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D6.2: Final report on estimation of parameters and elasticities with respect to public/private R&D

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1 Project Information Summary

Table 1.1: Project Information Summary

Project Acronym	FRAME
Project Full Title	Framework for the Analysis of Research and Adoption Activities and their Macroeconomic Effects
Grant Agreement	727073
Call Identifier	H2020 - SC6 - CO-CREATION - 2016 -1
Topic	CO-CREATION-08-2016/2017: Better integration of evidence on the impact of research and innovation in policy making
Funding Scheme	Medium-scaled focused research project
Project Duration	1st April 2017 - 31st March 2019 (24 months)
Project Officer(s)	Hinano SPREAFICO (Research Executive Agency) Roberto MARTINO (DG Research and Innovation)
Co-ordinator	Dr. Georg Licht, Zentrum für Europäische Wirtschaftsforschung GmbH (ZEW), Mannheim
Consortium Partners	Centre for Economic Policy Research, London Lunds Universitet, Lund Università Luigi Bocconi, Milan Universitat Pompeu Fabra, Barcelona London Business School
Website	http://www.h2020frame.eu/frame/home.html

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2 Deliverable Documentation Sheet

Table 2.1: Deliverable Documentation Sheet

Number	D6.2
Title	Final report on estimation of parameters and elasticities with respect to public/private R&D
Related WP	WP6
Lead Beneficiary	ULUND
Author(s)	Torben Schubert (ULUND), Maikel Pellens (ZEW), Diego Comin (CEPR), Georg Licht (ZEW)
Contributor(s)	
Reviewer(s)	All partners
Nature	R (Report)
Dissemination level	PU (Public)
Due Date	30.03.2018
Submission Date	
Status	

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3 Quality Control Assessment Sheet

Table 3.1: Quality Control Assessment Sheet

Issue	Date	Comment	Author
V0.1	16.01.2018	First draft	Torben Schubert
V0.2	28.01.2018	Second draft	Maikel Pellens
V0.3	12.02.2018	Peer review	Torben Schubert
V0.4	27.02.2018	Third draft	Maikel Pellens
V0.5	05.03.2018	Formatting third draft	Maikel Pellens
V0.6	07.03.2018	Peer review	Torben Schubert

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4 Disclaimer

The opinion stated in this report reflects the opinion of the authors and not the opinion of the European Commission.

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5 Acknowledgment

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6 Executive Summary

The main aim of WP 6 was to estimate and collect the key-parameters needed for the calibration of the models in WP1-WP4. The main parameters needed are P1-P6. Two parameters could be adopted from existing specialized datasets produced and estimated by Comin and Mestieri. These were the speed of adoption parameters P4 and P5. The parameters P1-P3 and P6 were estimated based on datasets, which were collected and constructed within the context of the FRAME-project. P6 refers to the elasticity of adoption with respect spending on applied research organizations. P6 is of central novelty to the project because at the inception of the project there was no single publication providing insight on this parameter. The team responsible for WP6 estimated this parameter for the German-based Fraunhofer Gesellschaft, which is the world's largest public applied research organization. For this end a unique and confidential dataset was constructed, which includes information on all research contracts Fraunhofer started with firms in Germany between 1996 and 2014 (more than 130.000 individual projects), which were linked to the German part of the Community Innovation Survey. Causal effects relating to P6 were estimated using IV-based methods relying on the exploitation of heteroscedasticity (Lewbel 2012).
Parameter P1-P3 were estimated first on the country-level based on methodologies proposed by Bottazzi and Peri (2007). The necessary data was compiled from information available through the OECD country level data on R&D expenditures, additional World Bank information and specifically complied information from the PATSTAT database. The main tenet of our analysis is that we were able to use more recent data until 2014 and that we were able to use more refined patent data (EPO application with fractional counts) as compared to earlier studies. So, we deem our results to be superior in terms of data quality. Eventually, although we detect some very interesting differences compared to earlier findings, our results appear to be in a reasonable range set by earlier works. In addition to the information on P1-P3 on the country-level, we also differentiated the estimated elasticities by the EU and the G7. So our information also allows to inform the multicountry-model in WP3. Providing differentiated estimates for the multi-sector model (WP2) turned out to lead to unsatisfactory results stemming from low data-quality. The first problem we encountered was that R&D data on the sectoral level was often missing or existing only in incomplete time series. The second problem related to the fact that patents are classified by IPC, while sectors are classified by NACE. We used existing concordance tables to match IPC and NACE, but these matchings introduced considerable noise. Third, during our observation time NACE codes were revised from NACE 1.1 to NACE 2.0, where both classifications are for many sectors incompatible, allowing us only for very few sectors to create stable R&D time-series. Nonetheless, we provide estimates for these sectors based on the methodology by Bottazzi and Peri (2007), but the elasticities turned out to be instable. As a remedy and in order to secure valid input for WP2, we have resorted to a micro-level based methodology using information from the German Community Innovation survey matched to all patents applications at the German Patent and Trademark Office (DPMA). We extracted the patenting elasticity with respect to R&D separated by manufacturing and services. These elasticities, although based on completely different methodology, closely resemble our results on the country-level, while in addition showing that the elasticity is somewhat higher in manufacturing.

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7 Do Companies Benefit from Public Research Organizations? The Impact of the Fraunhofer Society in Germany (Estimation of parameter P6)

Diego Comin, CEPR, Georg Licht, ZEW, Maikel Pellens, ZEW, Torben Schubert, Lund

7.1 Introduction

Most economists agree that innovation is the key driver of sustained economic growth in the advanced countries, which makes innovation-related policies an important channel for government intervention in many countries. Yet, we know too little about too few policy levers that may affect innovation. Much of the existing work on innovation policy both theoretical and empirical has been circumscribed to fiscal incentives to R&D, estimating the impact of R&D tax advantages on private R&D spending and patenting activity (compare Bloom et al. 2002, Cappelen et al., 2012, Knoll et al., 2014 and Cowling, 2016). However, the array of possible policy interventions aimed at innovation activity is much broader than just those that affect the private cost of financing innovation. Most notably public research organizations, can be directly involved in conducting innovation or in helping private companies develop or implement state of the art technologies. Most of the analyses in this field have focused on the role of universities as providers of basic knowledge (Lööf and Broström 2008, Maietta 2015). 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 no solid econometric analyses are available with respect to the effectiveness of such public applied science organizations in fostering innovation in firms.

This paper starts to fill this gap by studying the world's largest public applied research organization: the German-based Fraunhofer Gesellschaft (FhG). Founded in 1949, Fraunhofer currently 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 research activity, FhG scientists also engage in research contracts of a total volume of about € 641 m. in 2015, which aim at solving specific technical problems of the commissioning private firms. Anecdotal evidence suggests that Fraunhofer is indeed instrumental in increasing the firms' innovativeness.

The main goal of our paper is to analyze the causal effect of engaging in research contracts with FhG on the performance of firms. To study this question, we have combined two datasets. The first is a confidential dataset, which contains information on the more than 130,000 research contracts signed by Fraunhofer with firms between 1997 and 2013. The second dataset is the German contribution to the Community Innovation Survey, which contains information on the performance and innovation activities of a large panel of companies in Germany.

The key challenge that a study such as ours needs to confront is the possibility that companies self-select into contracting with Fraunhofer, thus biasing estimates of the effects of engagement in research contracts on firm performance. To deal with these endogeneity issues, we employ recently developed estimators (Lewbel 2012), which derive instrumental variables

1 See Comin, Trumbull and Yang (2016 a, b).

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based on the existence of scale heteroscedasticity in the relationship governing the selection into FhG interactions.

Our analysis suggests that FhG interactions have a large effect on firm performance. A one percent increase in FhG expenditures results in 1.4 percentage points higher growth in turnover and 0.7 percentage points higher growth in productivity. Compared to the average turnover and productivity growth rates of 6.6% and 6.7%, the increases, which Fraunhofer interactions induce, amount to 21% for turnover growth and 11% for productivity growth. These effects are at least partially driven by a shift in the firm's innovation strategy because of interacting with FhG, in line with its mission of knowledge dissemination and application. A first piece of evidence for this is that interacting with FhG relates to changes in firm's hiring strategy: A one percent increase in FhG expenditures leads to a 0.2 percentage point increase in the share of employees with tertiary education background employed by the firm. We interpret this as a shift towards a more knowledge-based strategy. Second, FhG expenditures also relate to a more successful innovation strategy: a one percent increase in FhG expenditures translates to a 0.7 percentage point increase in the share of sales drawn from new products and services.

Further analyses show that the benefits from interacting with Fraunhofer are not homogeneous among companies. They are greater for companies that have interacted previously with Fraunhofer than for those that interact for the first time. They are also higher for interactions where the goal of the project is to generate new knowledge, e.g. through studies or applied research, than for interactions where the project aims to implement a given solution in a firm. In addition, the benefits of interacting with Fraunhofer are larger for younger as compared to older firms. We also provide evidence that smaller firms are more strongly affected than larger firms are.

Under certain assumptions, we can use the firm-level results to infer to the per annum macroeconomic effects in Germany. Our results indicate that Fraunhofer induces a total increase in value added of € 2.15 bn. Since even Fraunhofer's total per annum budget including state provisions and funding from other sources is less with about € 2.08 bn., the overall benefits in terms of increased value added exceed the costs of Fraunhofer. The effects are more pronounced when comparing the value added increases only to project revenue from private firms, which were approximately € 0.68 bn. in 2016.

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.

7.2 Background and Data

7.2.1 Innovation, market failure, and state action

In their groundbreaking works, Nelson (1959) and Arrow (1962) argued that research and development activities are subject to positive externalities, which result from the public goods nature of knowledge. A consequence of the positive externalities is that the on the free market there is and undersupply of innovative activities. The classical policy solution to positive externalities related to R&D and innovation is to lower the private costs of R&D, e.g. by providing state subsidies. A large strand of this literature has focused on tax subsidies to private R&D activities. The estimates of the impact of R&D tax advantages on private R&D spending and patenting activities vary considerably but they tend to be positive.[2] Berger (1993) and Hall (2003) obtain an estimate of the R&D elasticity with respect to the cost of R&D of

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[2] See for example, Dechezleprêtre et al. (2016), Montmartin and Herrera (2015), Castellacci and Lie (2013), Guceri and Liu (2015), Rao (2016), Cerulli and Poti (2012).

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between 1 and 1.5 in the U.S. Bloom et al. (2002) conduct a similar analysis in nine OECD countries and find short-term elasticities of R&D of 0.1, but long-term elasticities of around 1. Other authors have looked at the effects of R&D tax subsidies and credits on patenting activity (Bronzini and Piselli, 2016, and Cappelen et al., 2012, Knoll et al., 2014 and Cowling, 2016) and the introduction of new products in the market (e.g., Czarnitzki et al., 2011), consistently showing positive effects.

An alternative to lowering the costs of private R&D is to establish public organizations performing parts of the research or development activities. Most of the papers dealing directly or indirectly with this solution focused on the role of universities. For example, Monjon and Waelbrock (2003) show that at least the subgroup of very innovative firms benefit from collaboration projects with universities. Lööf and Broström (2008) corroborate this finding for manufacturing firms and Miozzo and Derwick (2002) present similar results for firms in construction. Darby et al. (2004) show that firms benefit in terms of patenting from the participation in the Advanced Technology Program by the US Commerce Department when a university is also part of the project. Belderbos (2004) provides evidence that cooperation with universities has a positive effect on the share of turnover due to new products. Toole et al. (2014) show that collaborations with universities also increases employment growth. Maietta (2015) shows that R&D collaborations between firms and universities affects process innovation positively, in particular when there is close geographical proximity. Cardamone et al. (2015) provide additional evidence and show positive effects of collocation with universities on firm innovativeness. The overall positive effects of university research on firm performance thus appear to be well documented and hardly under dispute in the empirical literature.

However, universities differ substantially in their mission from extra-university public research organizations in general, and the Fraunhofer in particular. While universities follow a shared mission of teaching and research (Schubert 2009), extra-university public research organizations do not usually have a teaching mission (Schmoch 2011). In addition, the research at Fraunhofer is dedicatedly oriented towards applied research and technological co-development with firms rather than basic research. Thus the type of scientific knowledge originating from Fraunhofer presumably differs considerably from the basic knowledge universities typically supply. The difference in the type of knowledge makes it conceptually problematic to take for granted that positive effects on firms found for universities automatically extend to the case of Fraunhofer or similar organizations. On the one hand, applied knowledge provided by Fraunhofer, may be easier to protect, e.g. by legal means such as patents, which may mean that the issue of underprovision may be less severe in the case of Fraunhofer. On the other hand, a number of analysis have shown that firms need a sufficient absorptive capacity to benefit from basic knowledge provided by universities (Toole et al. 2014). An important mechanism to develop an absorptive capacity is to conduct own basic research (Cohen and Levinthal 2000). The reality however shows that only very few, typically large firms, conduct basic research themselves, which may imply that the majority of the firms in an economy find it difficult to make effective use of knowledge provided by public research organizations focusing on the provision of basic scientific knowledge. Applied public research organizations may thus be important for firms because they bridge the gap between basic knowledge originating from universities and the commercialization-oriented needs of firms. The motivations to support basic and applied research thus differ fundamentally. Financing basic research results from a concern about underprovision of knowledge due to its public goods character. Financing applied research results from a concern that firms are unable to exploit fully the potentials of basic knowledge without the help of intermediary organization such as Fraunhofer.

