Do Companies Benefit from Public Research Organizations? The Impact of Fraunhofer

Diego Comin,[a] Georg Licht,[b] Maikel Pellens,[b] and Torben Schubert[c]

[a] *Dartmouth College, Hanover (United States)*
[b] *Centre for European Economic Research (ZEW), Mannheim (Germany)*
[c] *Lund University, Lund (Sweden)*

Executive summary

Since its inception in 1949, the Fraunhofer-Gesellschaft (FhG) has become Europe's largest applied research organization. Today, it has more than 60 research institutes in Germany covering a wide range of topics in the natural sciences, engineering, informatics, and economics/social sciences. Taken together, Fraunhofer has approximately 24,500 employees and commands an annual budget of over €2.1 billion. Not only is Fraunhofer successful as a private organization, but it is also recognized for providing the economy with unique scientific knowledge crucial for the development of new and innovative goods and services. Founded with the dedicated mission to bridge the gap between basic science, technological development and commercial application, Fraunhofer has grown to be an attractive partner for industry. About 35% of its budget is financed through projects commissioned by industrial clients.

While the lasting and continuous commitment of Germany industry to Fraunhofer is indicative of its relevance for commercial innovation processes, the actual impact Fraunhofer has in terms of company performance has not been subjected to rigorous empirical testing. Available knowledge on the importance of Fraunhofer so far often relies on anecdotal evidence of particularly visible successes, such as the development of MP3 technology. While reference to specific successes can be insightful, a broad and solid empirical account of Fraunhofer's effects on the economy is needed for at least two reasons. First, being able to demonstrate the positive effect of Fraunhofer on the economy helps make the case for the allocation of public funds to research institutions such as Fraunhofer. Second, and arguably even more important, knowledge about the effects and in specific the conditions under which they emerge can help to improve and tailor the ways in which Fraunhofer organizes itself. Thus, knowledge on the specific contexts in which Fraunhofer's inputs are particularly valuable can give insights into specific paths to improve the Fraunhofer model.

This study tries to develop a deeper understanding of Fraunhofer's contribution to society by estimating the causal effects of engaging in contract research with Fraunhofer on company performance. To study this question, we combined the Mannheim Innovation Panel, which has information on the performance and innovation activity of a large number of German companies, with a confidential dataset containing information on all the research contracts signed by Fraunhofer with German companies during the 1997-2014 period. Analyzing a wide range of effects while controlling for econometric issues such as selection, unobserved heterogeneity, and simultaneity, our core results demonstrate significant and sizeable causal effects of research contracts with Fraunhofer on company performance. Specifically, we show that Fraunhofer contracts offer considerable growth potential for companies. In the year after a Fraunhofer interaction, companies experience a 9% increase in sales and a 7% increase in employment. Those increases are accompanied by a shift in the employment structure, as a Fraunhofer interaction also leads to a 1% increase in the share of employees with tertiary education. In addition, the sales structure also shifts towards innovative products. We observe that on average, a Fraunhofer interaction increases the share of companies' sales of innovative products by 1%.

Thus, we provide evidence that interactions with Fraunhofer do more than increase companies' growth rates; they also lead companies towards a more knowledge-intensive innovation path by expanding the share of highly qualified personnel on the input side and increasing the weight of innovative products in the sales base on the output side. Our results indicate that these effects are fairly persistent over time, with some effects being documented even seven years after the interaction took place. Furthermore, we can show that the effects are highly contingent on specific characteristics of the companies and the interactions. In particular, the effects increase with the size of the project. The effects are also larger for medium (50-249 employees) and large companies (250 or more employees) than for small companies (up to 49 employees), and are more pronounced for companies in manufacturing than in services. Finally, and especially worthy of note, companies experience much higher impacts when they interact with Fraunhofer repeatedly. Given that our analysis already controls for unobserved heterogeneity, the greater effects associated with repeated interactions suggest that the value of Fraunhofer for companies is not generic, but specific to each individual relationship between a Fraunhofer institute and a company. Thus, companies and the Fraunhofer institute must continuously invest in long-lasting relationships if they are to leverage the full potential of interacting with Fraunhofer. An important implication is that the broader economic value of Fraunhofer lies very much at the micro-level of the specific relationships. These findings also provide an explanation for why attempts to copy the Fraunhofer model, e.g. the Carnot institutes in France, usually have not lived up to expectations: the value of Fraunhofer is rooted in its almost 70 years of experience, in which repeated learning and continuous improvement of its business model have shaped its success today.

1 Introduction

Innovation is often touted as a direct path to productivity and output growth, business competitiveness, and job creation. Yet in contrast to the social value of these potential outcomes, policies that favor innovation are typically limited in scale and scope. Possible reasons for the failure to design effective innovation policies include (i) lack of a deep understanding of the underpinnings of innovation activity; (ii) insufficient guidance from economic theory, where most policies result in isomorphic results and (iii) lack of empirical evidence on the effectiveness of various innovation policies.

In this study, we try to fill in these gaps by studying a unique research institution: the Fraunhofer-Gesellschaft (FhG). Fraunhofer is a public research institution that was created in Germany in 1949. Currently, Fraunhofer employs approximately 24,500 employees who conduct applied research in all fields of science, leading to around 500 patents per year.[1] In addition to their basic research activity, Fraunhofer scientists also engage in contract research in which they solve specific technological problems faced by individual companies. The fulfillment of the research contracts often requires the use of the knowledge and technologies produced by Fraunhofer scientists.

The main goal of our investigation is to assess the impact of engaging in research contracts with FhG for German companies. To study this question, we have combined two datasets. The first is the Manheim Innovation Panel, which contains information on the performance and innovation activity of a large number of companies in Germany. The second is a confidential dataset that contains information on all the research contracts signed by Fraunhofer with German companies between 1997 and 2014.

The key challenge that a study such as ours needs to confront is the possibility that companies self-select to contract with Fraunhofer. As a result, the sample of companies that engage in research contracts is not random. Our analysis shows strong evidence that this is the case. In the presence of selection bias, a positive correlation between engaging in contract research and the evolution of a company's performance may be driven by the fact that more productive companies are more likely to engage in a contract, and does not necessarily mean that interacting with Fraunhofer had a positive impact on the company.

We employ various empirical strategies to overcome the selection problem in estimating the effect of engaging in contract research on the performance of German companies. These include (i) the use of company fixed effects; (ii) re-weighting the non-treated companies to obtain a sample that is identical to the treated companies in terms of observable variables (Azoulay et al., 2009); (iii) controlling for pre-treatment trends; and (iv) using instruments that exploit the heteroscedasticity of the data (see Lewbel, 2012). While issues of selection-induced heterogeneity remain, the robustness of the

[1] See Comin (2015).

estimates when we perform them suggests that the estimated effects can be interpreted as the impact on company performance caused by interacting with Fraunhofer.

Our key empirical findings are as follows:

1. One year after the fact, companies that interact with Fraunhofer tend to experience an increase in sales on the order of 9%; in employment, 7%; share of innovative sales, approximately 1%; average cost per employee, 1%; and share of workers with higher education, 1%. Of these, the most robust are the effects on sales and employment.

2. The effects are not short-lived. We observe impacts even seven years after the interaction.

3. The benefits from interacting with Fraunhofer are not homogeneous among companies.

    a. They are greater for companies that have interacted previously with Fraunhofer than for those that interact for the first time.

    b. They are greater when the projects have budgets of more than €100,000.

    c. They are greater for manufacturing than for service companies.

    d. They are greater for medium (50-249 employees) and large companies (250 or more employees) than for small companies (up to 49 employees).

    e. They are not affected by the age of the company and by the innovativeness of the project.

The rest of the report is organized as follows: Section 2 introduces the datasets used in the analysis; Section 3 presents the identification strategy; Section 4 presents the empirical results; and Section 5 concludes.

2 Data

The empirical analysis is based on two main data sources. The first is the project database provided by the Fraunhofer-Gesellschaft (FhG), which covers all projects started between 1997 and 2014.[2] For each of the 131,158 projects, the database contains information on the Fraunhofer institute and department involved; the client's name and address; the title, short description and time span of the project; and any project-related payments. Section 2.2 presents an in-depth description of the information in the database.

The second data source is the Mannheim Innovation Panel (MIP), a survey conducted every year since 1993 by the Centre for European Economic Research on behalf of the German Federal Ministry for Education and Research (BMBF). The MIP provides a representative annual sample of German companies with five or more employees (see Aschhoff et al., 2013 for further details). It follows the methodology outlined in the Oslo Manual (OECD and Eurostat, 2005) and is also Germany's contribution to the European Community Innovation Survey. The panel has been further amended with data from Germany's largest credit rating agency, Creditreform, for information on company's age. The present analysis makes use of the 2014 edition of the MIP, including information up to calendar year 2013. Excluding companies that were observed fewer than three times, the MIP covers 198,385 observations of 30,125 companies between 1996 and 2014.[3]

Care was taken to guarantee the confidentiality of the agreements delivered by FhG, particularly with regard to the identities of the client companies. The individuals responsible for matching the FhG data and MIP data did not have access to the agreement data, but only to the name and address of the client companies and organizations. Anonymous identifiers were constructed based on the matched data for use in the remainder of the analysis. Furthermore, individuals involved in the database matching were not involved in the remainder of the analysis.

Both datasets were merged by comparing company names and address information.[4] Of the 131,158 projects in the Fraunhofer database, 46,651 projects could be linked to 7,781 distinct companies which were surveyed at least once in the MIP. After eliminating companies for lack of response and the condition that a company needed to be observed at least three times, the remaining 32,568 projects, or 24.8% of the projects in the database, were used in the final analysis. They represent 4,495 companies in the MIP panel.

