71.37%	
w_{j1}	28.63%	63.41%	7.96%
$\Delta totprod$			€ 528.68
$totprod_0$			€ 96,965.70
% increase			0.55%

Thus, under the assumption that FhG doubles its revenues from industry, the employment share of non-co-operators would decrease from 71% to 63%. This reduction in employment share corresponds to an increase in employment share of new co-operators of 8%. New co-operators enjoy the long-term productivity gain from cooperating with FhG, which we estimated as €6,639.54 after 15-years. The total estimated increase in productivity in the German economy is € 528.68 or 0.55% when put in relative terms. Compared to a moderate increase in FhG industry revenues in absolute terms (€ 0.68 bn.) this appears to be a highly relevant and quite substantial increase in overall productivity.

5 Conclusion

This study presents empirical evidence on the effect of the world's largest applied research institute, the Fraunhofer Gesellschaft, on the performance of collaborating firms. To implement our study, we compiled a unique panel dataset of German firms covering the period 1997-2013, based on the German contribution to the Community Innovation Survey, to which we matched micro-data on all of FhG's contracts with firms starting 1997. To the best of our knowledge, our study is the first make use of such data to analyse the impact of applied research organizations.

To overcome selection effects, we based our identification strategy on methods deriving instruments from scale heteroscedasticity. Our results indicate a strong causal effect of contracting with FhG on turnover and productivity growth. Furthermore, the impact of FhG seems to be heterogeneous in characteristics of the participating firm as well as the project. Whereas the smallest firms only seem to benefit from FhG to a limited extent, young firms profit more from contracting with FhG than older firms. Manufacturing firms and firms in services industries benefit alike, but in different ways. Concerning project characteristics, our analysis distinguishes between projects resulting in innovative success and turnover growth, and projects resulting in efficiency gains. Whereas the former relates to smaller projects, focusing on the creation of new technology, and repeated interactions, the latter is realized through comparatively large projects focused on implementation of technologies, which do not yield additional benefits from further repeated interactions.

Our study makes an important contribution to understanding an understudied aspect of innovation policy. Investment in applied research organizations, alongside and complimentary to other pillars such as R&D subsidies, tax credits, and investment in public science, seems to be an effective way for policy to ease the absorption of scientific knowledge by firms, overcoming frictions due to its basic nature and thereby enhancing the impact of public research. Even though several countries, among which Germany, Sweden, and the Netherlands follow this strategy, empirical evidence is as of yet scarce. In that sense, our results hint that building applied research organizations could be a promising aspect of innovation policy, which has up to now been underutilized. This is further highlighted when we calculate the macroeconomic impact of FhG, which suggests that the return to public and private investment in FhG is of a comparable size to the estimated return to R&D subsidies.

6 References

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7 Appendix

Table A-1: Summary statistics

Variable	Name	Description	Obs.	Mean	S.D.	Min	Max
Interaction with Fraunhofer							
FHG	Fraunhofer expenditures	Total amount paid to FhG in year (tho. €)	198,385	3.355	55.112	0	5,084
Outcomes							
TR_{GR}	Turnover growth[a]	Year over year growth rate of turnover.	93,643	1.067	0.355	0.337	3.300
$PROD_{GR}$	Productivity growth[a]	Year over year growth rate of value added per employee	40,164	1.066	0.394	0.308	3.312
$\Delta TERT$	Change in human capital[b]	Year over year difference in share of workforce with tertiary education	62,716	0.00231	0.088	-0.500	0.500
$\Delta INNOSALES$	Change in innovative sales[b]	Year over year difference in share of turnover stemming from innovative products and services	57,940	-0.00540	0.124	-0.500	0.500
Controls							
$RDINT$	R&D Intensity[c]	€ of R&D expenditures per € turnover	77,974	0.025	0.099	0	1
AGE	Age	Years since founding	190,804	29.083	32.268	0	213
EMP	Employees	Number of employees	191,065	531.557	7,253.710	0.500	900,000
$EXPORT$	Group	1 if firm is member of a group of firms	198,385	0.536	0.499	0	1
$GROUP$	Exporter	1 if firm indicates to export in year	198,385	0.266	0.442	0	1
$EAST$	East-German	1 if firm is located in former Eastern Germany	198,385	0.332	0.471	0	1
TR	Turnover[a]	Turnover (mio. €)	131,822	213.527	3941.377	1.001	508623.5
$PROD$	Productivity[a]	Added value per employee (tho. €)	61,952	90.970	95.650	8.285	681.844
$TERT$	Human capital	Share of workforce with tertiary education	99,873	0.206	0.255	0	1
$INNOSALES$	Innovative sales	Share of turnover stemming from products and services which were introduced or significantly improved within the last three years	112,029	0.067	0.172	0	1