While the short review above has shown that a substantial literature exists on the effects of universities, only few analyses exist analyzing the effects of extra-university research organizations. Robin and Schubert (2013) and Kaiser und Kuhn (2012) are two exceptions, who analyze the effect on firm performance in terms of product innovation, patenting and

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productivity of public research organizations in general. Nonetheless, neither these authors are able to differentiate the effects into university and extra-university public research organizations. Thus, there remains a gap in the literature with respect to the effects of extra-university public research organizations focusing on applied research.

7.2.2 The Fraunhofer Gesellschaft

The Fraunhofer Gesellschaft is a partly publicly funded non-profit organization focused on the advancement of applied research. Together with the Helmholtz-Association, the Max-Planck-Society, and the Leibniz-Association, Fraunhofer is part of an extra-university research landscape, which is particularly well-developed in Germany. In 2013, of the 201,000 R&D employees in public research organization (including universities), 71,000 were employed by public extra-university research organizations. As concerns total employment, the Fraunhofer society was one of the largest extra-university organizations in Germany with 24,500 employees in 2016 second only to the Helmholtz-Association (38,000 employees). The Leibniz Association had 18,000 employees and the Max-Planck-Society had 17,000 employees.

While Leibniz, Helmholtz, and Max-Planck are more oriented-towards academic research, the founding of FhG in 1949 instead followed the strategic intent to complement the basic research with a research organization specifically focused on bridging the gap between basic research and industrial application. Because the foundation of an independent research organization focused on applied research was long under dispute, the FhG remained small for quite some time. 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, Fraunhofer is the biggest non-profit organization for applied sciences in the world, with a budget of € 2.1 bn. Fraunhofer is organized as a private registered association (“eingetragener Verein, e.V.”) and receives public funding amounting to roughly 25% of its total budget (90% common from the federal government and 10% from regional government where the respective institute is located). The Fraunhofer Society comprises 67 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.

Fraunhofer's mission makes it the natural organization to study the magnitude of scientific knowledge transfer to private firms. Of the total budget of € 2.1 bn. in 2015 almost 30% came from industry funds, which is by far the largest share compared to other the other extra university research organizations (Table 7.1). Likewise, the share in universities in Germany was with approximately 11% much smaller.

Overall, the Fraunhofer society organizes its core research within seven broad clusters presented in Table 7.2. Some institutes belong to more than one cluster.

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Table 7.1: Fraunhofer key-figures

	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 based funds (%)	29	22	22	25	24

Table 7.2: Activity areas

Cluster	Member institutes	Research topics
ICT	19	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
Microelec-tronics	18	Smart and healthy living, energy efficient systems, mobility and urbanization, industrial automation
Productio n	8	Product development, production technologies, production systems, production processes, production organization, logistics
Defense and security research	10	Security research, defense and effect, intelligence and suveillance, explosives, decision support for the governments and firms, localization and communication, image processing
Materials	17	Health, energy and environment, mobility, construction and living, mechanical engineering, microsystems technology, safety

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7.2.3 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.[3] 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 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 and Eurostat, 2005). The present analysis makes use 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 of 30,125 firms between 1996 and 2013. Of the 131,158 projects in the Fraunhofer project database, we were able to match 46.651 projects to 7.781 distinct firms, which were surveyed at least once in the MIP survey. Due to nonresponse and the condition of observing a firm at least three times, 32,568 projects, representing 4,495 firms in the MIP 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 centers, 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),[4] which does not capture all firms potentially entering contractual relationships with Fraunhofer. 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.

7.2.4 Overview of interactions

This section presents an overview of the FhG cooperation with firms through analysis of the project database. Figure 7.1 shows that between 1997 and 2014 FhG has initiated approximately 6.500 projects with clients per year. The number of initiated projects was especially high in 2009, when about 8.800 projects started.

[3] Excluding defense and security research.

[4] Sample size and coverage varies throughout time.

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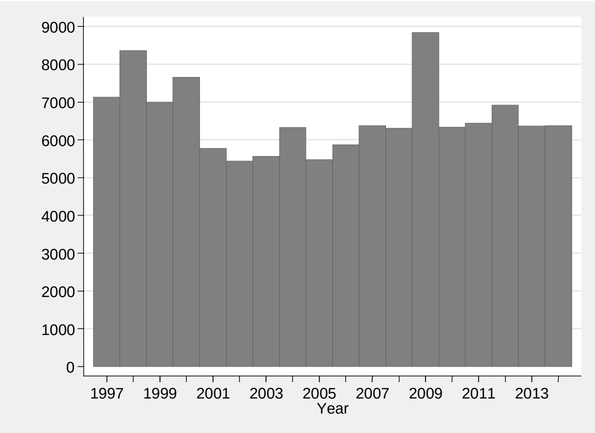

Figure 7.1: Projects started by year

The average project in our sample took one year and eight months to complete5 and amounted to a budgetary volume of approximately € 37 k.6 Both project cost and duration hint that the typical FhG project is relatively small-scaled. In line with FhG's mission, these data suggest that FhG mainly contributes to firms through well-defined and well-specified projects that are more likely to be rather applied in nature (in contrast to long-term open-ended research projects). However, in both cases, the tail is long: the top 5% of projects carry a cost of € 170 k. and take 5 years and 7 months to complete.

In terms of repeated interaction, 42% of firms collaborate with FhG once in the dataset, and 30.6% returns for more than three projects.7 The data therefore shows that FhG does not support a small number of specific firms, but rather supports thousands of firms throughout the German economy. However, there is a smaller share of FhG's client firms that form long-lasting relations involving many projects: in our sample there are 31 firms who engaged with FhG in more than 100 projects.

Table 7.3 lists the 20 most common keywords in the project descriptions.8 These 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 Fraunhofer 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

5 Not taking projects reported as lasting for 10 years or more into account (1% of projects).

6 Author's calculation from annual project payments listed in database. Real 2010 EUR. Approximately one percent of projects has a negative net revenue. For the purposes of the present analysis, these are set to zero. The data is moreover censored at the 99th percentile (€ 483 k.).

7 This analysis is restricted to the subset of the FhG data for which the client was identified as MIP firm and where clients can be reliably disambiguated. Some care must be taken in the interpretation of these data, as there might remain subsidiaries and the likes of MIP firms among unidentified firms. As such, these statistics should be seen as lower limit estimates. Multiple interaction also might constitute independent projects, or they might be direct follow-up projects, which are not easily differentiated.

8 These descriptions are short: the average description is 7 words long. Keywords in the descriptions were translated from German and harmonized. Common words as well as brands and any identifying information has been removed from the data.

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most implementation projects, although potentially providing substantial benefits to the firm, are typically quite routine tasks for Fraunhofer and thus of limited technological complexity. As an example, many Fraunhofer institutes grant access to the technical infrastructure by offering measurement services. Another example is the installment of a specialized machine park. Projects relating to technology generation instead are more distant from actual implementation implying a higher degree of novelty and technical complexity. 9

One quarter of projects in the FhG database is classified as implementation (24.8%), with the share remaining relatively stable over time: with the exception of 2009, when only 16.7% of projects were classified as implementing a technology, the share remains between 22 and 30%. Implementation projects tend to carry higher volume, at a mean of € 45.9 k., compared to € 33.7 k. for technology generation projects (two-sided t-test: $t(118,559) = -24.84$, $p < 0.001$).

Table 7.3: 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%

9 After extracting key-words and iterative process was started where 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. We adapted the list of key-words until the the resulting classification yielded good fit. The final list of key-words includes terms such as ‘adapt’, ‘build’, ‘create’, ‘construct’, ‘develop’, ‘improve’, ‘innovate’, ‘integrate’, ‘intervene’, ‘install’, ‘manufacture’, ‘modify’, ‘realize’, ‘restructure’.

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7.2.5 Variables

This section describes the variables used in the analysis (described in Table 7.4).

Interaction with Fraunhofer Gesellschaft

The key explanatory variable of the study captures how much the firm made use of FhG's services. This is captured on a yearly basis through the amount received by FhG from the firm (FHG).[10] The share of firms in the CIS sample who have made use of FhG's serviceswas 3.44% of observations (6,823 firm-year obersvations). This share corresponds to2,181 of the 30,125 distinct firms included in the CIS samples between 1996 and 2013. The average firm which collaborates with FhG at least once does so 3 times in the timespan of the analysis. A third (31%) of these firms collaborate in only one year, a further 23% does so twice. 5% of firms collaborates with FhG in 8 years or more.

Outcomes

Firms might benefit in different ways from working with FhG. They might be able to grow faster as a result of absorbing the public knowledge offered by FhG, become more productive, or change their strategy to a more knowledge-based one. The first possible effect is assessed through changes in growth, as captured by the growth rate of turnover (TR_{GR}). The average firm in the sample reports a growth rate of turnover of 6.7%. Productivity growth $(PROD_{GR})$ is proxied through added value per employee, which is approximately 6.7% on average.

As it is FhG's mission to bridge the gap between science and commercialization, we expect any growth or efficiency gained through working with FhG to be realized through innovation. To that end, we investigate two further variables. First, we consider the composition of the firm's labour force: part of turning to more innovation-based strategies and making investments such as contracting with FhG might be to hire more highly qualified personnel. This is captured in $\Delta TERT$, which represents the year-over-year change in the share of employees with tertiary education. More directly, we also consider how important innovation is for the firm: what share of turnover is is due to innovative products or services, i.e. products or services less than 3 years old $(\Delta INNOSALES)$?

Controls

In the econometric analysis, we control for a number of factors that might correlate with the firm's growth potential, innovative success, and the other outcomes. These include R&D intensity and size, which are likely to play an important role concerning self-selection into collaboration with FhG, but also correlate strongly with the outcome variables. We measure the R&D intensity by R&D expenditures as a share of turnover and the size of the firm by the number of employees. Other controls include the firm's age, whether the firm exports, and whether the firm is located in former Eastern Germany. The latter variable captures broad

10 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.

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regional economic differences within Germany. We further control for the economic activities of the firm through the inclusion of sector indicators and include year fixed effects to account for shared macroeconomic trends. Additionally, we control for lagged levels of the dependent variables.

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Table 7.4: 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. EUR)	198,385	3.355	55.112	0	5,084
Outcomes							
TR_{GR}	Turnover growth[a]	Growth rate of turnover.	93,643	1.067	0.355	0.337	3.300
$PROD_{GR}$	Productivity growth[a]	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]	EUR of R&D expenditures per EUR 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. EUR)	131,822	213.527	3941.377	1.001	508623.5
$PROD$	Productivity[a]	Added value per employee (tho. EUR)	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 innovative products and services	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 EUR.

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7.2.6 Descriptive analysis

Table 7.5 compares the outcome and control variables for firms with and without FhG interactions indicated by positive expenditures for FhG projects. [11] Firms report 4.2 percentage points higher turnover growth in years in which they contract with FhG (10.7% versus 6.5%). Differences between the other outcomes are however smaller and not statistically significant, with a productivity growth differential of 1.3 percentage points, and 0.1 and 0.3 percentage points lower changes in employees with tertiary education and the share of innovative sales, respectively.

Part of these small differences is likely due to the higher level of the outcomes coinciding with FhG expenditures: firms, which interacted with Fraunhofer, on average have higher turnover (1.6 bn. EUR versus 164 mio. EUR) and higher productivity (114 tho. EUR added value per employee versus 90 tho. EUR). Their workforces are more highly educated: 31.3% of employees with tertiary education when FhG expenditures occur, versus 25.4% when they do not. Likewise, FhG expenditures co-occur with high innovative sales (21.7% versus 16.6%). In the regressions, it is therefore crucial to keep the level of these variables constant.

Table 7.5 highlights some more differences in the controls. Firms reporting FhG expenditures are more R&D intense (8.4% versus 2.3%), older (37 years versus 29), and larger (4,400 employees versus 400). Furthermore, they are more likely part of a group (69% versus 53%) and to export their products (47% versus 26%). FhG firms are also less likely to be situated in former Eastern Germany (28% versus 33%).

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[11] All differences in means reported here are statistically significantly different at p <0.01, unless otherwise specified.

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Table 7.5: FhG and non-FhG firms in comparison

	FHG						
		0			>0		Difference
	Mean	S.D.	Obs.	Mean	S.D.	Obs.	
Outcomes							
TR_{GR}	1.065	0.354	90,246	1.107	0.364	3,397	-0.042***
$PROD_{GR}$	1.065	0.395	38,569	1.079	0.373	1,595	-0.013
$\Delta TERT$	0.002	0.089	60,487	0.001	0.085	2,229	0.001
$\Delta INNOSALES$	-0.005	0.122	56,356	-0.009	0.175	1,584	0.003
Controls							
$RDINT$	0.023	0.094	75,158	0.084	0.166	2,816	-0.061***
AGE	28.784	31.936	184,137	37.357	39.473	6,667	-8.574***
EMP	392.749	5081.942	184,472	4415.390	28048.113	6,593	-4022.640***
$EXPORT$	0.531	0.499	191,562	0.687	0.464	6,823	-0.156***
$GROUP$	0.259	0.438	191,562	0.470	0.499	6,823	-0.211***
$EAST$	0.334	0.472	191,562	0.276	0.447	6,823	0.059***
TR	164.461	3712.474	127,390	1623.831	7990.504	4,432	-1459.370***
$PROD$	90.095	95.384	59,694	114.092	99.713	2,258	-23.997***
$TERT$	0.202	0.254	96,596	0.313	0.258	3,277	-0.111***
$INNOSALES$	0.063	0.166	108,861	0.217	0.269	3,168	-0.154***

Notes: Unit is firm-year. Difference: outcome of two-sided t-test. Stars indicate significance level of t-statistic. ***(,**,*): p < 0.01(,0.05, 0,10). FhG Cooperation: FhG expenditures > 0 in at least one year.