[2] Approximately 10% of the projects in the database listed start dates before 1997. As these do not seem to represent a full picture of the projects, we omit these from the further analysis. Any payments made to Fraunhofer in the context of these projects in 1997 and onwards, however, are taken into account.
[3] We retain information from 1996 to allow control variables to be lagged with one year.
[4] The matching algorithm takes spelling deviations into account and assigns a score to each potential match. Potential matches with some uncertainty were manually screened for accuracy.

There are several reasons for the large number of unmatched projects. First, 17% of projects relate to clients outside of Germany. Second, any public-sector clients (such as universities, research centers and government institutes) are not covered by the MIP and hence remain unmatched. Third, the MIP presents only about 10% of German companies (Aschhoff et al., 2013),[5] which, though representative, does not capture all companies that might contract with Fraunhofer. Fourth, projects were assigned to MIP companies conservatively, requiring a match in both name and address. While this avoids errors based on duplicate names, it might also lead to potential underestimation of the degree to which companies make use of Fraunhofer's services.[6]

In the next section, we present a statistical description of the Fraunhofer project database. We base this analysis on the full database of projects starting from 1997 onwards, and not only the part of the data matched to the MIP. After that, we present the variables used for the multivariate analysis, and describe differences between MIP companies that interact with Fraunhofer and those that do not.

2.1 Fraunhofer projects: Descriptive analysis

Project volume

Figure 1 shows the number of projects initiated in each calendar year. Project volume was higher in 1997-2000 than it was in 2001-2006, dropping from an annual average of 7537 projects in the first period to 5742 in the second. After 2006, the annual average increased again to 6746 with a spike in 2009 when 8842 projects were started.

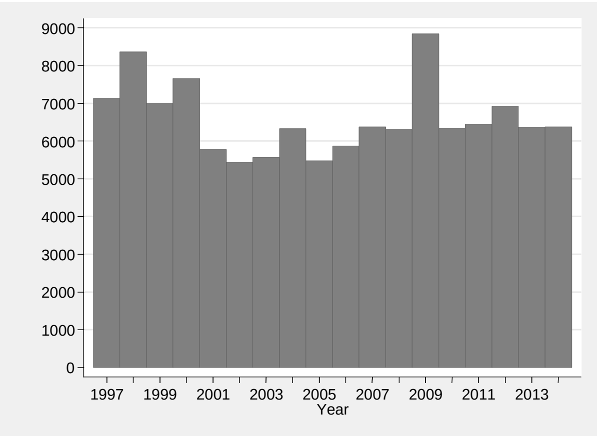

Figure 1: Projects started by year

[5] Sample size and coverage varies over time.

[6] This is not a crucial issue in the analysis, as we define interactions with Fraunhofer according to companies making a minimum payment. Therefore, the analysis presented here should be robust enough to render a certain amount of underestimation negligible.

Project length

The average project in the Fraunhofer database runs for 1 year and 8 months.[7] How long a typical project lasts is an important metric for assessing the magnitude of FhG projects. As Figure 2 shows, the distribution is markedly skewed towards longer project durations. Whereas half of all projects last 1 year or less (22% of projects take 6 months or less), 24% of the projects take between 1 and 2 years to complete. Another 11% last between 2 and 3 years. The remaining 17% of projects last from 3 to 10 years.

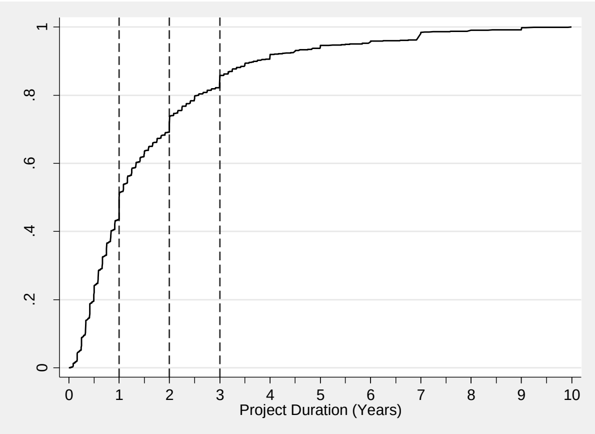

Figure 2: Cumulative distribution of project duration
Dashed lines indicate 1, 2 and 3 years

Project cost

Figure 3 shows the distribution of total project costs for those projects involving a payment to FhG.[8] The average cost amounts to €43,321 (median: €20,000). 88% of projects cost €100,000 or less, and 96% cost €200,000 or less. Both project duration and project cost indicate that the typical Fraunhofer project is rather small-scale: the median project (conditional on involving a payment) costs €20,000 for the company involved and takes a year or less to complete. This suggests that Fraunhofer contributes to companies through well-defined, concrete projects that are more likely to be rather practical in nature (in contrast to long-term open-ended research projects). However, short projects are complemented with about 20% more long-term and more expensive projects.

[7] Not taking projects reported as lasting for 10 years or more into account (1% of projects). These often represent “administrative” projects, such as projects marked as maintenance and basic cooperation agreements.
[8] 72% of the projects in the database involve a payment to Fraunhofer. The data has been cut at the 99th percentile, which is €463,122. The true maximum lies around €170 million.

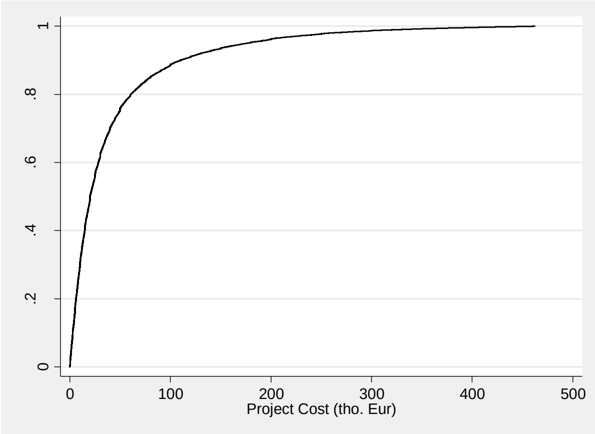

Figure 3: Cumulative distribution of project cost

Because we define our key independent variable on the timing of project payments, the latter merits further discussion. To illustrate the timing of payments, we calculated the difference between the average payment year and the starting year of each project.[9] For projects lasting two years or less, payment is typically made in within the first year of the project. For projects that last three years or longer, the average lag between the project start and payment increases by approximately 4 months per year increase in project duration.

Repetition of interaction

Figure 4 displays a histogram of the number of times each company interacted with FhG, in order to assess the companies' tendency to return to FhG over time.[10] 42% of all companies interact with FhG only once. Another 17.5% return do so twice, and 9.9% have three interactions with Fraunhofer. The remaining 30.6% interact with FhG more than three times. The fact that most companies in the data interact once or twice with Fraunhofer supports the idea that it has a broad impact in the business sector: FhG does not support a small number of specific companies, but instead supports thousands of companies throughout the German economy with its knowledge. At the same time, a smaller part of FhG's client companies seem to form long-lasting relationships involving many interactions.

[9] The average payment year was weighted by the share of the total paid in each year.

[10] This analysis is restricted to the subset of the FhG data for which the client was identified as an MIP company. Some care must be taken in the interpretation of this data, as the group of unidentified companies might include subsidiaries (or similar) of MIP companies. As such, these statistics should be seen as lower limit estimates. Multiple interactions may constitute independent projects, or they might be direct follow-up projects, with the two too difficult to differentiate. **Fehler! Verweisquelle konnte nicht gefunden werden.** has been truncated at the 99th percentile, 62 projects. The true maximum goes up to 1050 projects (31 firms are found to have engaged FhG for more than 100 projects).

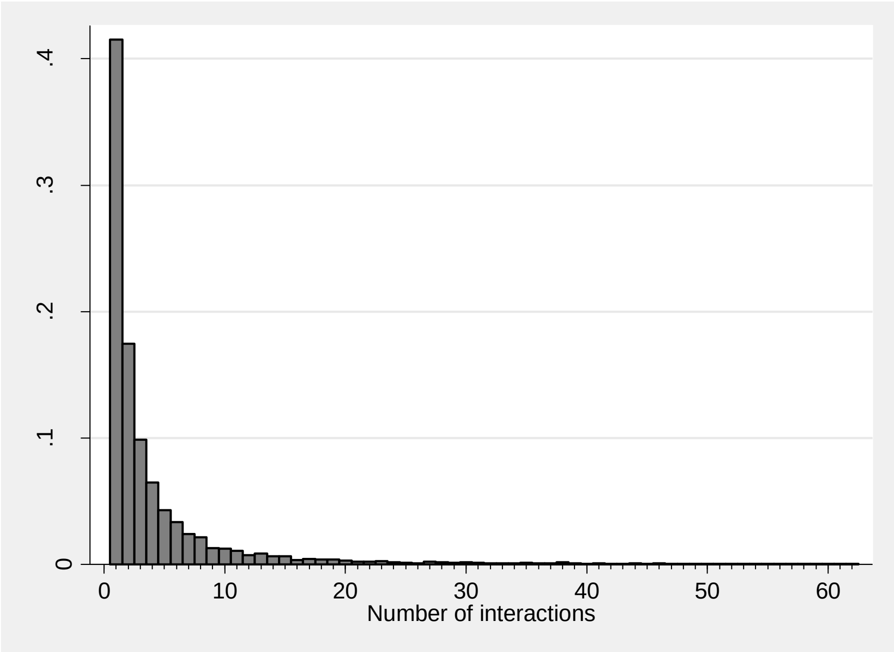

Figure 4: Number of projects per company

2.1.1 Project descriptions

To gain some insight into the goals and organization of FhG projects, a keyword analysis was performed based on the short project descriptions available in the database. Table 1 lists the 20 most common harmonized keywords in the project descriptions.[11] They show that FhG projects cover the full range, from studies and analysis to development, application and implementation. It is unlikely for the impact of FhG projects to be constant across all these different types of projects. However, the broad nature of the project descriptions limits the inference to be made. In the multivariate analysis, we differentiate between projects whose description indicates a clear intent to implement whatever is in the focus of the project (a technology, product, process, etc.) and those that indicate no such intention of practical implementation. This allows us to assess whether projects further downstream have an impact that differs from more upstream, abstract projects.[12]