a: Winsorized at 1st and 99th percentile. b:Censored at -0.500 and 0.500 c: Censored at 1. Growth rates are calculated as ${X_t}/{X_{t-1}}$, where X is the variable of interest. Amounts are GDP deflated and reflect real 2010 €.

Table A-2: Robustness check: level and fixed effects models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(TR_t)$		$\ln(PROD_t)$		$TERT_t$		$INNOSALES_t$	
	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE	OLS	Firm FE
$ln(FHG_{t-1})$	0.093***	0.019***	0.045***	0.008*	0.021***	0.001	0.017***	0.003
	(0.008)	(0.04)	(0.008)	(0.005)	(0.002)	(0.001)	(0.003)	(0.003)
$ln(EMP_{t-1})$	0.886***	0.402***	-0.047***	-0.040**	-0.011***	-0.021***	0.006***	-0.001
	(0.005)	(0.024)	(0.005)	(0.020)	(0.001)	(0.004)	(0.001)	(0.003)
$RDINT_{t-1}$	-0.461***	-0.124***	-0.420***	-0.130*	0.312***	0.018	0.533***	0.052
	(0.039)	(0.046)	(0.071)	(0.067)	(0.025)	(0.016)	(0.029)	(0.032)
$ln(AGE_{t-1})$	0.034***	0.046**	0.019**	-0.011	-0.014***	-0.011**	-0.010***	-0.020***
	(0.008)	(0.021)	(0.008)	(0.026)	(0.002)	(0.005)	(0.001)	(0.006)
$EXPORT_{t-1}$	0.180***	0.022**	0.190***	-0.001	0.036***	-0.003	0.046***	0.006
	(0.0144)	(0.010)	(0.016)	(0.015)	(0.004)	(0.003)	(0.003)	(0.004)
$GROUP_{t-1}$	0.053***		0.053***		0.007*		0.009***	
	(0.013)		(0.015)		(0.004)		(0.002)	
$EAST_{t-1}$	-0.216***		-0.275***		0.043***		0.010***	
	(0.014)		(0.016)		(0.004)		(0.003)	
$CONSTANT$	-1.487***	0.359**	3.588***	4.300***	0.315***		-0.018	0.120***
	(0.175)	(0.140)	(0.166)	(0.131)	(0.019)		(0.022)	(0.034)
Industry F.E. joint significance	F(25,14788)= 70.907***	F(25,14788)= 1.629**	F(25,9807)= 42.097***	F(25,9807)= 1.613**	F(25,13641)= 147.796***	F(25,13641)= 1.511**	F(25,14962)= 32.525***	F(25,14962)= 1.654**
Time F.E. joint significance	F(16,14788)= 10.006***	F(16,14788)= 21.148***	F(15,9807)= 5.628***	F(15,9807)= 8.221***	F(16,13641)= 17.630***	F(16,13641)= 8.298***	F(16,14962)= 90.731***	F(16,14962)= 27.302***
N	48268	48268	27279	27279	40784	40784	42364	42364
R^2	0.834	0.163	0.229	0.013	0.434	0.015	0.247	0.021