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7.3 Identification strategy

Identification of the key effects of Fraunhofer interactions on firm performance through regression techniques faces the issue that Fraunhofer interactions are not randomly assigned. Typically, selection will be mutual in the sense that both Fraunhofer institutes will select more innovative firms and that more innovative firms are more willing to self-select into an interaction with Fraunhofer institutes. This section describes the methods employed in this study to deal with the mutual selection issues. Assume the following simple model of the relationship between the firm performance y_{it} and the cooperation variable FHG_{it}:

$$\mathrm{y}_{\mathrm{it}} = \mathrm{x}_{\mathrm{it}}\beta + \mathrm{FHG}_{\mathrm{it}}\delta + \mathrm{u}_{\mathrm{it}} \text{ (7.1)}$$

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. (7.1) regular Pooled OLS (POLS) and obtain consistent estimates of δ. Even if x_{it} does not sufficiently control for all variables relevant in the selection process, assuming that any unobserved heterogeneity in u_{it} is time-constant allows us to 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 quite long period. FE may under such conditions contribute to reducing the bias inherent to POLS, but it will not lead to consistent estimates.

To prevent that, we need to identify δ from exogenous variation in the interaction with Fraunhofer 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 (Arrelano and Bond 1991, Arrelano and Bover 1996). Other applications relying on time-dependent heteroscedasticity in longitudinal data can be found in King et al. (1994), Sentana and Fiorentini (2000, 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:[12]

$$\mathrm{y}_{\mathrm{i}} = \mathrm{FHG}_{\mathrm{i}}\delta + \mathrm{a}_1\mathrm{capabil}_{\mathrm{i}} + \mathrm{e}_{1\mathrm{i}},$$

$$\mathrm{FHG}_{\mathrm{i}} = \mathrm{a}_2\mathrm{capabil}_{\mathrm{i}} + \mathrm{e}_{2\mathrm{i}}. \text{ (7.2a,b)}$$

12 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.

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where we allow that e_{2i} is heteroscedastic, i.e. it may depend on some vector h_i. Estimating Eq. (7.2a) by OLS without taking the unobserved capability-term into account will result in a biased estimate $\hat{\delta}$. In particular, setting $X = (\mathrm{FHG}_1, \dots, \mathrm{FHG}_n)'$, $z = (\mathrm{capabil}_1, \dots, \mathrm{capabil}_n)'$ and $y = (\mathrm{y}_1, \dots, \mathrm{y}_n)'$, $\hat{\delta}$ can be written as:

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

$$= (1/n \sum_{i=1}^{n} x_i' x_i)^{-1} \, 1/n \sum_{i=1}^{n} x_i' y_i = \delta + (1/n \sum_{i=1}^{n} x_i' x_i)^{-1} \, 1/n \sum_{i=1}^{n} x_i'(a_1 z_i + e_{1i}) \quad (7.3)$$

The probability limes of Eq. (7.3) is given by:

$$\hat{\delta} \overset{p}{\to} = \delta + a_1 \frac{E(FHG_{it} capabil_i)}{E(FHG_i^2)} = \delta + a_1 \frac{a_2 E(capabil_i^2)}{a_2^2 E(capabil_i^2) + E(e_{2i}^2)} \quad (7.4)$$

where the second equality follows from replacing $\mathrm{FHG}_{\mathrm{it}}$ with Eq. (1.2b). Although the OLS estimate is generally biased, interestingly, if $E(e_{2it}^2)$ is large, then 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 7.2, where we simulated the Eqs. (7.2a, b) using $\delta = \alpha_1 = \alpha_2 = 1, \mathrm{e}_{1\mathrm{i}} \sim \mathrm{capabil}_\mathrm{i} \sim N(0,1)$. The left panel is generated with $\mathrm{e}_{2\mathrm{i}} \sim N(0,1^2)$ and the right panel is generated with $\mathrm{e}_{2\mathrm{t}} \sim N(0,5^2)$. Obviously, the true parameter δ is 1. But when running the regression y_i on 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 quite close to the true parameter. Intuitively, the increase in the variance of $\mathrm{e}_{2\mathrm{i}}$ weakens the strength of the direct relationship between FHG_i and the omitted variable $\mathrm{capabil}_\mathrm{i}$, which is defined by Eq. (1.2b), leading to a drop in the bias.

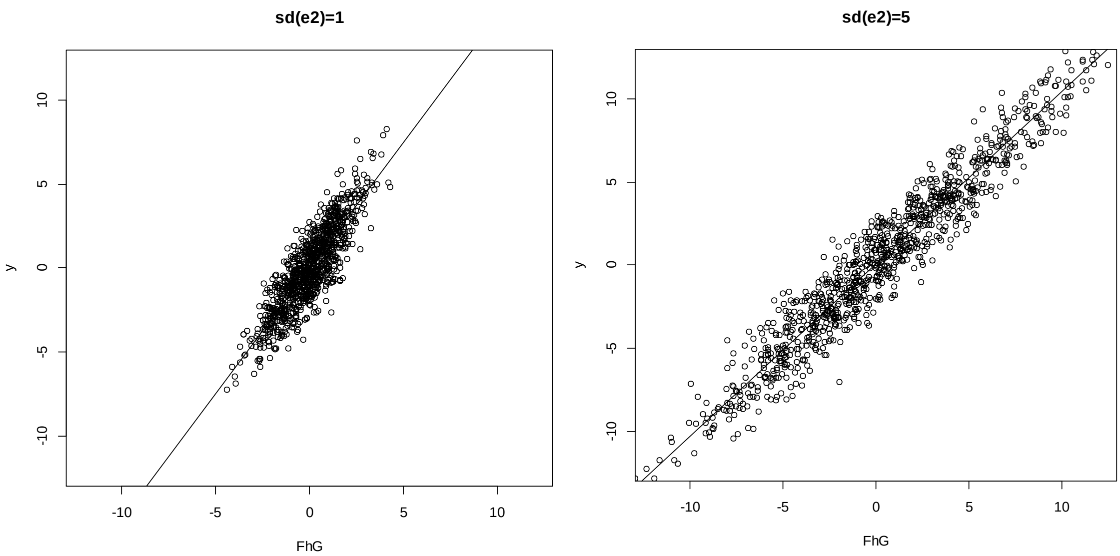

Figure 7.2: Higher degrees of heteroscedasticity lead to more accurate estimation of FHG.

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

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that in specific events the error variance becomes so large that OLS leads 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. (7.4) 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. (7.4) is a function of the vector h_i If for example we assume positive scale heteroscedasticity, the bias is the 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 instruments can be defined, which makes use this exogenous information to identify the causal effect. To illustrate that, we turn to more general version of Eqs. (7.2a, b) allowing for a vector of control variables $x_i \in \mathbb{R}^k$:

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

$$FHG_i = \mathrm{x_i}\zeta + \mathrm{v_i} \text{(7.5a,b)}$$

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: $E(x_i u_i) = 0$ and $E(x_i v_i) = 0$. Lewbel (2012) shows that $\mathrm{z_i} = (\mathrm{x_i} - \mathrm{E(x_i)})\mathrm{v_i}$ is a vector of valid instrument for $\mathrm{FHG_{it}}$ provided that:

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

$$\mathrm{cov}\big(\mathrm{x_i} - \mathrm{E(x_i)}, v_i^2\big) \neq 0 \text{ (7.6a, b)}$$

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. (7.6b), i.e. heteroscedastic first stage errors, implies that the instrument $\mathrm{z_i}$ and the endogenous variable are correlated. Using Eq. (7.5a,b) we can write:

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

$$= E(x_i v_i FHG_i - x_i v_i \mathrm{x_i}\zeta - \mathrm{E(x_i)}v_i FHG_i + \mathrm{E(x_i)}v_i \mathrm{x_i}\zeta) = \mathrm{E}(z_i FHG_i) \neq^! 0 \quad \text{(7.7)}$$

On the other hand, Eq. (7.6a) 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

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

$$= \mathrm{E}\big(\mathrm{x_i}(\mathrm{a_1 a_2 capabil_i^2} + \mathrm{a_1 capabil_i e_{2i}} + \mathrm{a_2 capabil_i e_{1i}} + \mathrm{e_{1i} e_{2i}})\big) = 0 \text{ (7.8)}$$

Thus, Eq. (7.6b) is similar to the regular rank condition in IV ensuring that the instruments display some sort of correlation with the endogenous variable. Eq. (7.6a) is equivalent to the exogeneity condition which is seen also from the fact that Eq. (7.8) shows that it is

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equivalent to requiring that the instruments and the structural error term are uncorrelated. Furthermore, Eq. (7.8) 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 $\mathrm{capabil_i}$.

Implementing the Lewbel estimator is easy by using the sample equivalent of $\mathrm{z_i}$:

$$\widehat{z_i} = (\mathrm{x_i} - \overline{\mathrm{x}})\widehat{v_i} \ (7.9)$$

where $\widehat{v_i}$ is the residual from reduced form regression of $\mathrm{FHG_i}$ on the exogenous regressors $\mathrm{x_i}$. $\widehat{v_i}$ is structurally identified because the parameters in the reduced form regression can always be consistently estimated (Wooldridge, 2002).[13]

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 Fraunhofer on firm performance, if and only if we detect a source of heteroscedasticy in the reduced form regression. We will now continue by providing evidence that in particular firm size induces positive scale heteroscedasticity, implying 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 they cannot be fruitfully be used to identify the causal effect of Fraunhofer interaction on firm performance. Mathematically, the size variable meets the condition in Eq. (7.6b) while the other controls don't. An important implication is that the identification strategy based on heteroscedasticity leads in our application to a model which is exactly (though not over) identified.

Table 7.6 presents an OLS regression of FhG expenditures on firm characteristics, which represents the first stage in eq. 7.5. 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 0.66% increase in FhG expenditures, and a one percent increase in size leads to a 0.101% increase in expenditures. Likewise, the sector and time fixed effects are statistically jointly significant at p<0.01.

As Figure 7.3 shows, FhG expenditures exhibit strong scale heteroscedasticity. The presence of heteroscedasticity is confirmed by Koenker's (1981) NR² test statistic (LM(47) = 4529.85, p<0.01) as well as White's (1980) NR² test (LM(655) = 4152.23, p<0.01), which both strongly reject homoscedasticity.

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13 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. (1.2a) and Eq. (1.2b) is admissible.

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Table 7.6: FhG expenditures

	(1)
Dependent: $ln(FHG_{t-1})$	
$RDINT_{t-1}$	0.667***
	(0.092)
$ln(AGE_{t-1})$	-0.001
	(0.007)
$ln(EMP_{t-1})$	0.102***
	(0.007)
$EXPORT_{t-1}$	0.011
	(0.013)
$GROUP_{t-1}$	-0.016
	(0.010)
$EAST_{t-1}$	0.007
	(0.011)
CONSTANT	-0.340***
	(0.040)
Industry F.E.	YES
Time F.E.	YES
N	57301
R^2	0.094

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

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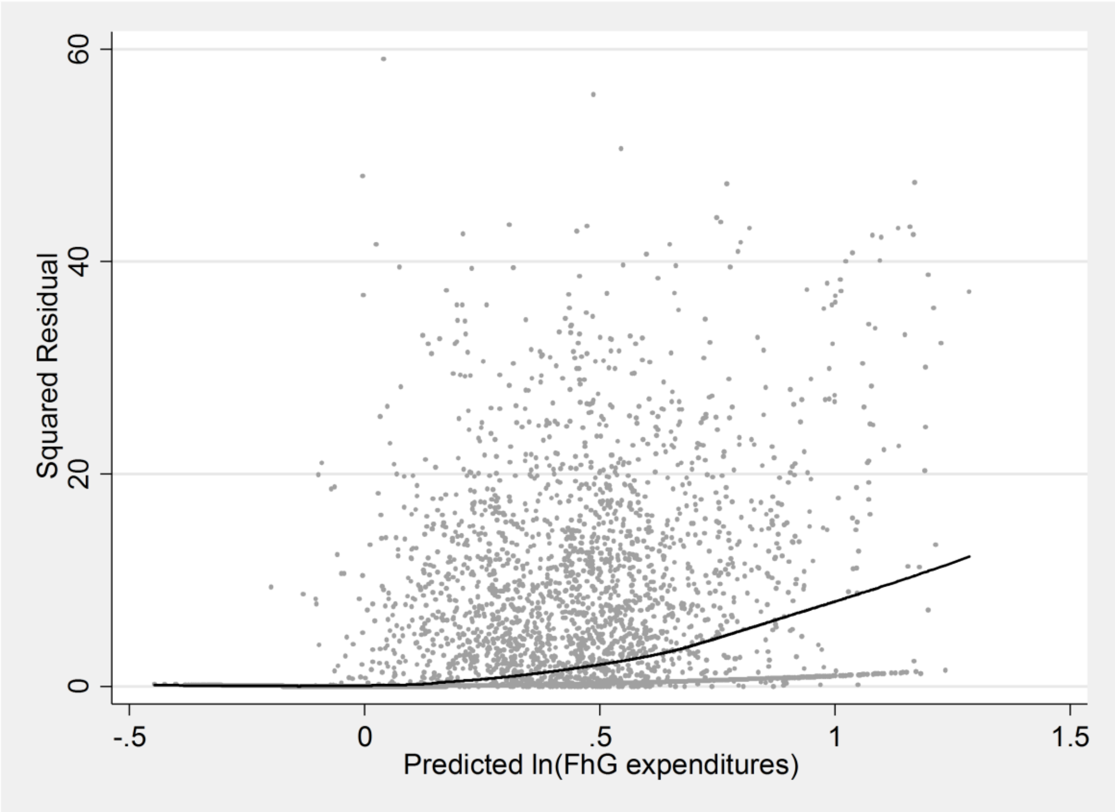

Figure 7.3: First stage heteroscedasticity
Notes: Lowess smoother. Bandwidth = 0.8.