Table 1: Project keywords

Rank	Term	No. of projects	Share of projects	Rank	Term	No. of projects	Share of projects
1	Development	6906	5.27%	11	Creation	1363	1.04%
2	Analysis	5348	4.08%	12	Feasibility	1354	1.03%
3	Study	4366	3.33%	13	Process	1336	1.02%
4	System	2481	1.89%	14	Application	1308	1.00%
5	Manufacturing	1776	1.35%	15	Technology	1248	0.95%
6	Supply	1740	1.33%	16	Structure	1112	0.85%
7	Project	1713	1.31%	17	Concept	1077	0.82%
8	Optimization	1687	1.29%	18	Simulation	1064	0.81%
9	Evaluation	1665	1.27%	19	Implementation	1059	0.81%
10	Test	1621	1.24%	20	Phase	1038	0.79%

[11] Descriptions were short: the average description is 7 words long, and 90% of descriptions consist of 14 words or less. Keywords in the descriptions were translated from German and harmonized. Common words as well as brands and any identifying information have been removed from the data.

[12] To achieve this, we developed and applied the following key: Projects were deemed “implementative” when they included words indicating a change or development, such as “adapt”, “build”, “create”, “construct”, “develop”, “improve”, “innovate”, “integrate”, “intervene”, “install”, “manufacture”, “modify”, “realize”, “restructure”.

2.2 Variables

In this section, we describe the variables used in the analysis (described in Table 2). This includes the variables that measure the interaction with Fraunhofer, the various outcomes and controls.

Interaction with Fraunhofer

The key explanatory variable of the study captures whether the company interacted with FhG. As many projects in the database involve little or no payment to FhG, indicating that they are small in size, a payment threshold needs to be defined to indicate when projects are of significant size.[13] At the same time, the project data needs to be transposed onto the company-year framework of the MIP. Therefore, the project data was aggregated to the money paid to FhG for each company in each year. As most companies are involved in one interaction at a time, this is not a strong assumption to make.[14] A significant interaction was then defined as making a total payment of €13,000 or more to Fraunhofer over the course of a given year.[15] We name this variable *FHG_INT*. We also define a broader interaction indicator, *FHG,* that takes value 1 if the company ever interacted with FHG over the timeframe of the data. Lastly, we define *FHG_AMOUNT* to capture the size of the annual payment made to FhG.

Outcomes

We approach the characterization of the effect of interaction with FhG on companies from different perspectives. First, companies might be able to grow larger as a result of their interactions. The size of the company is measured by sales (*TURNOVER*; million EUR) and by employee headcount (*EMPLOYEES).* Second, implementing technology with support from FhG might be an efficient way to increase productivity. To capture that, we calculate added value per employee (*ADDVAL).* Third, Fraunhofer might support companies in the development and commercialization of their own innovative products and processes. We capture these in a direct way through the share of sales stemming from new or improved products introduced by the company *(INNOSALES)*. Additionally,

[13] A small minority of projects involved negative payment, i.e. money going from Fraunhofer to the firm.
[14] In 64% of cases in which an MIP company interacts with FhG, there is only one interaction in that year. In 18% of cases there are two, and three or more only in 10% of cases.
[15] The Fraunhofer database lists payments made by year. While these could in principle occur at any point after starting a project, payments are typically made in the year after the project is started. Given the fact that the median project lasts one year, this means that payments can be used as a proxy for Fraunhofer activity in that time. A threshold of €13,000 was chosen to eliminate projects that are too small in scale to show a significant impact on company performance indicators, and approximates the median payment made by MIP companies to Fraunhofer in a given year, taking the total payment across all projects in which the company is involved into account. In the robustness checks, we show that this definition holds up even under stricter definitions of an interaction.

measures of average employee cost (*CPE*) and the share of employees with tertiary education (*EMP_HIGHED)* capture any changes in company strategy with regard to innovation and R&D by tracing changes in the composition of the workforce.

Table 2: Variable definitions

Name	Source		Description
Interaction with Fraunhofer			
FHG	FhG data	Binary	1 if company ever paid at least €13,000 to FhG
FHG_AMOUNT	FhG data	Numeric	Payment made by company to FhG in year (€ k), taking all projects in which the company is involved into account
FHG_INT	FhG data	Binary	1 if company paid at least €13,000 to FhG in year
Outcomes			
TURNOVER	MIP	Numeric	Turnover of company in year (€ million)
EMPLOYEES	MIP	Numeric	Number of employees in year
ADDVAL	MIP	Numeric	Added value per employee (€ million)
INNOSALES	MIP	Numeric	Share of sales stemming from new or improved products
CPE	MIP	Numeric	Average employee cost (€ k)
EMP_HIGHED	MIP	Numeric	Share of employees with tertiary education
Controls			
RD_INT	MIP	Numeric	R&D expenditures scaled by turnover (ratio)
AGE	Creditreform	Numeric	Years since company's founding
GROUP	MIP	Binary	1 if company is member of a corporate group
EXPORT	MIP	Binary	1 if company indicates plans to export in year
EAST	MIP	Binary	1 if company is located in former East Germany
SIZE_(SMALL, _MEDIUM, _LARGE)	MIP	Binary	Categoric indicator of company size. Small: up to 49 employees. Medium: 50-249 employees. Large: 250+ employees.
Sector	MIP	Categoric	Categoric indicator: 21 sectors (see Table 4)
Year	MIP	Categoric	Categoric indicator: calendar year

Controls

The analysis aims to estimate the effect of interacting with FhG on company performance. However, certain factors need to be held constant. The degree to which a company can profit from interacting with FhG is likely to be a function of internal R&D capacities (Cohen and Levinthal, 1990). To control for this, we include a measure of in-house R&D intensity (RD_INT, R&D expenditures scaled by turnover). Likewise, R&D intensity is expected to play an important role in selection for Fraunhofer interaction, as companies with more innovation-focused strategies are more likely to have projects with FhG.

We also include a number of more general indicators that capture the competitive situation of the company. These include the company's age (AGE) and a dummy indicating whether or not the company exports (EXPORT). Additionally, we control for broad economic differences within Germany by including a dummy that takes value 1 if the company is located in former East Germany

(EAST), and control for broad differences in company size through the inclusion of three company size categories[16] (SIZE_SMALL, SIZE_MEDIUM, and SIZE_LARGE). We further control for the economic activities of the company through the inclusion of 21 broad sector indicators and include year fixed effects to account for shared macroeconomic trends.

Company-level descriptives

Table 3 compares the outcome and control variables for companies that interacted or did not interact with Fraunhofer in the project database. Table 4 shows the same for sector distribution. As shown in the upper panel of Table 3, 6% of company-year observations in the MIP are found to contain interactions with Fraunhofer. On average, a year in which a company paid money to FhG involves a payment of approximately €37,000.

Companies that interact with FhG through projects are significantly ($p<0.01$, two-sided t-test) larger in terms of turnover and employees. The difference is strong, approximating a tenfold size differential. This is reflected in the company size categories: whereas 14% of companies that did not interact with FhG are classified as large, 54% of the companies that do are large companies. At the same time, companies that engage with FhG generate more sales from new or improved products (18% versus 6%). They also seem to be more productive, as added value per employee is approximately 20% higher among companies that interact with FhG than among those that do not. Lastly, companies that interact with FhG report higher average labor costs per employee (47.49 versus 35.22 € k) and a higher share of employees with higher education (30% versus 20%). A similar pattern emerges in terms of the controls: FhG companies are more R&D-intensive (10% compared to 3%), tend to be older (37 years versus 28), are more likely to export their products (45% versus 25%), and are more likely to be part of a group (68% versus 52%). FhG companies are more likely to be situated in former West Germany than in former East Germany.

Taken together, these descriptive differences underline the importance of accounting for positive selection bias in the empirical analysis. If left uncontrolled for, the impact of interacting with Fraunhofer will be biased upwards.

[16] Small: up to 49 employees. Medium: 50-249 employees. Large: 250+ employees. In estimations not related to size, we control for company size by including the number of employees as a control variable.