Notes: Notes: Standard errors in parentheses. Standard errors clustered by firm. * p <0.10, ** p<0.05, *** p<0.01

Table A-3: Full version of Table 9: Controlling for other science cooperation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(TR_t)$		$\ln(PROD_t)$		$TERT_t$		$INNOSALES_t$	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
$ln(FHG_{t-1})$	0.005*	0.012***	0.007*	0.004	0.002**	-0.001	0.002	0.004
	(0.003)	(0.004)	(0.004)	(0.006)	(0.001)	(0.002)	(0.002)	(0.003)
$ln(TR_{t-1})$	-0.008***	-0.009***						
	(0.002)	(0.002)						
$ln(PROD_{t-1})$			-0.162***	-0.162***				
			(0.007)	(0.007)				
$TERT_{t-1}$					-0.158***	-0.157***		
					(0.008)	(0.008)		
$INNOSALES_{t-1}$							-0.394***	-0.395***
							(0.015)	(0.015)
$COOPUNI_{t-1}$	0.021***	0.020***	0.012	0.012	0.011***	0.012***	0.041***	0.041***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.003)	(0.003)	(0.005)	(0.005)
$COOPINST_{t-1}$	0.010	0.006	0.014	0.016	0.007*	0.008**	0.017***	0.016**
	(0.009)	(0.010)	(0.012)	(0.012)	(0.004)	(0.004)	(0.006)	(0.006)
$ln(EMP_{t-1})$			0.013***	0.014***	-0.002***	-0.002***	0.001	0.001
			(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
$RDINT_{t-1}$	0.068**	0.067*	0.016	0.016	0.040***	0.040***	0.132***	0.132***
	(0.034)	(0.034)	(0.043)	(0.043)	(0.011)	(0.011)	(0.023)	(0.023)
$ln(AGE_{t-1})$	-0.005	-0.005*	0.002	0.002	-0.001	-0.001	-0.003**	-0.004***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
$EXPORT_{t-1}$	0.007	0.007	0.012	0.012	0.001	0.001	0.014***	0.014***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.002)	(0.002)	(0.003)	(0.003)
$GROUP_{t-1}$	0.008*	0.008*	0.014*	0.014*	-0.000	-0.000	0.003	0.003*
	(0.005)	(0.005)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
$EAST_{t-1}$	-0.007	-0.006	-0.042***	-0.042***	0.004**	0.004**	0.003	0.003
	(0.005)	(0.005)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)
CONSTANT	0.005	-0.025	0.653***	0.607***	0.040***	0.055***	0.017	-0.002
	(0.022)	(0.021)	(0.052)	(0.051)	(0.009)	(0.012)	(0.026)	(0.008)
Industry F.E.	F(25,6035)	Chi2(25)=	F(25,4515)=	Chi2(25)=	F(25,5568)=	Chi2(25)=	F(25,5274)=	Chi2(25)=
Time F.E.	F(8,6035)=	Chi2(8)=	F(7,4515)=	Chi2(7)=	F(8,5568)=	Chi2(8)=	F(8,5274)=	Chi2(8)=
N	13498	13410	9272	9272	11789	11789	11866	11866
R^2	0.038	0.039	0.111	0.111	0.089	0.089	0.253	0.253
Cragg-Donald Wald		6887.613		4164.942		5470.869		5740.132

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$, where $\hat{v}$ is the estimated first-stage error term. Collaboration data is available for 2002-2004 and, 2006-2013. Sample only includes innovation active firms, for which cooperation variables are observed.
* p <0.10, ** p<0.05, *** p<0.01