As argued above, this scale heteroscedasticity appears to be solely driven by firm size. This is shown explicitly in figure 7.4, where the results of linear partial regressions of the explanatory variables on the squared error are shown.[14] This result is relatively unsurprising: 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 t and firm outcomes.

[14] 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.

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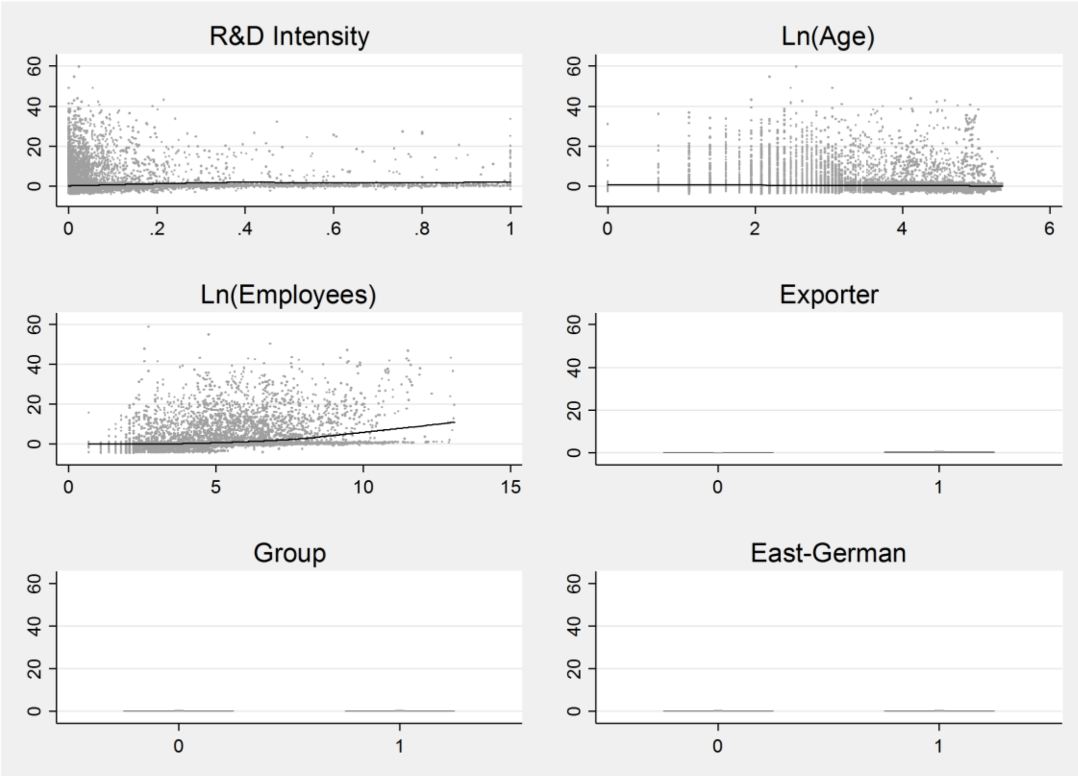

Figure 7.4: Linear partial regression of heteroscedasticity in first stage on firm characteristics

Notes: Y axis: squared residual of regression of FhG expenditures on lagged controls. Line: Lowess smoother. Bandwidth = 0.8.

7.3.1 Specification

As argued above, we analyze the effects of interactions with Fraunhofer in two respects. First, we analyze actual performance measures both in terms of turnover and productivity growth.[15] 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 productivities are typically related to increasing resource efficiency following process innovations or higher sales increases resulting from successful product innovation.

Second, we analyze to which extent interactions with Fraunhofer 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 Fraunhofer, firms need to invest in their human capital. Consequently, we expect that firms will adjust their hiring strategy

15 The results are robust to using employment growth instead of turnover growth as performance measure. These results are presented in Table 7.A.1.

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and increase the share of employees with tertiary education background. Second, we expect that firms engage with Fraunhofer as a means to achieving their innovative goals, and expect that innovative success, as measured through the share of turnover achieved through the sales of innovative products, will increase post interaction.

In order to account for unobserved heterogeneity between firms, we do not analyze the level of turnover, productivity, workforce education, and innovative sales, but rather calculate year-on-year growth rates (for turnover and productivity) or differences (workforce education and innovative sales). This correction removes variation due to common factors among firm-year combinations from the data.

In the case of turnover and productivity growth, we can write the baseline model as follows:

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

The left hand side of the equation, $\ln\left(\frac{y_{it}}{y_{it-1}}\right)$, represents the logged growth rate of respectively turnover and productivity. Both the outcome as FhG expenditures, $\ln(FhG_{it-1})$, are estimated in logs in order to interpret the results as elasticities, i.e. the relative increase in growth rate associated with a relative increase in FhG expenditures.[16] 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[17], 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 adopt this model 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 estimate the model in differences, which allows us to interpret the coefficient of $\ln(FhG_{it-1})$ as an effect on the outcome variable in percentage points.

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

We estimate the models through OLS regression, as well as by instrumenting $\ln(FhG_{it-1})$ through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP_i)}]$, 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, which are clustered by firm.

16 Employing binary indicators for the presence of any FhG expenditures leads to qualitatively equivalent conclusions. The results are presented in Table 7.A.2. Note, however, that the identification strategy described above relies on strong assumptions regarding the first stage functional form in the case of binary endogenous variables; cf. Lewbel (2016).

17 We omit the latter from the specification focusing on turnover growth, as lagged turnover and number of employees are highly correlated (0.89).

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7.4 Results

7.4.1 Turnover Growth and productivity growth

Table 7.7 presents OLS and Lewbel-IV estimates of the relation between lagged FhG expenditures, $ln(FHG_{t-1})$, on the right-hand side and the logged turnover growth factor ($\ln(TR_{GR_t})$) and productivity growth factor $\ln(PROD\_GR_t)$) on the left-hand side. Column 1 of Table 7.7 shows the OLS estimates of turnover growth, indicating that a one percent increase in a firm's FHG expenditures implies a large 1.0 percentage point in the firms' annual growth rate. Focusing on the IV-results, we even obtain a slight higher effect of 1.4 percentage points. If we compare the latter to the average growth in the sample, which is 6.7 percent (Table 7.4), the Fraunhofer effect is substantial. It amounts to approximately 21% of the total average growth in the sample.

With respect to the control variables, the model shows the expected relations: turnover growth rates increases in the R&D intensity ($RDINT_{t-1}$), indicating that on average higher intramural R&D positively affects growth prospects. Turnover growth decreases with size (as measured through the lagged level of turnover ($ln(TR)_{t-1}$)) and age of the firm ($ln(AGE)_{t-1}$). Exporting firms and firms which are part of groups experience higher turnover growth, and firms from former Eastern Germany tend to grow more slowly. The sector and year dummies are each jointly significant at p<0.01. Column 2 instruments presents the IV results (cf Section 7.4).[18] The estimated elasticity between FHG_{t-1} and TR_GR_t is in this model still positive and highly significant (p<0.01), with an estimated effect of 1.4 percentage points, which is quite comparable to the OLS case. Moreover, the model shows a strong first stage with Cragg-Donald Wald F-statistic far exceeding Stock-Yogo (2005) critical values.

Having established that interacting with Fraunhofer results in firm growth, we address the question whether Fraunhofer also helps firms to become more efficient. To that end, we employ the same regression strategy to consider the elasticity between FHG_{t-1} and growth in value added per employee $PROD\_GR_t$. The results of respectively OLS and IV estimations are presented in Columns 3 and 4 of Table 7. Both estimate the effect at 0.7 percentage points. The IV estimations are however less precise than the OLS estimates, with double standard errors and weaker statistical significance (p<0.10 in the IV specification compared to p<0.01 in OLS). Nevertheless, the evidence supports that engaging with FhG-interactions increase also the firms' productivity growth.

Turning to the control variables, the regressions show that productivity growth covaries positively with R&D intensity (albeit at weak statistical significance) and the size of the firm as measured by the number of its employees. 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 $PROD_{t-1}$: -0.155%, compared to -0.009% for TR_{t-1} and TR_GR_t)

[18] 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. The appendix additionally shows results based on employee growth rates instead of turnover growth rates. The estimates closely match those presented in Table 7.

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Table 7.7: FhG expenditures and firm performance

	(1) OLS	(2) IV	(3) OLS	(4) IV
	$\ln(TR\_GR_t)$		$\ln(PROD\_GR_t)$	
$ln(FHGEXP_{t-1})$	0.010***	0.014***	0.007***	0.007*
	(0.002)	(0.004)	(0.002)	(0.004)
$ln(TR_{t-1})$	-0.009***	-0.009***		
	(0.001)	(0.001)		
$ln(PROD_{t-1})$			-0.155***	-0.155***
			(0.005)	(0.004)
$RDINT_{t-1}$	0.154***	0.149***	0.055*	0.056*
	(0.024)	(0.022)	(0.029)	(0.028)
$ln(AGE_{t-1})$	-0.009***	-0.009***	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
$ln(EMP_{t-1})$			0.013***	0.013***
			(0.001)	(0.001)
$EXPORT_{t-1}$	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)	(0.015)	(0.051)	(0.031)
Industry F.E.	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
N	48268	48268	25468	25468
R^2	0.031	0.031	0.100	0.100
Cragg-Donald Wald F-statistic		21406.768		10280.202

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

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7.4.2 Human capital and innovation success

We now turn to innovation as potential driver of the positive effects in terms turnover and productivity growth. We have argued that we expect that FhG-interactions most likely exert their effects through increasing the firms' innovative success on the one hand and through affecting the firms' hiring strategy on the other hand. Table 7.8 presents the impact of FhG expenditures on the change in employees with tertiary education (column 1 and 2) and on the change in the share of innovative products and services in turnover (column 3 and 4).

The OLS coefficient of $ln(FHG_{t-1})$ is positive and statistically highly significant (p<0.01). In terms of size, 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. When instrumenting FhG coefficients (column 2), however, the effect drops slightly to 0.2 percentage points. In addition, the coefficient is only weakly significant (p<0.10). Interesting is also the comparison to the average share of employees with tertiary education. From Table 7.4, we see that about 20% of the employees on average have a university or comparable degree. Compared to this average the induced increase of 0.2-0.3 percentage points, although statistically significant, appears to be small.

In terms of control variables, the regression shows an expected negative relation between the lagged share of employees with tertiary education ($TERT_{t-1}$) and the differenced share, as well as higher changes when R&D intensity is higher. Additionally, we find stronger increases among exporting firms and firms in former Eastern Germany. The effects of age and size, $ln(AGE_{t-1})$ and $ln(EMP_{t-1})$, are however negative.

Finally, 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 as well as IV estimations show an estimated semielasticity between FHG_{t-1} and $\Delta INNOSALES_{t,t-1}$ of 0.7% points, implying that a one percent increase in FhG expenditures leads to a 0.7 percentage points increase in innovative sales by the firm. Comparing that increase to the average share of turnover with due to new products of 6.7%, we find an economically sizeable effect of slightly more than 10% of the overall average. Thus, FhG expenditures results in higher innovative success. One reason for that is that by interacting with Fraunhofer firms get access to unique scientific knowledge. Interacting with FhG might also allow firms to realize innovation goals beyond their own knowledge base, which would otherwise require significant additional R&D investments.

In the extensions below, we show, among others, that firms with lower as well as firms with higher R&D intensities benefit from interacting with FhG. In terms of controls, older firms, and firms with higher levels of innovative sales, show lower increases. The estimations further show a positive relation between increases in innovative sales and R&D intensity, firm size, exporting, group membership, and being located in former Eastern Germany.