Table 3: Company summary statistics

	Total			By Fraunhofer interaction				
				Interacted		Did not interact		Difference
	Mean	St. Dev	Obs.	Mean	Obs.	Mean	Obs.	
Interaction with FhG								
FHG	0.06	0.24	198385	1.00	17103			
FHG_INT	0.02	0.14	198385	0.24	17103			
FHG_AMOUNT	3.23	53.80	198385	37.23	17103			
Outcomes								
TURNOVER	199.00	3593.82	131822	906.95	11239	133.02	120583	-773.93***
EMPLOYEES	531.56	7253.71	191065	2735.27	16571	322.28	174494	-2412.99***
INNOSALES	0.07	0.17	112029	0.18	7734	0.06	104295	-0.12***
ADDVAL	0.10	0.38	61955	0.12	5641	0.10	56314	-0.02***
CPE	36.23	17.16	77831	47.49	6376	35.22	71455	-12.27***
EMP_HIGHED	0.21	0.25	99873	0.30	8163	0.20	91710	-0.10***
Controls								
RD_INT	0.04	0.58	77974	0.10	6989	0.03	70985	-0.07***
AGE	29.08	32.27	190804	37.44	16707	28.28	174097	-9.16***
EXPORT	0.27	0.44	198385	0.45	17103	0.25	181282	-0.20***
GROUP	0.54	0.50	198385	0.68	17103	0.52	181282	-0.16***
EAST	0.33	0.47	198385	0.27	17103	0.34	181282	0.07***
Company Size								
SIZE_SMALL	0.56	0.50	191065	0.20	16571	0.59	174494	0.39***
SIZE_MEDIUM	0.27	0.44	191065	0.26	16571	0.27	174494	0.01**
SIZE_LARGE	0.17	0.38	191065	0.54	16571	0.14	174494	-0.40***

Notes: Firm-years. Difference: outcome of two-sided t-test. Stars indicate significance level of t-statistic. ***(,**,*): p < 0.01(,0.05, 0.10). Interaction with Fraunhofer: split made along having ever had Fraunhofer project between 1997 and 2014

Table 4 shows the sector distribution of all companies, whether they interacted with FhG or not. Companies interacting with FhG are more likely to be situated in medium and high-tech manufacturing industries (specifically, petroleum and chemical industry, machinery and domestic appliances, electrical machinery, communication equipment, instruments, and automotive), and less likely to be active in low-tech manufacturing or service industries. The multivariate analysis needs to correct for these differences in the composition of the samples for companies that have interacted with FhG (FhG companies) and those that have not (non-FhG companies).

Table 4: Sector distribution of companies that interacted with Fraunhofer versus those that did not

	Total	By Fraunhofer interaction		
Sector	Share	Yes Share	No Share	Difference
Mining	0.02	0.01	0.02	0.01***
Food and tobacco	0.04	0.01	0.05	0.04***
Textiles and leather	0.03	0.01	0.03	0.02***
Wood, paper, and printing	0.06	0.02	0.06	0.04***
Petroleum, coke, and chemical industry	0.04	0.08	0.03	-0.05***
Rubber and plastics	0.04	0.03	0.04	0.00
Glass, ceramics, other non-metallic minerals	0.03	0.03	0.02	-0.01***
Basic metals and metal products	0.07	0.09	0.07	-0.01***
Machinery and domestic appliances	0.07	0.16	0.06	-0.10***
Office appliances and computers, electrical machinery, communication equipment	0.05	0.11	0.04	-0.06***
Medical, precision, and optical instruments	0.05	0.11	0.04	-0.07***
Transportation equipment	0.03	0.07	0.03	-0.05***
Furniture, jewelry, musical instruments, sports equipment, games and toys	0.02	0.01	0.02	0.01***
Intermediation of trade and wholesale (excl. trade in motor vehicles)	0.04	0.01	0.05	0.03***
Trade of motor vehicles, maintenance and repair of motor vehicles, petrol stations, repairs	0.02	0.01	0.03	0.02***
Transportation, traffic, and courier services	0.08	0.03	0.08	0.05***
Credit and insurance	0.05	0.03	0.05	0.02***
Data processing and databases; telecommunications	0.05	0.05	0.05	-0.00
R&D and engineering	0.08	0.08	0.08	-0.01**
Legal and tax advice; consultancy; marketing	0.05	0.02	0.05	0.03***
HR, information, and security services, other services for companies	0.07	0.02	0.08	0.06***
Estate and housing, renting of movable items	0.02	0.01	0.02	0.01***

Notes: Difference: outcome of two-sided t-test. Stars indicate significance level of t-statistic. ***(,**,*): p < 0.01(,0.05, 0.10). Interaction with Fraunhofer: split made along having ever had Fraunhofer project between 1997 and 2014

3 Identification strategy

Estimating the causal effects of project interactions with Fraunhofer institutes can mainly be accomplished by regression techniques. Estimating the causal effect, however, is not straightforward because of selection on unobservables and endogeneity. Furthermore, treatment (i.e. research projects with Fraunhofer) is time-dependent in our setting, which can imply that the causal effect accumulates over time (Robins et al., 2000; Azoulay, 2009). This section describes the methods employed in this study to mitigate these statistical issues. The nontechnical reader can skip this section and move on to the results.

If we abstract from the time dependence a simple model of the relationship between the company performance y_{it} and the cooperation variable FHG_INT_{it} , this can be written as follows:

$$y_{it} = x_{it}\beta + FHG\_INT_{it}\delta + u_{it} \ (1)$$

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 company performance. Commissioning research projects from Fraunhofer institutes, however, is not randomized, but will depend on a process of mutual selection. If the factors governing the selection process can be sufficiently controlled for in x_{it} ,δ can be structurally identified by regular panel data models. But if selection is based on (time-varying) unobservables, the estimates δ will generally be biased, because the central identification condition that u_{it} is uncorrelated with any of the vector of observed variables in $1, \dots T$ (strict exogeneity) will not be met.

An often discussed case is when u_{it} includes unobservable capabilities of the company. This variable will be very likely to be correlated with the interaction variable, because more capable companies will are more likely to self-select for collaborative projects and in turn will be more likely to be selected by the Fraunhofer institutes. The capabilities are likely to be largely constant over time. If this is the case, we can control for the unobserved company-specific capabilities by including a company-level fixed effect (i.e. intercept) in equation (1).

However, if the company capabilities are time-varying, including fixed effects in (1), this does not prevent a potential upward bias in the estimate of δ in (1). To prevent that, we need to identify δ from exogenous variation in the interaction with Fraunhofer induced by instrumental variables. Unfortunately, finding appropriate instrumental variables is difficult. Recently, Lewbel (2012) has demonstrated how heteroscedasticity can help to generate instrumental variables. Specifically, suppose our structural model takes the following form:

$$y_{it} = x_{it}\beta + \text{FHG\_interact}_{it}\delta + u_{it}$$

$$\text{FHG\_interact}_{it} = x_{it}\zeta + y_{it}\vartheta + v_{it} (2)$$

Unless $\vartheta = 0$ the model is fully simultaneous and the performance equation cannot be consistently estimated by regular regression techniques. Lewbel (2012) proved that for some vector z_{it} if $\text{cov}(x_{it}, u_{it}^2) \neq 0$, $\text{cov}(x_{it}, u_{it}^2) \neq 0$, and $\text{cov}(z_{it}, u_{it}v_{it}) = 0$, the system can be consistently identified. The first two assumptions mean that heteroscedasticity exists in the error terms while the second assumption is the pendant to a more conventional exogeneity assumption. To see why heteroscedasticity can identify our effects, we define

$$z_{it} = (x_{it} - \overline{x_t})\epsilon \ (3)$$

where ϵ is the residual from reduced form regression of FHG_interact_{it} on the exogenous regressors x_{it}. ϵ is structurally identified because the parameters in the reduced form regression can always be consistently estimated (Wooldridge, 2002). These residuals furthermore have zero covariance with x_{it} by construction. However, the element-wise products with the regressors will not be zero throughout. Furthermore, the elements will be the larger in absolute terms the larger the heteroscedasticity is. Thus, the degree of heteroscedasticity is directly proportional to the correlation between the generated instruments z_{it} and the endogenous company performance measure, which can provide explanatory power of the generated instruments. In order for the variation in the instruments to be exogenous, Lewbel (2012) shows that condition $\text{cov}(z_{it}, u_{it}v_{it}) = 0$ needs to hold. This assumption is technical, but Lewbel (2012) shows that it generally holds if the error term can be written in an error-component form. While the Lewbel result is more general, in our case if we are willing to assume that selection occurs on unobservable company capabilities, we can rewrite the error-term as $u_{it} = \text{capabil}_{it}\pi + e_{it}$, where e_{it} is assumed to be an uncorrelated random error. The importance of the Lewbel result is that our reasoning on why endogeneity exists leads directly to an error-component model, for which the exogeneity assumption $\text{cov}(z_{it}, u_{it}v_{it}) = 0$ automatically holds. Thus, the results based on Lewbel (2012) provide a means to construct a valid instrumental variable for the likelihood that a company will interact with Fraunhofer.

A separate issue from the econometric model described by Eq. (1) is that this specification assumes that only contemporaneous Fraunhofer interactions have an effect on company performance. This is a strong assumption, because past interactions may also have time-persistent effects, suggesting that these may accumulate over time (Azoulay et al., 2009). A natural approach is thus to model the causal interaction effect as a distributed lag model:

$$y_{it} = x_{it}\beta + \gamma \sum_{\tau=1}^{t} w_{it}\, \text{FHG\_interact}_{it-\tau} + u_{it} \ (4)$$

Two problems emerge when trying to estimate Eq. (4): First, the vector of weights is unknown. Second, if past levels of the interaction variable affect the current levels of the exogenous regressors, estimating Eq. (4) cannot generally be estimated without bias when past regressors affect later treatment. A solution to both problems has been provided by Robins (1999) who introduces the Sequential Conditional Independence Assumption (SCIA), which means that the contemporaneous cooperation is independent of company performance, conditional on a one-period lag of the interactions, the contemporaneous vector x_{it} and a one-period lag of any other observable variables affecting selection, z_{it-1}. Robins (1999) shows that under SCIA, the weights in Eq. (4) are given by the following formula:

$$w_{it} = \frac{1}{\prod_{\tau=1}^{t} P(\mathrm{FHG\_interact}_{i\tau} | \widetilde{\mathrm{FHG\_interact}}_{i\tau-1}, z_{i\tau-1}, x_{i\tau})} \quad (5)$$

where $\widetilde{\mathrm{FHG\_interact}}_{i\tau-1}$ represents a distributed lag of past interactions. Because of the structure of the weights, this method is called Inverse Probability of Treatment Weights (IPTW) and has originated from bio-statistics but recently has been applied also in economics. Azoulay et al. (2009) make the point that the probabilities $P(\mathrm{FHG\_interact}_{i\tau} | \widetilde{\mathrm{FHG\_interact}}_{i\tau-1}, z_{i\tau-1}, x_{i\tau})$ could vary strongly among companies in the event that time-varying confounders are strongly associated with interaction, and note that this could lead to large outliers in w_{it}. Therefore, they propose using the stabilized weight:

$$sw_{it} = \frac{\prod_{\tau=1}^{t} P(\mathrm{FHG\_interac}_{i\tau} | \widetilde{\mathrm{FHG\_interact}}_{i\tau-1}, x_{i\tau})}{\prod_{\tau=1}^{t} P(\mathrm{FHG\_interac}_{i\tau} | \widetilde{\mathrm{FHG\_interact}}_{i\tau-1}, z_{i\tau-1}, x_{i\tau})} \quad (6)$$

The probabilities in Eq. (6) can be estimated from the data from simple probability models such as logistic or probit regressions (see Table 5). Based on the estimated weights all terms in Eq. (4) can be derived and the regression can be estimated.