TableA-4: Full version of Table 9: Placebo test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Placebo Test (OLS)				2SLS with dynamic first stage			
	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta INNOSALES_{t,t-1}$	$\Delta TERT_{t,t-1}$	$\ln(TR_{GRt})$	$\ln(PROD_{GRt})$	$\Delta INNOSALES_{t,t-1}$	$\Delta TERT_{t,t-1}$
$ln(FHG_{t+3})$	0.007**	0.005	0.004	0.001	0.006	0.004	0.0004	0.003**
	(0.003)	(0.004)	(0.002)	(0.001)	(0.004)	(0.006)	(0.003)	(0.001)
$\ln(TR_{t-1})$	-0.007***				-0.007***			
	(0.001)				(0.001)			
$\ln(PROD_{t-1})$		-0.147***				-0.149***		
		(0.006)				(0.006)		
$TERT_{t-1}$			-0.400***				-0.395***	
			(0.011)				(0.011)	
$INNOSALES_{t-1}$				-0.133***				-0.137***
				(0.006)				(0.006)
$ln(EMP_{t-1})$		0.012***	0.004***	-0.001**		0.012***	0.004***	-0.001***
		(0.002)	(0.001)	(0.000)		(0.002)	(0.001)	(0.000)
$RDINT_{t-1}$	0.153***	0.028	0.232***	0.036***	0.144***	0.017	0.230***	0.037***
	(0.030)	(0.036)	(0.021)	(0.009)	(0.032)	(0.037)	(0.022)	(0.009)
$ln(AGE_{t-1})$	-0.013***	-0.002	-0.003***	-0.001	-0.014***	-0.004	-0.003***	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)
$EXPORT_{t-1}$	0.012***	0.033***	0.021***	0.001	0.016***	0.037***	0.020***	0.001
	(0.005)	(0.007)	(0.003)	(0.002)	(0.005)	(0.007)	(0.003)	(0.002)
$GROUP_{t-1}$	0.013***	0.005	0.004*	-0.000	0.014***	0.002	0.005**	0.000
	(0.004)	(0.006)	(0.002)	(0.001)	(0.004)	(0.006)	(0.002)	(0.001)
$EAST_{t-1}$	-0.014***	-0.042***	0.005**	0.007***	-0.014***	-0.043***	0.006***	0.007***
	(0.004)	(0.006)	(0.002)	(0.001)	(0.004)	(0.007)	(0.002)	(0.001)
CONSTANT	0.091***	0.687***	0.033***	0.040***	0.100***	0.705***	0.029***	0.038***
	(0.024)	(0.044)	(0.010)	(0.008)	(0.026)	(0.047)	(0.011)	(0.008)
Industry F.E. joint significance	Chi²(25)= 88.180***	Chi2(25)= 188.857***	Chi2(25)= 224.814***	Chi2(25)= 244.355***	Chi2(25)= 76.561***	Chi2(25)= 176.190***	Chi2(25)= 204.080***	Chi2(25)= 233.665***
Time F.E. joint significance	Chi2(13)= 597.761***	Chi2(13)= 98.780***	Chi2(13)= 426.345***	Chi2(13)= 70.420***	Chi2(13)= 566.229***	Chi2(13)= 92.148***	Chi2(13)= 387.377***	Chi2(13)= 69.440***
N	22395	14113	14485	19494	20357	12970	13405	17843
R^2	0.041	0.093	0.260	0.078	0.041	0.094	0.258	0.080
Cragg-Donald Wald F-statistic	25400.589	17871.980	15329.832	19951.995	6398.739	4237.055	3958.610	5164.762

Notes: Standard errors clustered by firms in parentheses. Dynamic 2SLS: include $ln(FHG_{t-1})$ in first stage.* p <0.10, ** p<0.05, *** p<0.01