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Table 7.8: FhG expenditures and firm strategy

	(1) OLS	(2) IV	(3) OLS	(4) IV
	$\Delta TERT_{t,t-1}$		$\Delta INNOSALES_{t,t-1}$	
$ln(FHG_{t-1})$	0.003***	0.002*	0.007***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
$TERT_{t-1}$	-0.143***	-0.143***		
	(0.004)	(0.004)		
$INNOSALES_{t-1}$			-0.425***	-0.425***
			(0.008)	(0.008)
$RDINT_{t-1}$	0.042***	0.043***	0.212***	0.212***
	(0.007)	(0.007)	(0.017)	(0.015)
$ln(AGE_{t-1})$	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
$ln(EMP_{t-1})$	-0.001***	-0.001***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
$EXPORT_{t-1}$	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.	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
N	39019	39019	35019	35019
R^2	0.083	0.083	0.313	0.313
Cragg-Donald Wald F-statistic		16102.203		15537.327

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

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7.4.3 Further analysis

This section presents how the results depend on various project and firm characteristics. In order to obtain results differentiated by type of project and firms, we introduce dummy interaction terms representing certain cut-off points (e.g. small in contrast to large firms). In terms of project characteristics, we consider whether the effects differ between projects relating to technology implementation or generation. We also test whether the effects differ for firms with a longer history of FhG interactions. In addition, we analyze whether FhG expenditures are subject to diminishing returns. On the firm side, we study variation among the effect of FhG along the firm's 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 7 and Table 8. In the case of the growth variables, and k levels of interaction term D, we can write our model as follows:[19]

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha + \ln(y_{it-1})\,\gamma + \sum_{j=1}^{k} \ln(FhG_{it-1})\, D_{jit-1}\delta_j + X_{it-1}\beta + T_t\zeta + I_{it-1}\eta + \varepsilon_{it}$$

7.4.3.1 Project characteristics

Table 7.9 differentiates between effects of project expenditures relating to projects focused on technology implementation as compared to projects focused on technology generation. To differentiate technology implementation and generation projects we make use of the keyword-based definitions outlined in Section 7.3, where we argued that implementation projects relate to activities, such as the installation of new equipment, the introduction of a new product, etc., and the latter relates to more abstract projects, involving for instance 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 differential effect is reflected in the results: only expenditures for technology generation projects 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 a higher demand for 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.

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19 For reasons of parsimony, we limit reporting to key coefficients in this section.

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Table 7.9: Impact of FhG expenditures by project focus

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
Panel A: Project focus				
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 7.10 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 Fraunhofer does not lead to immediate positive effects. Instead, the benefits need time to materialize, suggesting that probably need to make adjustments to their processes and their internal capability base in order to reap the full benefits of FhG-interactions.

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Table 7.10: Impact of FhG expenditures by interaction number

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$
1st	0.006	0.011*
	(0.004)	(0.007)
2nd	0.012***	0.021***
	(0.004)	(0.006)
3rd	0.010**	0.010
	(0.004)	(0.006)
4th	0.009*	0.008
	(0.005)	(0.007)
5th+	0.010**	0.010***
	(0.004)	(0.003)

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0

Notes: OLS regression. Coefficient represents interaction with $ln(FHG_{t-1})$. Other controls included. * p<0.10, ** p<0.05, *** p<0.01 Stand

Table 7.11 explores the returns scale associated with FhG expenditures. To that end, differential effects are estimated for each quartile of the distribution of FhG expenditures. The results differ by type of outcome we consider. The smallest volumes of expenditures realize neither turnover growth nor productivity gains. Higher expenditures consistently result in increased turnover growth along the spectrum of expenditures levels, however, with comparable marginal effects. 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 estimates a high levels of statistical significance (p<0.01) for the largest category of FhG expenditures. In contract, increased innovative sales show up significant at most ranges. However, the estimated coefficient is highest at the lower end of the FhG expenditures distribution.

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Table 7.11: Impact of FhG expenditures by expenditures level

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
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.

This exploration of the effects of FhG expenditures along the nature of the project shows that there seems to be a difference between projects resulting in increased innovative success and turnover growth on the one hand, and projects resulting in efficiency gains. For the former, projects focusing on rather upstream elements, repeat interactions, and relatively lower levels of expenditures are shown to be effective. The latter is realized when projects are more downstream, do not yield additional benefits along further interactions, and are conditional on comparatively high levels of FhG expenditures.

7.4.3.2 Firm characteristics

Table 7.12 shows the impact of FhG expenditures interacting with the R&D intensity of the firm incurring the expenses. Economic theory predicts that firms require certain levels of internal knowledge in order to optimally internalize and apply externa knowledge (Cohen and Levinthal, 1989). An interesting question therefore is to which extent firms without high level of R&D expenditures can benefit from FhG's mission of knowledge transfer. Table 1.12 shows that some level of R&D expenditures is a precondition for internalizing FhG expenditures into productivity and innovation. Firms without R&D expenditures enjoy higher turnover growth in the wake of R&D expenditures. 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.

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Table 7.12: Impact of FhG expenditures by R&D intensity

R&D Intensity in t-1	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
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.

A related question is to which extent not only large firms, but also start-ups or SMEs can benefit from coordinating with FhG. Recall that firms with FhG expenditures are significantly larger in terms of employees than firms that show none. Table 7.13 shows differential effects of FhG expenditures for respectively small firms (with less than 50 employees), medium-sized firms (50-249 employees), and large firms. Only large firms show significant turnover growth after FhG expenditures (the estimated coefficient for small firms is however comparable to that of large firms, albeit with broader estimated standard errors). The impact of FhG expenditures for turnover growth is not statistically significant, but medium-sized firms do show increased productivity growth, increases in highly skilled human capital, and innovative sale. In terms of effect size, the impact on medium-sized firms is comparable to that on large firms. Small firms, however, only show a statistically weakly significant increase in the share of employees with tertiary education.

Table 7.13: Impact of FhG expenditures by firm size

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
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.

Along the same lines, FhG might have a different impact on incumbent firms and on start-ups. The latter group might be in higher need of short-term knowledge support in order to develop of production and innovation lines, but at the same time likely has fewer resources with which to fund external research expenses such as FhG. Start-ups in particular might especially benefit from knowledge transfer early on, when they are better

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able to react to opportunities brought by it. To assess this possibility, table 1.14 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 7.14: Impact of FhG expenditures by firm age

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
≤ 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 7.15, finally, differentiates between firms in manufacturing and service sectors. Whether service firms also benefit from interacting with FhG to the same degree as firms in manufacturing sectors is an open question, considering FhG to large extent focuses on manufacturing sectors. 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 7.15: Impact of FhG expenditures by manufacturing versus services firms

	$\ln(TR\_GR_t)$	$\ln(PROD\_GR_t)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
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 shed 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

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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.

7.4.4 Excursus: Inferring the macroeconomic effects on turnover

So far we have analyzed the effects on the firm level, showing considerably positive effects for the interacting firms. However, the firm-level results say little on whether Fraunhofer is macroeconomically desirable from a policy point of view. For that end, we have to analyze whether the economic benefits exceed the costs associated with Fraunhofer, e.g. in terms of base-funding. Calculating macroeconomic effects from relationship derived on the basis of firm-level data is complicated and needs a number of further assumptions. Beside assumptions about the representativeness of the sample - we take this for granted because CIS is representatively stratified by sector and size of the firm - most notably, we need to invoke an additionality assumption, which implies that an increase in e.g. turnover of one firm is not at the expense of other firms. This assumption is strong and, and from economic intuition about substitution effects, is unlikely to hold fully. Because of that the following calculations should be treated with care and probably reflect an upper bound.

To implement a methodology allowing us to infer to the total macroeconomic effects on turnover and employment the models, the causal effects representing the relationship between firm expenditures for Fraunhofer projects and turnover growth are not ideal (see Table 7.7), because they express the effects in terms of turnover growth rather than turnover in absolute terms. We therefore use a specification in which we regressed the absolute turnover on the absolute expenditures for Fraunhofer projects. The resulting coefficient had a size of 13.18 and was highly significant. Under the additionality and the representativeness assumption, the effect of Fraunhofer projects on the whole German economy can be calculated by multiplying the total Fraunhofer revenue from projects with firms by the regression coefficient. From Fraunhofer's annual report in 2015 we know that the total project revenue from firms was € 0.68 bn. in 2015. Thus, the overall effect on turnover was € 8.99 bn. Arguably, more interesting than turnover is value added, which is in Germany on average about 24% of turnover. Using this share, the estimated effect of Fraunhofer interactions on turnover was approximately € 2.15 bn. Compared to the industry expenditures this is very large. As an upper bound, we may want to compare the figure to the total Fraunhofer budget, because project results valuable for firms may be indirectly caused by research cross-financed by other projects or available base-funds. In any case, even when comparing the € 2.15 bn. in additional value added to the total budget of approximately € 2.05 bn., the multiplier is still above. We thus conclude that the total benefits of Fraunhofer, even when looking only at the induced increase of value added and ignoring effects on long-term competitiveness or employment, exceed the total costs for Fraunhofer.

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7.5 Conclusions

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 Fraunhofer's contracts with firms starting 1997. To the best of our knowledge, our study is the first make use of such data to analyze 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. We also find evidence that a driver of these performance increases might be that contracting with FhG induces firms to switch to more knowledge-intensive production. In particular, we showed that contracting with FhG increased the share of employees with tertiary education, and the importance of the sale of new products and services in the firm's turnover.

Furthermore, the impact of FhG seems to be heterogeneous in characteristics of the participating firm as well as the project. Even though 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 is as of yet underutilized. This is further highlighted when we calculate the macroeconomic impact of FhG, which suggests that the return to public and private investment in Fraunhofer is of a comparable size to the estimated return to R&D subsidies.

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7.6 References

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7.7 Appendix

Table 7.A-1: FhG expenditures and employee growth

	(1) OLS	(2) IV	(3) OLS
		$\ln(EMP\_GR)$	
$ln(FHGEXP_{t-1})$	0.009***	0.010***	
	(0.002)	(0.004)	
$1(FHGEXP > 0)$			0.032***
			(0.006)
$RDINT_{t-1}$	0.012	0.011	0.012
	(0.014)	(0.014)	(0.014)
$ln(AGE)_{t-1}$	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
$ln(EMP_{t-1})$	-0.015***	-0.015***	-0.015***
	(0.001)	(0.001)	(0.001)
$EXPORT_{t-1}$	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)
$GROUP_{t-1}$	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)
$EAST_{t-1}$	-0.011***	-0.011***	-0.011***
	(0.002)	(0.003)	(0.002)
CONSTANT	0.129***	0.051***	0.129***
	(0.034)	(0.014)	(0.035)
Industry F.E.	YES	YES	YES
Time F.E.	YES	YES	YES
N	56239	56239	56239
R^2	0.013	0.013	0.013
Cragg-Donald Wald F-statistic		24660.772	

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

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Table 7.A-2: Binary interaction indicator

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
	$\ln(TR\_GR)$	$\ln(PROD\_GR)$	$\Delta TERT_{t,t-1}$	$\Delta INNOSALES_{t,t-1}$
$1(FHGEXP > 0)$	0.036***	0.022***	0.011***	0.022***
	(0.007)	(0.008)	(0.002)	(0.005)
$ln(TR)_{t-1}$	-0.008***			
	(0.001)			
$ln(PROD)_{t-1}$		-0.155***		
		(0.005)		
$TERT_{t-1}$			-0.143***	
			(0.004)	
$INNOSALES_{t-1}$				-0.425***
				(0.008)
$RDINT_{t-1}$	0.154***	0.056*	0.042***	0.212***
	(0.024)	(0.029)	(0.007)	(0.017)
$ln(AGE_{t-1})$	-0.009***	-0.001	-0.001***	-0.002***
	(0.002)	(0.002)	(0.000)	(0.001)
$ln(EMP_{t-1})$		0.014***	-0.001***	0.003***
		(0.001)	(0.000)	(0.000)
$EXPORT_{t-1}$	0.013***	0.028***	0.004***	0.018***
	(0.003)	(0.005)	(0.001)	(0.002)
$GROUP_{t-1}$	0.014***	0.011***	0.001	0.005***
	(0.003)	(0.004)	(0.001)	(0.001)
$EAST_{t-1}$	-0.012***	-0.043***	0.006***	0.005***
	(0.003)	(0.005)	(0.001)	(0.001)
CONSTANT	0.054*	0.494***	0.005	-0.011
	(0.028)	(0.051)	(0.008)	(0.013)
Industry F.E.	YES	YES	YES	YES
Time F.E.	YES	YES	YES	YES
N	48548	25468	39019	35019
R^2	0.031	0.100	0.081	0.288

Notes: Notes: Standard errors in parentheses. Standard errors clustered by firm. IV: $1(FHGEXP > 0)$ instrumented through $\hat{v}_{i,t-1} * [\ln(EMP_{i,t-1}) - \overline{\ln(EMP_i)}]$, where $\hat{v}$ is the estimated first-stage error term. * p <0.10, ** p<0.05, *** p<0.01

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8 The long-run dynamics between R&D and patenting in a country comparison: Taking into account the role of international spillovers and public R&D (Estimation of parameters P1, P2, and P3 and notes on the extraction of parameters P4 and P5)

Maikel Pellens, ZEW, Torben Schubert, Lund

8.1 Introduction and background

During the recent decades, production has become increasingly knowledge-intensive, with ever-growing importance of innovation-related activities such as R&D. Not only innovation scholars, but also policy-makers, have become firm believers in the dogma "innovate or perish". Dogmatic positions however easily run a risk of becoming sacrosanct, even when empirical observations challenge them. One such observation is that during the last 20 years R&D expenditures have risen to unprecedented heights in most developed economies while at the same time these economies have gone through considerable periods of crisis with rising unemployment and low productivity growth (Gordon 2014, 2015).