In our analysis, we will present various types of regressions. We will start with simple pooled OLS models, which are likely to be biased due to selection. Then we will try to overcome this bias by introducing fixed effects, IV models based on Lewbel instruments, and IPTW estimators.

4 Results

Determinants of interaction

Before describing the impact of Fraunhofer interactions on companies, it is worth exploring the process of selection for the interaction. Table 5 displays selection estimates with and without time-varying confounders. The results in column 1 confirm that interaction with FhG is strongly determined by past payments: at the mean, having interacted with FhG in the year before increases the probability of interaction by 30 percentage points, compared to a base probability of 2.6%. Company size is also a strong predictor of interaction. Compared to small companies, medium companies are 19% more likely to interact with FhG, while large companies are 50% more likely to do so. Exporting companies are 11% more likely to interact with FhG than non-exporting companies. The other confounders, while statistically significant, are less strong predictors: with all other factors constant, a 1% increase in R&D intensity corresponds to a 0.06% increase in the probability of interacting with FhG, and a 1% increase in R&D stock corresponds to a 0.19% increase. Companies located in former East Germany are 3.8% more likely to interact.

This analysis thus confirms the descriptive statistics: large competitive companies are the most likely to interact with Fraunhofer. In order to not overestimate the effect of interacting with Fraunhofer, we need to correct for this selection through econometric techniques. One such technique involves calculating IPTW weights.

Table 5: Probability of interacting with Fraunhofer

	(1)	(2)
	FHG_INT	
	Denominator	Numerator
FHG_INT_{t-1}	4.286***	4.721***
	(0.098)	(0.092)
RD_INT_{t-1}	0.059**	
	(0.023)	
$RD\_INT\_STOCK_{t-2}$	0.064***	
	(0.022)	
$EXPORT_{t-1}$	0.442***	
	(0.083)	
$FIRM\_MEDIUM_{t-1}$	0.798***	
	(0.104)	
$FIRM\_LARGE_{t-1}$	1.954***	
	(0.104)	
$ln(AGE+1)_{t-1}$	-0.031	0.139***
	(0.042)	(0.043)
$GROUP_{t-1}$	-0.102	0.208**
	(0.087)	(0.083)
$EAST_{t-1}$	0.201**	-0.079
	(0.083)	(0.079)
Intercept	-5.587***	-5.966***
	(0.421)	(0.408)
Observations	64232	64232
Pseudo R-squared	0.463	0.429
Joint significance test of time-variant variables	458.251	

included: 21 sector indicators and 17 year indicators. Cluster-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

FhG interaction and company performance

Tables 6, 7 and 8 provide the main results of the paper through estimates of the relationship between an interaction with FhG and company size (turnover and employees, Table 6); productivity and innovative sales (Table 7); and the composition of the labor force (average employee cost and share of highly educated employees, Table 8). Each outcome is estimated by 5 methods. The first is an OLS model including a dummy indicating that the company interacted with FhG in the previous period. Second is the same model including IPTW weights, which should account for selection based on observable characteristics such as company size, R&D investment and past treatment. The third is a model including the same dummy and company-specific intercepts to account for constant unobserved company effects. The final two models are an OLS exploiting the volume of treatment instead of a treatment dummy, and the same model where the treatment volume is instrumented through heteroscedasticity-based instruments employing the Lewbel (2012) technique. In each model, we hold company size constant (in the models taking company size as dependent, we include broad indicators as to whether the company is a small, medium or large company. In the other models, we include employee headcount as an explanatory factor), as well as R&D intensity, company age, whether the company exports, whether the company is part of a group, and whether the company is situated in former East Germany. All explanatory variables, including the interaction indicator, are lagged with one year. Hence, the interpretation of the key coefficient is the impact one year after treatment.

Below we present the main conclusions for each outcome. We note that the OLS and IPTW results, compared to those from the fixed effects models, confirm the presence of strong selection effects that cannot be completely controlled for. The coefficients for all OLS and IPTW specifications are much larger than the fixed effects estimates, and likewise the instrumented effects of volume are much lower than those shown by the OLS specification. The unrealistic magnitude shown by the OLS models (for instance, the OLS estimate of the effect of FhG interaction in the previous year is a 115% increase in turnover) underscores the importance of correcting for selection. Therefore, we consider the (most conservative) fixed effect and IV estimates to be our main result.

Turnover (Table 6, columns 1-5): The OLS estimate of 77% decreases to 54% once the likelihood of treatment as calculated through IPTW has been taken into account. However, the fixed effects model shows a lower, but still significant, effect of 9.4%. Likewise, the estimated elasticity of payment to FhG with regard to turnover of 20% in the OLS specification sinks to 9.2% once it has been instrumented for. Even though the specifications decrease the magnitudes of the effects, they remain – economically and statistically – highly significant: our most conservative estimates indicate that an interaction with Fraunhofer is followed by a 9% increase in turnover the following year.

Employees (Table 6, columns 6-10): Similar results hold for the number of employees in the company as measure of company size. The OLS estimates are very large, at an impact of 57% when considering an interaction indicator (column 6) and an elasticity of 15% when considering payment volume (column 9). When correcting for selection through the use of IPTW, the effect is still large (8.6%), but becomes statistically insignificant. This may relate to the inclusion of company size indicators in the calculation of the weights (even though the size indicators constitute broad categories). Nevertheless, in the fixed effects model, we estimate a statistically and economically significant impact of 6.8% after an interaction, and an elasticity of payment volume to employees of 6.9%.

Value added (Table 7, columns 1-5): The strong effects of interacting with FhG on company size are weaker when considering added value per employee as an outcome measure. Whereas the OLS and IPTW specifications show statistically significant increases in added value following an interaction – around 1.6% and 2.5%, respectively – and whereas an elasticity of 0.4% of payment volume to added value is found, the fixed effects model does not find a statistically significant relationship. Nevertheless, the instrumental variable specification also results in a statistically significant (albeit only weakly so) elasticity of some 0.1%.

New or improved product sales (Table 7, columns 6-10): The impact that interacting with FhG has on new or improved sales is somewhat ambiguous. Whereas the OLS indicates an effect of 9.7%, the IPTW as well as fixed effect specifications show very low and statistically insignificant impacts (1.4% and 0.4%, respectively). This indicates that most of the OLS impact is due to selection effects. Nevertheless, the IV model shows a statistically significant semi-elasticity of FhG payment volume on new or improved sales of 0.8%. This leads to the conclusion that while the impact of an average interaction is not statistically significant, it increases when projects become larger.

Average employee cost (Table 8, columns 1-5): The results pattern found for new or improved product sales is also found in average employee cost: while the OLS (9.6%) and IPTW (14.1%) models show a large and significant impact, this is mainly due to selection effects, as the fixed effects model shows an insignificant and small impact (1.5%). Nevertheless, the impact of interaction increases as payment volume grows larger, with elasticities of 2.5% in the OLS specification and 1.5% in the IV model.

Share of highly educated employees (Table 8, columns 6-10): Similarly, the share of highly educated employees does seem to respond to interaction with FhG in the OLS specification (with an impact of 9.4%) and the IPTW models (8.4%). However, at least some of the effect shown by the IPTW model seems to be due to selection on unobservable company effects, and the fixed effects model does not support a positive impact. At the same time, the impact increases with project size, with estimated elasticities by the OLS of 2.4% and 1.4% according to the IV specification.

The analysis yields valuable insights on the effects of interacting with FhG. While we cannot claim to have accounted for all endogeneity issues, the fixed effect models and heteroscedasticity-based instrumentation of payment volume show robust positive correlations between FhG interactions and company size. While the effect of the average interaction on added value, innovative performance and innovative strategy cannot be confirmed through fixed effects models, the IV models support the ideas of positively significant elasticities between more intense interaction with FhG and added value, innovative performance and innovative strategy.