Table A-5: Full version of Table 10: 2SLS with dynamic first stage

	(1) 2SLS First Stage	(2) OLS	(3) 2SLS	(4) OLS	(5) 2SLS	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	$\ln(FHG_{t-1})$	$\ln(TR_{GRt})$		$\ln(PROD_{GRt})$		$\Delta TERT_{t,t-1}$		$\Delta INNOSALES_{t,t-1}$	
$\ln(FHG_{t-2})$	0.752***								
	(0.014)								
$ln(FHG_{t-1})$		0.010***	0.013***	0.008***	0.008**	0.003***	0.001	0.0006***	0.003
		(0.002)	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
$ln(TR_{t-1})$		-0.008***	-0.008***						
		(0.001)	(0.001)						
$ln(PROD_{t-1})$				-0.154***	-0.154***				
				(0.005)	(0.005)				
$ln(EMP_{t-1})$				0.012***	0.012***				
				(0.002)	(0.002)				
$TERT_{t-1}$						-0.143***	-0.142***		
						(0.005)	(0.005)		
$INNOSALES_{t-1}$								-0.425***	-0.424***
								(0.008)	(0.008)
$RDINT_{t-1}$	0.174***	0.146***	0.144***	0.053*	0.053*	-0.001***	-0.001***	0.003***	0.003***
	(0.040)	(0.025)	(0.024)	(0.030)	(0.030)	(0.000)	(0.000)	(0.000)	(0.001)
$ln(AGE_{t-1})$	-0.003	-0.009***	-0.009***	0.001	0.001	0.042***	0.043***	0.210***	0.212***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)	(0.017)	(0.017)
$EXPORT_{t-1}$	0.030***	0.013***	0.013***	0.028***	0.028***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
$GROUP_{t-1}$	0.007	0.013***	0.013***	0.013***	0.013***	0.004***	0.004***	0.019***	0.019***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
$EAST_{t-1}$	-0.002*	-0.011***	-0.011***	-0.041***	-0.041***	0.001	0.001	0.005***	0.005***
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
CONSTANT	0.001	0.059**	0.008	0.657***	0.620***	0.006***	0.006***	0.005***	0.005***
	(0.004)	(0.028)	(0.013)	(0.034)	(0.032)	(0.001)	(0.001)	(0.002)	(0.002)
Industry F.E. joint significance	F(25,16436)= 6.979***	F(25,13864)= 4.992***	Chi²(25)= 123.948***	F(25, 9166)= 12.797***	Chi²(25)= 320.540***	F(25,12657)= 20.250***	Chi²(25)= 507.929***	F(25,12452)= 13.828***	Chi²(25)= 347.064***
Time F.E. joint significance	F(15,16436)= 2.960***	F(15,13864)= 61.960***	Chi²(15)= 930.890***	F(14,9166)= 12.436***	Chi²(14)= 174.411***	F(15,12657)= 6.934***	Chi²(15)= 106.105***	F(15, 12452)= 40.946***	Chi²(15)= 614.439***
N	51878	43848	43848	23949	23949	36076	36076	33679	33679
R^2	0.572	0.033	0.033	0.100	0.100	0.081	0.081	0.287	0.287
Cragg-Donald Wald F-statistic			11129.816		5884.586		8355.850		7342.186
Hansen J Statistic (p-value)			Chi²(1)=0.000 (0.986)		Chi²(1)=0.085 (0.771)		Chi²(1)=1.066 (0.302)		Chi²(1)=0.164 (0.686)
First stage *t*-statistic of z_{emp}			21.224		16.163		17.814		14.852
First stage *t*-statistic of $z_{fhg_{t-2}}$			8.072		6.503		6.798		6.169

Notes: Standard errors in parentheses. Standard errors clustered by firm. 2SLS: $ln(FHG_{i,t-1})$ instrumented through $z_{emp} = \hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP)}]$ and $z_{fhg_{t-2}} = \hat{v}_{i,t-1} * [\ln(FhG_{i,t-2}) - \overline{\ln(FhG)}]$, where $\hat{v}$ is the estimated first-stage error term. Specifications 1-2: $ln(EMP_{t-1})$ omitted to avoid multicollinearity with $ln(TR_{t-1})$. The results do not change substantially when $ln(EMP_{t-1})$ is included.
* p <0.10, ** p<0.05, *** p<0.01