That seems to suggest that the underlying simple input-output relationship, i.e. R&D will lead to new technologies, which when brought to the market will spur growth and welfare, may be much more complex. Indeed, innovation economics suggests that the knowledge undergirding innovation processes is a public good and - as such - exhibits features that differ fundamentally from regular non-public, i.e. excludable and rival, goods. Despite that recognition, most studies have treated knowledge as if it were a regular good. An important example of this is the many authors analyzing the contribution of R&D to patent generation on the firm or country level through models in which they regressed a measure of intramural/domestic patenting activity on intramural/domestic R&D (see e.g. Hall and Ziedonis 2000, Meliciani 2000). In doing so, however, one implicitly assumes away a fundamental characteristic of knowledge, i.e. that it spills over. A couple of authors have addressed the concerns of spillovers in particular in a literature analyzing the R&D-patenting relationship on the country-level by incorporating international spillovers (Bottazzi and Peri 2007, Bottasso et al. 2015, Westlund 2013). A second concern directly following from the public goods nature of knowledge is that the efficient provision of knowledge requires an institutional organization of knowledge production, which differs from a setting in which firms invest in R&D and reap the profits in terms of marketable products. If knowledge spills over firms will underinvest in R&D in particular when it is basic (Nelson 1959). In all Western economies, the state has responded to the underinvestment issue by providing parts of the knowledge stock through the funding of public research organizations. When innovating, private firms can therefore not only draw on their own research, but also on spillovers from other firms. They can also draw on knowledge stocks originating from public research.

We therefore argue that analyzing the R&D-patenting relationship requires us, besides domestic R&D, to take into account also the spillovers associated with knowledge. On

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the country level, we propose that spillovers relate to international spillovers as well as spillovers from the public research sector.

In this paper, we will develop a model that explicitly incorporates these mechanisms, testing them using a panel dataset for OECD countries for the period 1981-2013. Conceptually, we extend the empirical framework developed by Bottazzi and Peri (2007), who already allow for spillovers between countries, by explicitly including a distinction between whether R&D is performed by private firms or by public sector organizations. Our results show that although the elasticity of patent stocks with respect to business R&D is significant and positive on the average of all countries, international spillovers and the public knowledge stock are more important. In particular, for the leading G7 economies, the importance of spillover and knowledge stocks generated by public organizations exceeds the importance of business R&D by far.

8.2 Methodology & data

8.2.1 Methodology

The methodology is based on a well-established model initially developed by Bottazzi and Peri (2007). We enrich the model by allowing also draw on the public patent stock and public R&D expenditures. A reasonable generalized model suggests the following relationship:

$$\ln\left(bPAT_{i,t}\right) = \theta_b \ln\left(bR\&D_{i,t}\right) + \phi_b \ln bA_{i,t-1} + \xi_b \ln bA_{ROW,t-1} + \theta_p \ln\left(pR\&D_{i,t}\right) + \phi_b \ln pA_{i,t-1} + v_i + u_{it} \quad (8.1)$$

where $bPAT_{i,t}$ is the change in the knowledge stock by firms in country i in period t as measured by patents. $bR\&D_{i,t}$is the business R&D expenditures (BERD) in country i. $bA_{i,t-1}$ is the one period lag of the knowledge stock of firms in country i, $bA_{ROW,t-1}$ is the one period lag of firms' knowledge stock available in the world. $pR\&D_{i,t}$ is the public R&D expenditures (BERD) in country i. $pA_{i,t-1}$ is the one period lag of the public knowledge stock of country i and v_i is a country-specific time-constant error-term. Following Botazzi and Peri (2007) along the stationary-growth path we can use the identity $\frac{bPAT_{i,t}}{bA_{i,t-1}} = g_{i,t} + \delta$, with g being the growth rate of the knowledge stock and δ th the time constant depreciation rate, to rearrange Eq. (8.1):

$$\ln\left(g_{i,t} + \delta\right) - v_i = \theta_b \ln\left(bR\&D_{i,t}\right) + (\phi_b - 1) \ln bA_{i,t-1} + \xi_b \ln bA_{ROW,t-1} + \theta_p \ln\left(pR\&D_{i,t}\right) + \phi_p \ln pA_{i,t-1} + u_{it} \quad (8.2)$$

If the economy converges to a deterministic growth path, $\ln\left(g_{i,t} + \delta\right) - v_i$ converges to a country-specific constant $\ln(g_i + \delta)$. If all time-series are stationary, a reduced-form version of Eq. (2.2) can be estimated by regressing $\ln bA_{i,t-1}$ on $\ln bR\&D_{i,t}$, $\ln bA_{i,t-1}$, $\ln bA_{ROW,t-1}$, $\ln pR\&D_{i,t}$, and $\ln pA_{i,t-1}$ using fixed effects regression to account for potential country differences. However, if the time-series are non-stationary, which is the case if they follow e.g. growing trends, regular panel data methods do not deliver consistent estimates.

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Eq. (8.2) however does not only provide guidance on the estimation technique under the assumption of a stationary panel, it also suggests a consistent method for estimation if all time series are non-stationary. In particular, Eq. (8.2) also represents a long-term economic law which binds the time series on the right-hand-side together even if all are non-stationary. Such laws relating non-stationary time series are called cointegrating relationships. Again, we are able to estimate a reduced-form version of Eq. (8.2) by regressing $\ln bA_{i,t-1}$ on $\ln bR\&D_{i,t}$, $\ln bA_{i,t-1}$, $\ln bA_{ROW,t-1}$, $\ln pR\&D_{i,t}$, and $\ln pA_{i,t-1}$. Fixed effects can be implemented by adding country dummies. It must be noted however that plain OLS will deliver consistent estimates. Nonetheless, the asymptotic variances are not consistent. A robust and simple estimation procedure for cointegrated variables is the so-called dynamic OLS (DOLS) estimator, which uses the heteroscedasticity and autocorrelation-consistent Newey-West variance estimator and additionally adds leads and lags of the differenced dependent variables to account for the short-term deviations from the long-run cointegrating relationship.

The implementation of the estimator follows three steps. We first test the hypothesis that all time-series are non-stationary using so-called panel-unit root tests. Second, we test whether the non-stationary time series are cointegrated using panel-cointegration tests. In specific, we rely on the panel/group t-tests, which are known to outperform alternative tests in terms of power and size in finite samples (Örsal 2007). Finally, we stimate the several variants of the cointegrating relationship inspired by Eq. (8.2) using DOLS. Specifically, we first estimate a restricted model which excludes public knowledge and R&D. This model, although based on different data, structurally replicates the model by Bottazzi and Peri (2007):

$\ln(bA_{i,t-1}) = \lambda_1 \ln\left(bR\&D_{i,t}\right) + \lambda_2 \ln(bA_{ROW,t-1}) +$
$\sum_{j=-1}^{i} \gamma_j \Delta\ln(bR\&D_{i,t-j}) + \sum_{j=-1}^{i} \varepsilon_j \Delta\ln(bA_{ROW,t-1}) + \ u_{it}$ (8.3, COINT-1)

where $\lambda_1 = \theta_b/(1-\phi_b)$ and $\lambda_2 = \xi_b/(1-\phi_b)$We then go on and extend the model to include public R&D and public knowledge to estimate the full model as following from Eq. (2.2).

$\ln(bA_{i,t-1}) = \lambda_1 \ln\left(bR\&D_{i,t}\right) + \lambda_2 \ln(bA_{ROW,t-1}) + \lambda_3 \ln\left(pR\&D_{i,t}\right) + \lambda_4 \left(\ln pA_{i,t-1}\right) +$
$\sum_{j=-1}^{i} \gamma_j \Delta\ln(bR\&D_{i,t-j}) + \sum_{j=-1}^{i} \varepsilon_j \Delta\ln(bA_{ROW,t-1}) + \sum_{j=-1}^{i} \xi_j \Delta\ln(pR\&D_{i,t}) +$
$\sum_{j=-1}^{i} \rho_j \Delta\ln(pA_{i,t-1}) + u_{it}$ (8.4, COINT-2)

where $\lambda_3 = \theta_p/(1-\phi_b)$ and $\lambda_4 = \phi_p/(1-\phi_b)$.

Finally, by similar procedure, we can also define a relationship that links the public knowledge stock to public R&D. The structural equation for this model is:

$\ln(pA_{i,t-1}) = \lambda_5 \ln\left(pR\&D_{i,t}\right) + \sum_{j=-1}^{i} \pi_j \Delta\ln(pR\&D_{i,t}) + u_{it}$ (8.5, COINT-3)

We estimate all regression in Eqs. (8.3)-(8.5) with country dummies to allow for country specific heterogeneity. In some specifications, we allow for additional control variables. Lastly, we test whether country-specific time trends change the results.

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8.2.2 Data

Estimating Eq. (8.3), Eq. (8.4), and Eq. (8.5) requires country-level data on public and private R&D as well as data on public and private knowledge stocks. The R&D data are publicly available from the OECD at the country level for most OECD countries since 1981 until 2013. Missing values however reduce the available time dimension and the set of included countries. More details on the effective sample used for the regression analyses can be found in 8.3.1. Using the definitions of the OECD it is easy to distinguish between total R&D expenditures and R&D expenditures by respectively firms and R&D the public sector. For the firm R&D expenditures we use the business expenditures on R&D (BERD), while for the public R&D expenditures we use the sum of R&D expenditures in the higher education sector (HERD) and the government expenditures on R&D (GERD). Further control variables such as GDP, imports and exports, and the share of human capital as measured by the share of people with tertiary education were drawn from the data sources provided by the World Bank. We also provide estimates of the COINT-1 and COINT-2 on the sectoral level. Problems however emerge from the fact that on the sectoral level, more R&D data is missing. Even more problematic is that fact that industrial classification schemes have changed from NACE rev. 1.1 to NACE rev. 2 during the observation period, and that the two classification schemes are largely not compatible. While conversion tables exist on the 5-digit NACE-level, on the 2-digit level many sectors cannot be unambiguously converted from one scheme to the next. The OECD therefore does not provide harmonized data but reports its figures adopting NACE 1.1 for earlier years and NACE 2 for more recent years. A few of the relevant patent-intensive manufacturing sectors however map consistently on each other (see Table 8.1). For those we manually created longer R&D time-series. For the sectors in Table 8.1 also concordance tables with respect to the International Patent Classification (IPC) exists, which allows assigning patents to the NACE sectors. Estimates for these sectors can be found in Appendix 1.

Table 8.1: Conversion between NACE 1.1 and NACE 2

	NACE rev. 1.1	NACE rev. 2	IPC concordance
Chemicals & Pharmaceutical	C42	20-21	yes
Electrical equipment n.e.c.	C74	27	yes
Machinery n.e.c.	C72	28	yes
Motorvehicles and trucks	C77	29	yes
Other transport equipment (includes spacecraft)	C78	30	yes

However, as the macroeconomic models generated in WP2 (development of a Multi-sector extenstion of the baseline model) also require broader estimates of the elasticity of knowledge generation with regard to R&D inputs, we additionally provides micro-level estimates of the elasticity of R&D expenditure and knowledge stocks among manufacturing and service firms, based on a sample of German innovative firms drawn

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from the Mannheim Innovation Survey.[20] These estimates are also shown in Appendix 1.

Knowledge stocks are proxied by the accumulated stock of patents filed by inventors in each country, discounted by a depreciation rate. Patent stocks are calculated based on on EPO patent applications at the European Patent office (EPO), which functions as a regional patent office allowing for a single patent filing and grant procedure for member states of the European Patent Convention (EPC). Compared to national offices, patent data taken from the EPO are less biased towards the country in which the office is situated (De Rassenfosse et al., 2013).

Whereas patent flows can be readily retrieved from sources such as Eurostat, they are not available on the sectoral level. We therefore calculated knowledge stocks using the PATSTAT database (Spring 2017). Patent statistics were calculated using fractional counts, in line with international standards (OECD, 2009). Patents are dated according to priority date (the first date of filing), which is closest to the date of invention compared to other options such as the date of application, publication or granting. Reference countries were determined based on inventor address, which best reflects where R&D efforts took place (OECD, 2009). Patents with inventors located in multiple countries were assigned fractionally to those countries. To differentiate public and private knowledge stocks, patent applications were fractionally assigned to the public or private sector according to assignee type, as developed for Eurostat by Van Looy et al. (2006). Table 8.2 shows the mapping. Note that assignees can be part of the public as well as private sector. Similarly, knowledge stocks have been generated for economic sectors based on the IPC to NACE rev. 2 concordance developed by Van Looy et al. (2015). Fractional counting has been applied in case where patents are assigned to multiple sectors.

Table 8.2: Assignee type to sector concordance

Assignee Type	Public	Private	Share
Individual	No	Yes	6.44%
Company	No	Yes	87.11%
Hospital	No	Yes	0.12%
Government non-profit	Yes	No	2.45%
University	Yes	No	2.72%
Total single code assignees			98.84%
Company government non-profit	Yes	Yes	0.08%
Company hospital	Yes	Yes	<0.01%
Company university	Yes	Yes	<0.01%
Government non-profit university	Yes	No	0.02%
Government non-profit hospital	Yes	No	<0.01%
Total multi code assignees			0.10%
Unknown	No	No	1.05%
Share: % of EPO patent volume assigned to code in Patstat spring 2017			

[20] In this part of the analysis, knowledge stocks are based on applications at the German Patent and Trade Mark Office.