Table 6: Interaction with FhG and company performance 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(TURNOVER+1)$					$ln(EMPLOYEES+1)$				
	OLS	IPTW	F.E.	OLS	IV	OLS	IPTW	F.E.	OLS	IV
FHG_INT_{t-1}	0.768***	0.539***	0.094***			0.571***	0.086	0.068***		
	(0.095)	(0.121)	(0.021)			(0.078)	(0.125)	(0.018)		
$ln(FHG\_AMOUNT+1)_{t-1}$				0.199***	0.092***				0.151***	0.069***
				(0.024)	(0.012)				(0.020)	(0.010)
RD_INT_{t-1}	-0.085***	0.003	-0.040**	-0.090***	-0.118***	-0.001	0.012***	-0.011	-0.003	0.002
	(0.023)	(0.026)	(0.018)	(0.024)	(0.019)	(0.005)	(0.003)	(0.009)	(0.006)	(0.005)
$ln(AGE+1)_{t-1}$	0.080***	0.054	0.062**	0.080***	0.073***	0.055***	0.014	0.054**	0.055***	0.050***
	(0.012)	(0.037)	(0.026)	(0.011)	(0.008)	(0.009)	(0.051)	(0.021)	(0.009)	(0.006)
$EXPORT_{t-1}$	0.315***	0.181***	0.042***	0.313***	0.331***	0.156***	-0.024	0.043***	0.154***	0.168***
	(0.019)	(0.059)	(0.011)	(0.019)	(0.013)	(0.014)	(0.056)	(0.011)	(0.014)	(0.010)
$GROUP_{t-1}$	0.140***	0.288***		0.140***	0.133***	0.138***	0.135**		0.138***	0.134***
	(0.017)	(0.051)		(0.017)	(0.011)	(0.013)	(0.062)		(0.013)	(0.009)
$EAST_{t-1}$	-0.188***	-0.162***		-0.189***	-0.181***	-0.003	-0.252***		-0.004	0.000
	(0.018)	(0.053)		(0.018)	(0.012)	(0.014)	(0.094)		(0.014)	(0.010)
$FIRM\_MEDIUM_{t-1}$	1.544***	1.466***	0.320***	1.541***	1.547***	1.834***	1.771***	0.455***	1.832***	1.839***
	(0.020)	(0.037)	(0.028)	(0.020)	(0.013)	(0.014)	(0.038)	(0.025)	(0.014)	(0.009)
$FIRM\_LARGE_{t-1}$	3.477***	3.337***	0.700***	3.459***	3.474***	3.679***	3.473***	0.925***	3.664***	3.657***
	(0.036)	(0.084)	(0.052)	(0.036)	(0.024)	(0.027)	(0.083)	(0.045)	(0.027)	(0.017)
Intercept	0.399***	0.469***	1.849***	0.408***	1.224***	2.479***	2.912***	3.442***	2.482***	2.255***
	(0.063)	(0.129)	(0.093)	(0.062)	(0.050)	(0.070)	(0.157)	(0.075)	(0.070)	(0.040)
Industry F.E.	YES	YES	NO	YES	YES	YES	YES	NO	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	44507	40152	48283	44507	44507	51941	46725	56254	51941	51941
r2	0.722	0.862	0.625	0.723	0.721	0.780	0.894	0.766	0.781	0.780
Cragg-Donald Wald F-statistic					5180.624					5739.282
J-test statistic					238.964					140.839

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01 Note that FHG_AMOUNT reflect € k. F.E.: Overall R2 listed.

Table 7: Interaction with FhG and company performance 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(ADDVAL+1)$					$INNOSALES$				
	OLS	IPTW	F.E.	OLS	IV	OLS	IPTW	F.E.	OLS	IV
FHG_INT_{t-1}	0.016***	0.025***	0.011			0.097***	0.014	0.004		
	(0.006)	(0.005)	(0.007)			(0.013)	(0.021)	(0.010)		
$ln(FHG\_AMOUNT+1)_{t-1}$				0.004***	0.001*				0.024***	0.008***
				(0.001)	(0.001)				(0.003)	(0.002)
RD_INT_{t-1}	-0.006**	-0.006**	-0.000	-0.006**	-0.010***	0.017*	0.001	-0.002	0.017*	0.030***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)	(0.010)	(0.002)	(0.002)	(0.010)	(0.008)
$ln(AGE+1)_{t-1}$	-0.001	-0.000	-0.004	-0.001	-0.001	-0.014***	-0.011	-0.021***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.007)	(0.006)	(0.002)	(0.001)
$EXPORT_{t-1}$	0.009***	0.008***	-0.000	0.009***	0.012***	0.060***	0.035***	0.006	0.060***	0.060***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.010)	(0.004)	(0.004)	(0.003)
$GROUP_{t-1}$	0.006***	0.006**		0.006***	0.005***	0.009***	0.033***		0.009***	0.008***
	(0.002)	(0.003)		(0.002)	(0.002)	(0.003)	(0.010)		(0.003)	(0.002)
$EAST_{t-1}$	-0.024***	-0.018***		-0.024***	-0.023***	0.015***	0.042*		0.015***	0.015***
	(0.002)	(0.003)		(0.002)	(0.002)	(0.003)	(0.025)		(0.003)	(0.002)
$ln(EMPLOYEES+1)_{t-1}$	0.004***	0.003***	-0.002	0.004***	0.004***	0.006***	-0.002	-0.001	0.005***	0.005***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Intercept	0.154***	0.159***	0.118***	0.155***	0.172***	0.023**	-0.047	0.122***	0.025**	0.007
	(0.016)	(0.017)	(0.023)	(0.016)	(0.011)	(0.011)	(0.030)	(0.022)	(0.011)	(0.006)
Industry F.E.	YES	YES	NO	YES	YES	YES	YES	NO	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	24734	23236	27282	24734	24734	38733	36569	42372	38733	38733
r2	0.148	0.200	0.001	0.148	0.146	0.178	0.384	0.032	0.179	0.174
Cragg-Donald Wald F-statistic					2382.897					3987.425
J-test statistic					101.641					167.188

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01 Note that FHG_AMOUNT reflect € k. F.E.: Overall R2 listed.

Table 8: Interaction with FhG and company performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\ln(CPE + 1)$					EMP_{HIGHED}				
	OLS	IPTW	F.E.	OLS	IV	OLS	IPTW	F.E.	OLS	IV
FHG_INT_{t-1}	0.096***	0.141***	0.015			0.094***	0.084***	0.002		
	(0.018)	(0.029)	(0.012)			(0.010)	(0.017)	(0.005)		
$ln(FHG\_AMOUNT + 1)_{t-1}$				0.025***	0.015***				0.024***	0.014***
				(0.005)	(0.003)				(0.002)	(0.002)
RD_INT_{t-1}	0.018	0.018	-0.001	0.018	0.042***	0.040***	0.056***	0.007**	0.040***	0.043***
	(0.018)	(0.020)	(0.004)	(0.018)	(0.012)	(0.011)	(0.019)	(0.003)	(0.011)	(0.010)
$ln(AGE + 1)_{t-1}$	0.020***	0.011	0.005	0.020***	0.020***	-0.016***	-0.011	-0.011**	-0.016***	-0.016***
	(0.005)	(0.018)	(0.016)	(0.005)	(0.004)	(0.002)	(0.008)	(0.005)	(0.002)	(0.001)
$EXPORT_{t-1}$	0.137***	0.120***	0.015*	0.137***	0.126***	0.044***	0.060***	-0.003	0.044***	0.044***
	(0.010)	(0.017)	(0.009)	(0.010)	(0.008)	(0.004)	(0.009)	(0.003)	(0.004)	(0.003)
$GROUP_{t-1}$	0.013	0.058***		0.013	0.010	0.005	0.001		0.005	0.006**
	(0.010)	(0.020)		(0.010)	(0.007)	(0.004)	(0.013)		(0.004)	(0.003)
$EAST_{t-1}$	-0.215***	-0.356***		-0.215***	-0.222***	0.045***	0.065		0.045***	0.046***
	(0.010)	(0.018)		(0.010)	(0.007)	(0.004)	(0.041)		(0.004)	(0.003)
$ln(EMPLOYEES + 1)_{t-1}$	0.063***	0.052***	0.024*	0.063***	0.069***	-0.012***	-0.015***	-0.021***	-0.018***	-0.011***
	(0.003)	(0.007)	(0.013)	(0.004)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.001)
Intercept	2.977***	3.064***	3.477***	2.979***	3.488***	0.121***	0.121**	0.332***	0.124***	0.293***
	(0.040)	(0.048)	(0.076)	(0.040)	(0.030)	(0.011)	(0.050)	(0.022)	(0.011)	(0.011)
Industry F.E.	YES	YES	NO	YES	YES	YES	YES	NO	YES	YES
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	30629	27632	33342	30629	30629	37575	34554	40797	37575	37575
r2	0.255	0.859	0.050	0.256	0.254	0.435	0.924	0.059	0.436	0.435
Cragg-Donald Wald F-statistic					3526.526					3912.822
J-test statistic					211.546					122.611

Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Note that FHG_AMOUNT reflect € k. F.E.: Overall R2 listed.

Effects over time

How long these effects persist is a relevant question. To gain more insights into this, we estimate the following (OLS) model:

$$y_{it} = FHGPAY_{i,t-1} + FHG\_PAY_{i,t-2/t-4} + FHG\_PAY_{i,t-5/t-7} + FHG_{i} + TREND_{t} + FHG_{I} * TREND_{T} + X_{t-1} + \varepsilon_{it}$$

This model allows us to compare differences in outcomes at 1 year after treatment, 2 to 4 years after, and 5 to 7 years after. Systematic differences between companies that have or have not interacted with FhG (FhG and non-FhG companies, respectively) are accounted for in the term FHG, and systematic time trends are accounted for in TREND. Note that for FhG companies, TREND is set to zero after the first interaction. Together with an interaction with FHG, TREND thus captures time trends for non-FhG companies, and pre-treatment trends for FhG companies. This specification allows us to take into consideration the effect of FhG and non-FhG companies from multiple perspectives. First, we can trace the impact of an interaction over time by comparing the coefficients of FHG_INT as time goes on. Second, we can calculate whether the effect is higher than where the company would be expected to be, had it followed the trend just before treatment. Finally, this model allows us to explicitly compare the trends followed by treated and untreated FhG companies (i.e. FhG companies after they interacted, and had they not interacted – as predicted by the model) to non-FhG companies.

Table 9 shows the results of this specification. In all but two specifications (added value and average employee cost), FhG companies perform systematically better than non-FhG companies. In two specifications (turnover and average employee cost), FhG companies also follow a more positive trend before treatment, compared to non-FhG companies. Turning to the post-interaction effects, the strongest effects are observed for turnover and employees, which show positive coefficients up to 7 years after treatment. While the coefficients are largest in the first year after treatment, the effects remain significant throughout the period. The share of new and improved product sales shows a positive coefficient up to 4 years after treatment, but not after 5 years. EMP_HIGHED shows a positive coefficient in the first year after treatment, but becomes insignificant again in the years after. CPE and ADDVAL show no significant coefficients in this specification.

To ensure correct interpretation, this effect of interaction needs to be compared to the trend and level of non-FhG companies and untreated FhG companies, respectively. Therefore, Table 10 provides significance tests comparing the coefficient of FHG_INT with the projected trend (and level) of both groups at 1, 3 and 6 years after interaction. Figure 5 provides a graphical illustration.

Panel A of Table 10 and Figure 5 confirm persistent large and statistically significant differences between FhG companies and non-FhG companies. At virtually every point in time, the projected trend and level of FhG companies is statistically significantly higher than those of non-FhG companies.

Panel B further shows that interacting FhG companies are significantly different from non-FhG companies. However, this is only weakly statistically significant for added value per employee, where the differences are small, and is not significant for average employee cost immediately after treatment.

Table 9: Interaction with FhG: Effect over time

	(1) $ln(TURNOVER+1)$	(2) $ln(EMPLOYEES+1)$	(3) $ln(ADDVAL+1)$	(4) $INNOSALES$	(5) $ln(CPE+1)$	(6) EMP_HIGHED
FHG_INT_{t-1}	0.425***	0.307***	0.004	0.029**	0.007	0.024**
	(0.084)	(0.069)	(0.006)	(0.013)	(0.018)	(0.010)
$FHG\_PAY_{t-2,t-4}$	0.158***	0.136***	-0.004	0.031***	0.022	0.013
	(0.055)	(0.043)	(0.008)	(0.012)	(0.018)	(0.009)
$FHG\_PAY_{t-5,t-7}$	0.217***	0.165***	0.008	0.019	0.026	0.006
	(0.080)	(0.062)	(0.008)	(0.015)	(0.020)	(0.010)
FHG	0.276***	0.255***	0.007	0.068***	-0.010	0.075***
	(0.069)	(0.053)	(0.005)	(0.016)	(0.022)	(0.012)
$TREND$	0.005	0.010**	-0.001	0.002	-0.010***	-0.000
	(0.007)	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)
$TREND*FHG$	0.015**	0.006	0.001	-0.002	0.012***	0.001
	(0.007)	(0.006)	(0.001)	(0.002)	(0.003)	(0.001)
RD_INT_{t-1}	-0.103***	-0.004	-0.007**	0.016*	0.014	0.037***
	(0.028)	(0.006)	(0.003)	(0.010)	(0.017)	(0.010)
$ln(AGE+1)_{t-1}$	0.081***	0.056***	-0.001	-0.014***	0.020***	-0.016***
	(0.011)	(0.008)	(0.001)	(0.002)	(0.005)	(0.002)
$EXPORT_{t-1}$	0.293***	0.133***	0.008***	0.058***	0.133***	0.041***
	(0.019)	(0.014)	(0.002)	(0.004)	(0.010)	(0.004)
$GROUP_{t-1}$	0.133***	0.127***	0.006***	0.009***	0.013	0.005
	(0.017)	(0.013)	(0.002)	(0.003)	(0.010)	(0.004)
$EAST_{t-1}$	-0.186***	0.001	-0.024***	0.015***	-0.216***	0.045***
	(0.018)	(0.014)	(0.002)	(0.003)	(0.010)	(0.004)
$FIRM\_MEDIUM_{t-1}$	1.540***	1.857***				
	(0.020)	(0.013)				
$FIRM\_LARGE_{t-1}$	3.443***	3.708***				
	(0.036)	(0.025)				
$ln(EMPLOYEES+1)_{t-1}$			0.003***	0.003***	0.059***	-0.016***
			(0.001)	(0.001)	(0.004)	(0.001)
Intercept	1.116***	2.034***	0.193***	0.002	3.666***	0.319***
	(0.152)	(0.116)	(0.023)	(0.027)	(0.055)	(0.025)
N	44445	52115	24734	38733	30629	37575
r2	0.739	0.812	0.149	0.184	0.258	0.442

included: 21 sector indicators and 17 year indicators. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Panel C shows the difference between companies that interacted with FhG compared to FhG companies that did not interact but follow the predicted pre-interaction trend. The graphs show that FhG companies grow after interaction and draw more of their sales from new products or services than the projected trend would have indicated. These differences decrease over time, but remain statistically significant for employees (and for turnover 4 years after interacting, but not 7 years after). The analysis also shows an increase of approximately 3 percentage points in terms of new product sales, which persists up to 4 years after treatment. After 5 years, it turns statistically insignificant but remains similar in magnitude. An interaction with FhG coincides with an increase in the share of highly educated employees of 2 percentage points, which does not persist over time. We find no statistically significant differences between interacting FhG companies and the projected trend of these companies for added value per employee and average employee cost.

These findings supplement the results concerning the immediate impact of interacting with FhG shown in the previous section. We find persistent differences between companies that interacted with FhG and their predicted pre-treatment path for turnover, employees, and new or improved product sales. We find no persistent statistically significant differences for added value per employee, average employee cost, and the share of employees with tertiary education.

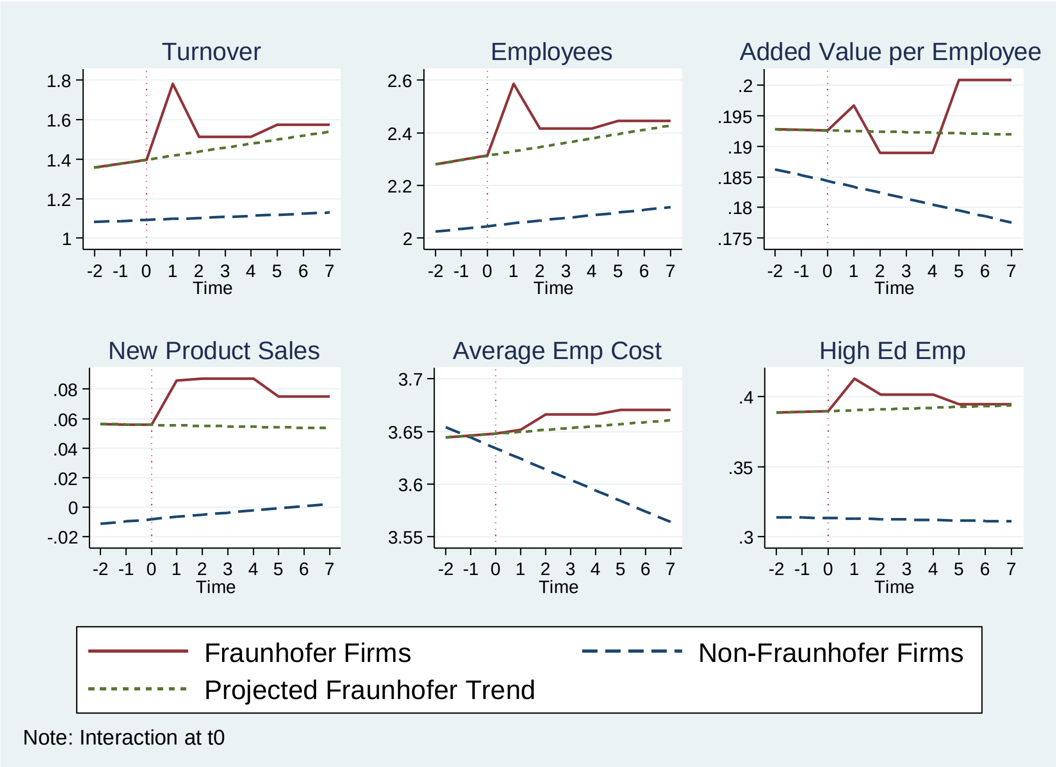

Figure 5: Interaction with FhG over time: Graphical illustration

Table 10: Interaction with FhG over time: Significance tests

	LN(TURNOVER+1)		LN(EMPLOYEES+1)		LN(ADDVAL+1)		INNOSALES		LN(CPE+1)		EMP_HIGHED	
t	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Panel A: FhG companies compared to non-FhG												
1	0.285***	(0.060)	0.251***	(0.047)	0.008*	(0.004)	0.064***	(0.014)	0.012	(0.019)	0.076***	(0.010)
3	0.304***	(0.049)	0.243***	(0.038)	0.012***	(0.004)	0.058***	(0.010)	0.056***	(0.015)	0.078***	(0.008)
6	0.333***	(0.054)	0.230***	(0.042)	0.017***	(0.006)	0.048***	(0.009)	0.121***	(0.018)	0.082***	(0.009)
Panel B: Interacting FhG compared to non-FhG												
1	0.695***	(0.097)	0.552***	(0.079)	0.011*	(0.006)	0.096***	(0.018)	0.007	(0.024)	0.099***	(0.014)
3	0.418***	(0.068)	0.360***	(0.052)	0.006	(0.007)	0.094***	(0.015)	0.042*	(0.022)	0.089***	(0.012)
6	0.461***	(0.077)	0.358***	(0.057)	0.020*	(0.010)	0.077***	(0.017)	0.077***	(0.025)	0.083***	(0.012)

Panel C: Interacting FhG compared to non-interacting FhG												
1	0.410***	(0.084)	0.301***	(0.069)	0.003	(0.006)	0.031**	(0.013)	-0.004	(0.018)	0.023**	(0.001)
3	0.113*	(0.060)	0.118**	(0.047)	-0.006	(0.008)	0.036***	(0.012)	-0.013	(0.021)	0.010	(0.010)
6	0.128	(0.098)	0.128*	(0.076)	0.003	(0.011)	0.030	(0.018)	-0.045	(0.028)	0.001	(0.014)

Note: t: years after interaction. Panel A: FHG + t* TREND#FHG - t*TREND. Panel B: Coef reflects outcome of the relevant FHG_INT coefficient + FhG - t*TREND. Panel C: FHG_INT - t* TREND#FHG. Significance stars reflect whether result is different from zero at p<0.1(,0.05,0.01): *(,**,***).