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From the so calculated flows of patent applications, knowledge stocks were generated, in line with the literature (Botazzi and Peri, 2007) as the depreciated cumulative sum of patent applications:

$$A_{i,t} = App_{i,t} + (1-\delta)A_{i,t-1} \text{ (8.6)}$$

δ, the depreciation rate, captures idea obscolesence, and is set at 10% following Bozazzi and Peri. The initial value A_{i,t_0} of the knowledge stock is calculated through the perpetual inventory method:[21]

$$A_{i,t_0} = \frac{APP_{i,t_0}}{g_i+\delta} \text{(8.7)}$$

g_i represents a country-specific knowledge growth rate and is estimated for each country as the average annual growth rate in patent applications between t_0 and $t_{0+\tau}$. We set τ to 10. While Bottazi and Peri set τ to 5, a wider calibration window reduces issues with larger variation in the flow of patent applications earlier on in the timelines.

8.3 Results

8.3.1 Descriptive results

As a point of reference, summary statistics of the main variables can be found in Table 8.3. These summary statistics are based on all available, i.e. non-missing observations. It should be noted, however, that most of the proposed time-panel-series tests and estimators require strongly balanced panels. The requirement of balanced panels however implies that the actual time series operator will be based on subsamples of countries and periods for which the data is complete. It turns out that the cointegrating relationship in in Eq. 8.3 results in the largest effective sample of countries.

Table 8.3: Summary statistics

	Obs	Mean	Std. Dev.	Min	Max
Private EPO patent stock	1119	16549.30	40812.70	3.71	283212.00
Public EPO patent stock	1119	734.09	1967.93	0.00	16593.20
GERD+HERD in mln. US$	1095	5929.81	13266.90	17.80	117409.00
BERD in mln. US$	1098	13286.90	36739.80	1.97	322528.00
GDP in mln. US$	1107	880000.00	1900000.00	2800.00	17000000.00
Tertiary ed. enrollment	1095	47.87	22.24	2.84	110.26
Exports to imports ratio	1107	1.03	0.17	0.58	2.12

The countries included in this sample, covering the time period of 1981-2013, are listed in Table 8.4. That means that all regression results, which we present in Section 8.8.3.3,

21 Patent timelines were calculated from 1978 to 2013.

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are based on these countries at most. Regressions based on Eq. 8.4 or Eq. 8.5 or regressions including additional control variables may include fewer countries.

Table 8.4: Countries included in the baseline regressions

	Freq.	Percent	Cum.
AU	32	5.00	5.00
AT	32	5.00	10.00
BE	32	5.00	15.00
CA	32	5.00	20.00
DE	32	5.00	25.00
DK	32	5.00	30.00
ES	32	5.00	35.00
FI	32	5.00	40.00
FR	32	5.00	45.00
UK	32	5.00	50.00
GR	32	5.00	55.00
IR	32	5.00	60.00
IS	32	5.00	65.00
IT	32	5.00	70.00
JP	32	5.00	75.00
NL	32	5.00	80.00
NO	32	5.00	85.00
NZ	32	5.00	90.00
SE	32	5.00	95.00
US	32	5.00	100.00
Total	640	100.00	

We have argued that adopting a cointegration framework to estimate the elasticities of long-run production functions necessarily assumes that all time series are non-stationary. Loosely speaking, non-stationarity means that the distribution of the variable changes over time and does not return to a fixed long-run distribution. The most obvious case of non-stationarity emerges when the mean of a variable diverges over time. This is the case with many macroeconomic time series, which increase over time. Looking at the time series for business R&D, public R&D, business and public patent stocks for the G7 countries in Figure 8.1-Figure 8.4 we see that indeed all are, without exception, strongly upward shifting. That observation provides some indication that the time series might indeed be non-stationary. Visual evidence, however, usually gives only a first impression and does not substitute for formal stationarity tests. One reason is that upward shifting time-series in fact may be stationary after a deterministic time trend is included. If this was the case, it would be easier simply to include the time trend as an additional control variable or to detrend all variables and then use a regular panel approach, rather than using a more complex cointegration framework,. We present the results of the formal unit root tests in the next subsection.

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Figure 8.1: BERD in G7

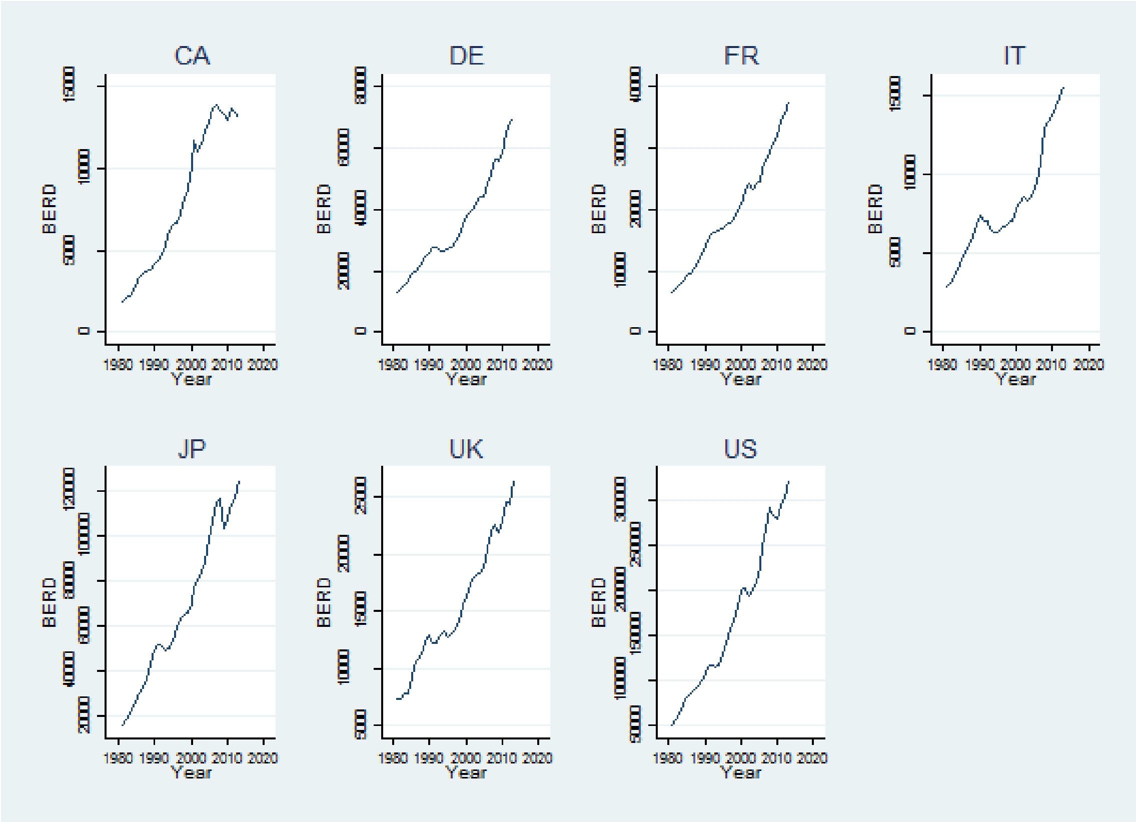

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Figure 8.2: Public R&D (GOVERD+HERD) in G7

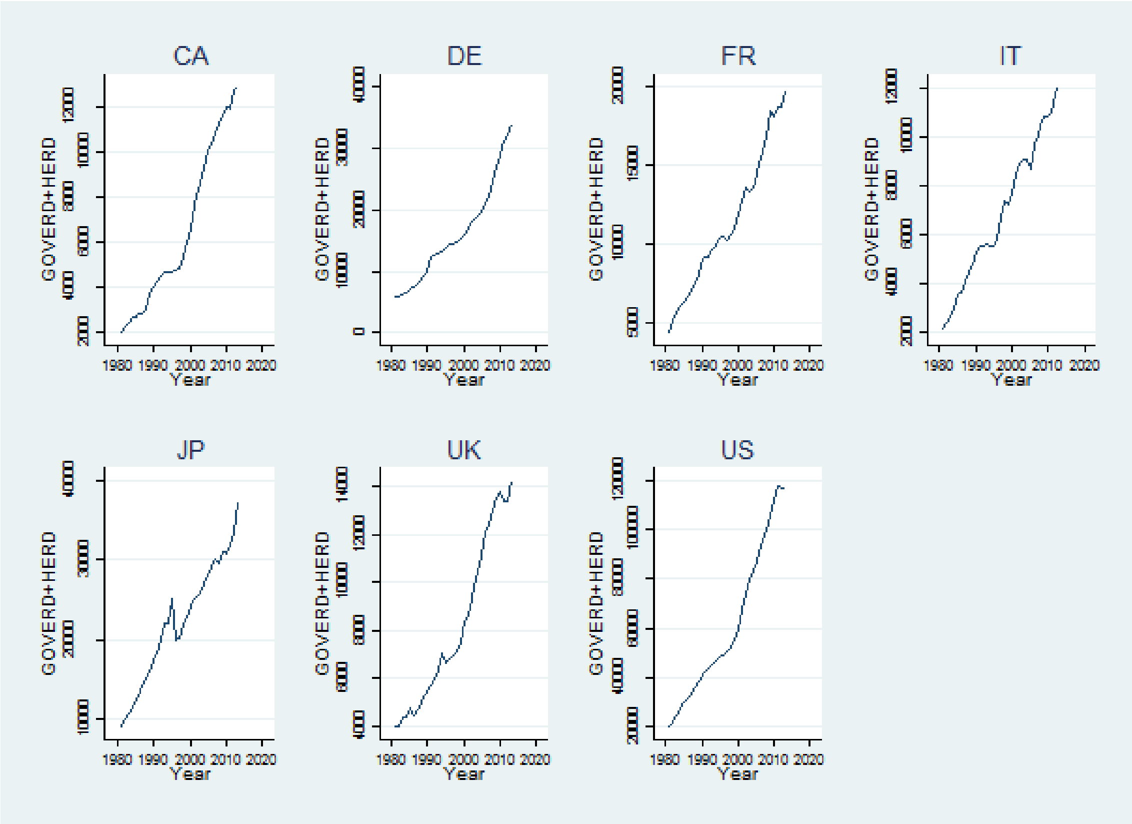

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Figure 8.3: EPO patent stock in G7 (applied by business)