Robustness checks and extensions

Lastly, we perform several additional analyses to further explore the impact of interacting with FhG and to test the validity of our results. The results are presented in Table 11.[17]

Panel A of Table 11 splits interactions into those that involve an implementation and those that do not (see above for the definition). Whereas we find positive effects for both kinds for company size (turnover and employees), we find a positive effect on added value per employee only when the project involves implementing a change at the company. Thus, interacting with FhG seems to have an effect on company efficiency only when projects are especially downstream and lead to real changes in the organization.

Panel B explores the impact of interacting with FhG by considering the effect of first interactions coupled with the effect of follow-on interaction. The results provide a strong indication that benefits from interacting with FhG are concentrated in follow-on interactions. In consequence, it is important for companies to build long-term relationships with FhG if they wish to reap the maximum benefits of interacting with them.[18]

Panel C tests the robustness of the analysis to different definitions of interaction. As seen in the top half of Panel C, which lists different payment thresholds for an interaction, the results are robust to changes in the payment threshold. The sole exception is €50,000, which yields less statistically significant results. The bottom half of Panel C shows the effects of interactions in different payment ranges. Interactions involving payments of €0 to 5,000 generate no significant impact (the coefficient of added value per employee is even negative). Payments between €5,000 and 10,000 and between €10,000 and 50,000 generate similar impacts. However, those between €50,000 and 100,000 generate some impacts, whereas interactions constituting a payment of €100,000 or more generate the greatest impacts. This indicates that there are some nonlinearities with regard to the relationship between project size and impact.

[17] Due to space constraints, the results are restricted to fixed effects model estimates.
[18] This effect should be interpreted with care, as it is difficult to distinguish separate, independent interactions from multiple interactions within the context of a larger overarching project. Part of the larger effect of follow-on interaction might therefore be that these firms are engaged in large projects that involve interaction with FhG at multiple stages.

Panel D splits the samples into manufacturing and services sectors. The effects uncovered in the present analysis in terms of company size are concentrated in manufacturing companies, in line with the mission of FhG.

Panel E further splits the sample into three categories of company size: small (up to 49 employees), medium (50-249 employees), and large (250+ employees). Whereas small companies do not significantly benefit from interacting with FhG in terms of turnover, they do achieve employment growth of around 8%. Medium and large companies, on the other hand, benefit more in terms of turnover. The different effects observed here could indicate different projects pursued by small and large companies, and a different role played by FhG in the development of each.

Panel F splits the results by company age, distinguishing young companies (10 years of age or less) from older companies. While we find positive impacts on companies of all ages, the effects are statistically more significant for older companies. In all likelihood, this is due to the relative lack of young companies in interactions with FhG.

Table 11: Split estimates

	LN(TURNOVER+1)	LN(EMPLOYEES+1)	LN(ADDVAL+1)	INNOSALES	LN(CPE+1)	EMP_HIGHED
Panel A: By project implementation status						
Yes	0.063**	0.044*	0.006**	0.011	-0.004	0.010*
	(0.027)	(0.023)	(0.003)	(0.012)	(0.018)	(0.006)
No	0.099***	0.081***	0.010	0.003	0.011	0.002
	(0.027)	(0.023)	(0.008)	(0.011)	(0.014)	(0.006)
Panel B: By repetition of interaction						
First	0.004	0.016	-0.002	-0.002	0.019	0.000
	(0.025)	(0.019)	(0.003)	(0.014)	(0.017)	(0.006)
Follow-on	0.124***	0.082***	0.017*	0.007	0.011	0.001
	(0.026)	(0.023)	(0.009)	(0.013)	(0.015)	(0.005)
Panel C: By payment size threshold (€ k)						
All	0.070***	0.055***	0.001	0.008	0.015	0.001
	(0.017)	(0.014)	(0.004)	(0.009)	(0.013)	(0.005)
5+	0.093***	0.065***	0.006	0.013	0.019	-0.002
	(0.018)	(0.016)	(0.005)	(0.010)	(0.012)	(0.005)
10+	0.076***	0.055***	0.011*	0.009	0.017	-0.001
	(0.020)	(0.017)	(0.006)	(0.010)	(0.012)	(0.005)
50+	0.078**	0.039	0.008	0.016	0.007	0.017***
	(0.031)	(0.026)	(0.006)	(0.012)	(0.019)	(0.006)
100+	0.133***	0.113***	0.008	0.026	-0.029	-0.001
0-5	-0.033	-0.004	-0.012***	-0.009	-0.003	0.009
	(0.026)	(0.019)	(0.005)	(0.013)	(0.023)	(0.007)
5-10	0.094***	0.058**	-0.010	0.015	0.013	-0.006
	(0.033)	(0.024)	(0.006)	(0.018)	(0.016)	(0.009)
10-50	0.047***	0.046***	0.008	0.002	0.018*	-0.012**
	(0.018)	(0.016)	(0.007)	(0.010)	(0.010)	(0.005)
50-100	-0.001	-0.040	0.005	0.001	0.034*	0.027***
	(0.033)	(0.024)	(0.005)	(0.015)	(0.018)	(0.007)
100+	0.133***	0.113***	0.008	0.026	-0.029	-0.001
	(0.035)	(0.032)	(0.005)	(0.016)	(0.029)	(0.008)
Panel D: Between manufacturing and services						
Manufacturing	0.067***	0.065***	0.008	-0.000	0.012	0.002
	(0.023)	(0.019)	(0.007)	(0.012)	(0.014)	(0.005)
Services	0.077	-0.007	0.006	0.019	0.020	0.011
	(0.053)	(0.046)	(0.006)	(0.026)	(0.031)	(0.013)
Panel E: By company size						
Small (up to 49 empl.)	0.034	0.076***	-0.001	-0.001	0.003	-0.004
	(0.036)	(0.027)	(0.003)	(0.030)	(0.028)	(0.014)

Medium (50-249 empl.)	0.082**	0.036	0.005	0.011	0.049*	0.008
	(0.032)	(0.024)	(0.004)	(0.017)	(0.029)	(0.009)
Large (250 or more empl.)	0.072**	0.053*	0.017	-0.008	-0.007	-0.001
	(0.029)	(0.028)	(0.012)	(0.012)	(0.013)	(0.007)
Panel F: By company age						
10 years or less	0.079*	0.080**	0.005	0.021	0.034	-0.033**
	(0.043)	(0.033)	(0.005)	(0.027)	(0.021)	(0.016)
More than 10 years	0.081***	0.063***	0.012	0.004	0.004	0.011**
	(0.024)	(0.022)	(0.009)	(0.011)	(0.015)	(0.005)

FE regressions. Full tables in appendix. Panel B: Small/large defined according to median total payments by company in year (median: €53,128). Stars indicate significance of coefficients. * p<0.10, ** p<0.05, *** p<0.01

5 Conclusion

In this study, we presented rigorous empirical estimates of the effects of Fraunhofer research on company performance based on microeconomic company-level data. To conduct our study, we compiled a unique dataset of German companies covering the 1996-2013 period based on the Mannheim Innovation Panel, to which we matched microdata on all Fraunhofer contracts with companies that had start dates in 1997. To identify the performance effects, we paid considerable attention to the issue of endogeneity and self-selection. Selection effects, or selection bias, refer to a situation in which standard statistical methods, e.g. regressions, confound causal impacts and effects due to the fact that high-performing companies are more likely to interact with Fraunhofer. Our results have demonstrated that selection is a very important mechanism in our application and must be explicitly dealt with in order to obtain reliable estimates of the causal effects of Fraunhofer interaction on performance. Controlling for selection and related endogeneity issues is often tedious and warrants the use of advanced statistical models. We have applied such models as the basis for our estimation of the causal performance effects. In particular, we used IV-based approaches, fixed effects regressions and IPWT estimators to control for a wide variety of econometric problems that typically plague statistical analyses in the performance-evaluation context.

Our results indicate that interacting with Fraunhofer causally increases various dimensions of company performance, including employee headcount, turnover and labor productivity. We also find evidence that a driver of the performance increases may be linked to our results, indicating that Fraunhofer interactions induce companies to switch to more knowledge-intensive production and innovation strategies. Specifically, we showed that Fraunhofer interactions increased the sales share of innovative products and increased the share of employees with tertiary education.

In general, Fraunhofer interactions should not be seen merely as a means for gaining access to unique and complementary knowledge sources. Instead, they also change the fundamental strategies by which companies produce, innovate, create value, and ultimately prosper. We show that the effects are heterogenous across companies. Manufacturing companies as well as medium and large companies seem to benefit more strongly from Fraunhofer interactions than small companies and companies in services. Consistent with the view of Fraunhofer as more than a repository and provider of scientific knowledge, our results indicated that the performance effects are greatest in cases where companies have multiple interactions with Fraunhofer. This core finding strongly suggests that deriving performance increases from Fraunhofer interactions requires long-lasting relationships and mutual commitments between companies and institutes. This also has implications for the organizational locus of the value creation, which is likely to be on the idiosyncratic level of the individual relationship between each institute and company. An important implication is that the success mechanism underlying the documented performance effects is very easy for competing organizations to replicate. What makes Fraunhofer successful is not its formal overarching structure, but its many years of technical, economic, scientific, and collaborative experience rooted in its individual institutes.

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