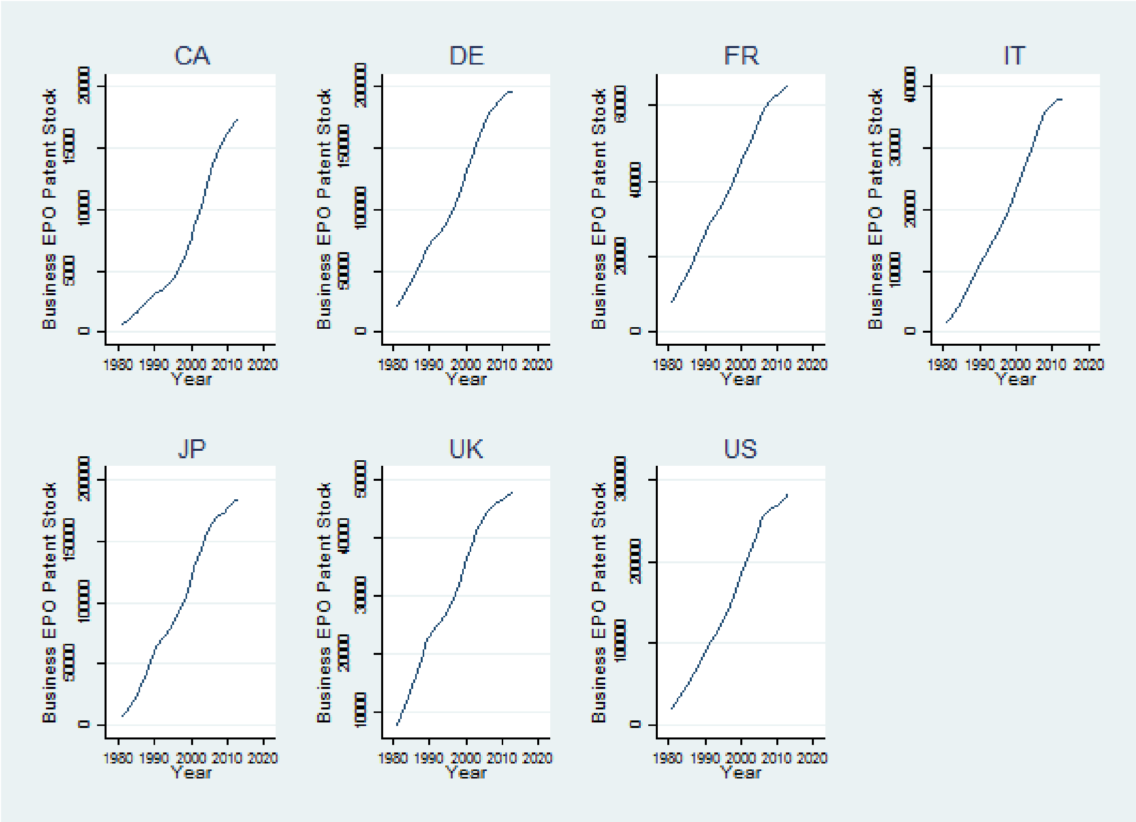

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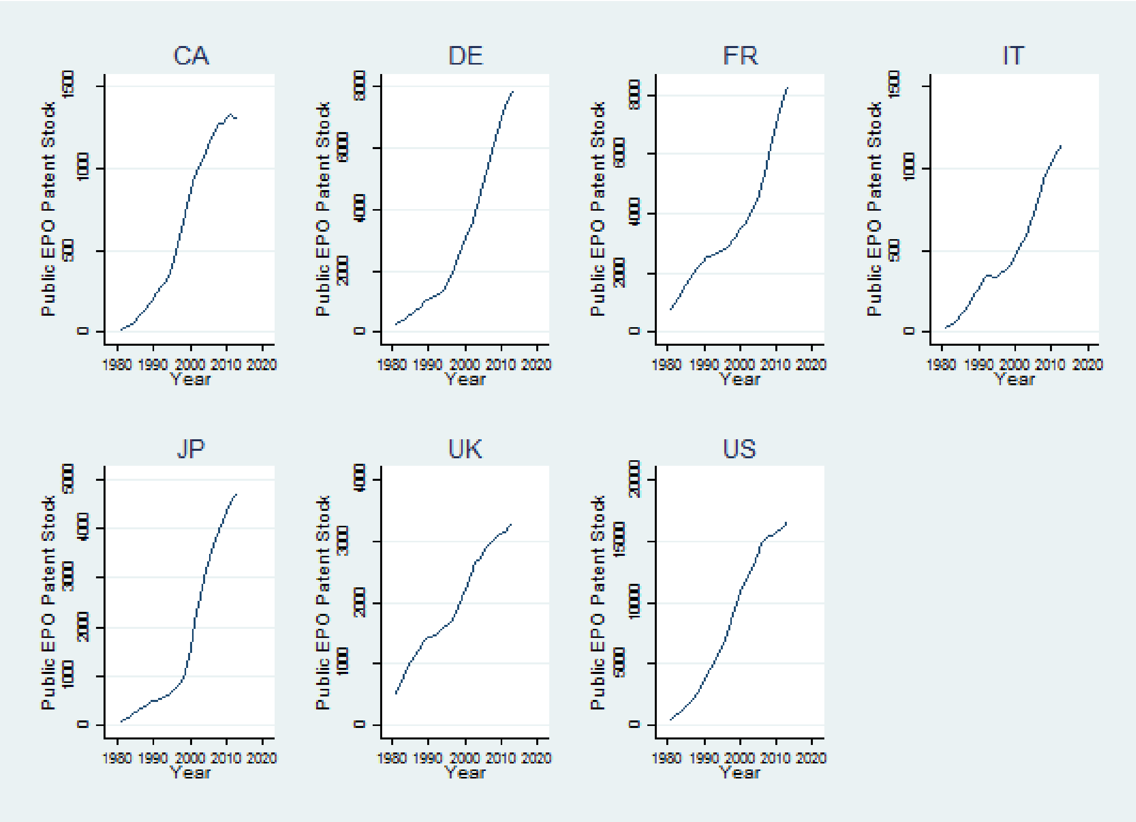
Figure 8.4: EPO patent stock in G7 (applied by public organizations)



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8.3.2 Testing for unit roots and cointegration

The unit-root tests are used to test the null hypothesis that all panel time-series are non-stationary. Thus, small enough p-values would indicate a rejection of the null hypotheses and mean that at least some panel time series are stationary. When not including a time trend, the tests presented in Table 8.5 in fact do not find any systematic evidence that the time-series could be treated as stationary. That finding does not come as a surprise, as we already could observe strong upward shifts in the evolution of the series over time (see Figure 8.1-Figure 8.4). However, even when allowing for a common time trend, the p-values become only marginally smaller. For none of the time-series, we find any evidence of stationarity at any conventional levels for the p-values. We therefore can safely assume that indeed all relevant time series are non-stationary.

Table 8.5: Unit root tests (ADF-tests with L1, with and without trends)

	BERD	GERD+HERD	Business EPO patent stock	Public EPO patent stock
pval: Mod. inv. chi-sq without trend	1.0000	1.0000	0.9915	0.9997
Pval: Mod. inv. chi-sq with trend	0.7252	0.9981	0.8474	0.9990

H0: Unit root exists in all panel series

While non-stationarity implies that conventional panel data methods such as fixed effects regression will lead to biased results, cointegration methods require that the non-stationary time-series are cointegrated, meaning that they, even if individually diverging, are bound together by a long-run relationship. The existence of cointegrating relationship can be tested by panel cointegration tests, which take the null-hypothesis of no cointegration. While there exists a large number of panel cointegration tests, which are asymptotically consistent, in finite samples Monte Carlo evidence has shown that the t-tests proposed by Pedroni (1999) perform best in terms of size and power of the tests in finite samples (Örsal 2007). In Table 8.6 we show the result of the panel and the group versions of the t-tests. In addition, we report both types of types with and without the inclusion of a deterministic time trend. For the relationship COINT-1 (as summarized by Eq. 8.3) and for COINT-3 (as summarized by Eq. 8.5) all tests are in agreement and strongly suggest that the time series are indeed cointegrated. For COINT-2 (Eq. 8.4) describing the relationship between public patenting and the public R&D expenditures, however, only the tests without the time trend show evidence of cointegration. If we include the time trend, the test are not significant anymore. Nonetheless, because absence of cointegration for otherwise non-stationary variables would imply an inability to draw any meaningful conclusions, we continue with the assumption of cointegration, which is empirically supported at least for the tests excluding a trend.

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Table 8.6: Cointegration tests (t-tests with and without trend)

	COINT-1	COINT-2	COINT-3
panel-t without trend	-3.835***	-3.525***	-4.391***
group-t without trend	-4.734***	-3.904***	-5.095***
panel-t with trend	-5.346***	-0.658	-3.206***
group-t with trend	-4.360***	-1.035	-5.014***

H0: No cointegrating relationship
COINT-1: Business EPO patent stock, BERD, Business EPO patent stock (ROW)
COINT-2: Public EPO patent stock, GERD+HERD
COINT-3: Business EPO patent stock, BERD, Business EPO patent stock (ROW), Public EPO patent stock, GERD+HERD

8.3.3 The long-term relationship between patenting and R&D

8.3.3.1 Choosing a specification

The estimated elasticities may depend on whether we incorporate a time trend in the regressions. We therefore analyze whether the central results are robust to changing the specifications of the trends. We compare the estimates when not allowing for a trend (Table 8.7), when allowing for a homogeneous deterministic trend (Table 8.8), and when allowing for a country-specific (heterogeneous) trend (

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Table 8.9). We focus on the COINT-1 relationship defined by Eq. (8.3) because this restricted equation has been estimated by other authors (Bottazzi and Peri 2007, Deloitte 2017, Bottasso et al. 2015), which allows for a comparison with results found in the literature. Note that apart from the time trends all versions include country-fixed-effects. In addition, we present a geographic split of the sample into all countries, all (available) EU countries, and the G7 countries.

Table 8.7: Regression results for COINT-1 (country fixed effects, no controls, no trend)

	(1) All	(2) EU	(3) G7
Log BERD	0.52331***	0.59191***	0.60448***
	(8.92)	(7.40)	(4.01)
L1: Log business EPO patent stock (ROW)	0.67816***	0.56238***	0.57765***
	(11.74)	(7.69)	(5.96)
Country fixed effects	Yes	Yes	Yes
Observations	580	377	203
R^2	0.954	0.954	0.964
Number of groups	20	13	7

t statistics in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results ignoring time trends deliver remarkably similar results between the geographic subsamples. For business R&D the elasticity is 0.52 for all countries and with 0.59 and 0.60 only slightly higher for the EU and the G7 countries respectively. The results for elasticity of the international knowledge stocks are with 0.56 for the EU and 0.58 for the G7 of about a comparable size. For the whole sample, this elasticity is with 0.68 even a bit higher than the corresponding elasticity for intra-country business R&D expenditures. The results therefore confirm our argument that international spillovers resulting from the non-rivalry of knowledge are of considerable importance. One important implication is that any models ignoring international spillovers are likely to over-estimate the importance of domestic R&D. In fact, when we exclude the spillover term the elasticity of the BERD term increases to 1.05 in the full sample, which corresponds to a doubling (not presented).

Table 8.8: Regression results for COINT-1 (country fixed effects, no controls, homogeneous trend)

	(1) All	(2) EU	(3) G7
Log BERD	0.53253***	0.62430***	0.68880***
	(8.41)	(7.12)	(4.31)
L1: Log business EPO patent stock (ROW)	0.79450***	0.81910***	0.77084***
	(11.70)	(10.11)	(7.80)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	580	377	203

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R^2	0.954	0.956	0.965
Number of groups	20	13	7

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In fact, allowing for a homogeneous time trend amplifies the importance of spillovers. While the elasticities of BERD do not or only marginally change (all: 0.53, EU: 0.62, G7: 0.69), the elasticities of international knowledge stock as measured by EPO patents increase 0.79 (all countries), 0.82 (EU), and 0.77 (G7).

When allowing for heterogeneous time trends, we even observe a strong drop in the BERD elasticities to 0.20 for all countries, 0.08 for the EU and 0.17 for G7. At the same time, the elasticities of the international knowledge stock increases to values of about 1 or slightly above. The heterogeneous trend results thus seem to tremendously reduce the relative importance of business R&D, which holds true in particular for the EU, where the elasticity is with 0.08 almost negligible. It should be however noted that including country specific time trends implies the inclusion of a number of additional regressors, which is equal to the number of included countries. Given that the not overwhelmingly large number of observations and the risk of multicollinearity between the country-specific trends, it may therefore be dubious to allow for this flexibility.

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Table 8.9: Regression results for COINT-1
(country fixed effects, no controls, heterogeneous trend)

	(1) All	(2) EU	(3) G7
Log BERD	0.20375***	0.08003*	0.16926**
	(5.66)	(1.77)	(2.14)
L1: Log business EPO patent stock (ROW)	1.02108***	1.09887***	0.99241***
	(31.13)	(31.45)	(20.82)
Country fixed effects	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes
Observations	580	377	203
R^2	0.988	0.992	0.992
Number of groups	20	13	7

t statistics in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Although differing by the underlying data, definition of the variables and by employed estimation technique to some degree, in total three studies provided analyses comparable to those found in Table 8.7-

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Table 8.9. In particular, these studies provide results for the baseline model without trends as in Table 8.7 and for the model including heterogeneous trends.

Table 8.10: Comparison with estimates from the literature

	Bottazzi and Peri (2007)		Deloitte (2017)		Bottasso et al. (2015)	
	Base	Het. trends	Base	Het. trends	Base	Het. trends
Log BERD	0.786	0.304	0.64	0.07	0.547	0.282
L1: Log business EPO patent stock (ROW)	0.557	0.168	0.81	0.99	0.56	0.71

Table 8.10 shows for the baseline model that, although there exist differences, the models are in overall agreement about the approximate size of the elasticities. The business R&D elasticity is with 0.79 highest in Bottazzi and Peri (2007) and with 0.55 lowest in Bottasso et al. (2015). Deloitte (2017) reports an intermediate elasticity of 0.64. The elasticity of the international patent stock varies between 0.56 and 0.81. The results obtained in this study are with 0.52 and 0.68 largely of the same magnitude. When including heterogeneous time trends both Deloitte (2017) and Bottasso et al. (2015) report a drop in the size of the R&D elasticity to 0.07 and 0.28 as well as an increase of the elasticity of the international patent stock to 0.99 and 0.71. The results by Bottazzi and Peri (2007) differ from that pattern to some degree. While they too observe a drop in the R&D elasticity, they also report a considerable drop in the elasticity of the international patent stock to 0.17 (compared to 0.56 in the baseline model). Our results are clearly more in line with the results by Deloitte (2017) and Bottasso et al. (2015) since we too observe a decrease in the R&D elasticity and an increase in the elasticity of the patent stock. This holds both for the specification including a homogeneous time trend and for the specification including a heterogeneous time trend. Also in terms of size, the results obtained in this study largely have comparable magnitude as those obtained by Bottasso et al. (2015), Deloitte (2017) and - at least with respect to R&D - Bottazzi and Peri (2007). Nonetheless, we would consider our R&D elasticity resulting from the inclusion of heterogeneous time trends in particular for the EU (0.08) as unreasonably small. Since including heterogeneous time trends inflates the number of regressors, we propose to use the model based on homogeneous trends, which provides a middle ground between controlling for autonomous time trends and not inflating the regressors.

8.3.3.2 Including public knowledge stocks

The preceding section has provided some guidance on a useful specification of the type of trends indicating that most likely homogeneous time trends may be a reasonable choice. Furthermore, our results indicated that international knowledge spillovers are large and at least of the size the of the elasticities associated with contemporaneous business R&D. The results for the spillovers largely confirm the in particular found in the very recent literature, which also reported elasticities exceeding the ones of R&D. While it is reassuring that the results for the baseline models are largely in line with those found in the literature, the conceptual implication of the importance of spillovers may be even

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more important. Specifically, spillovers are the result of the non-rivalry and the (partly) non-excludability of knowledge, rendering knowledge a partly free good. The typical conclusion resulting from knowledge being a free good subject to positive externalities that private actors such as firms underinvest in the generation of knowledge. The solution which is applied by all developed economies is to supply knowledge (in particular basic) in parts by public and state-funded organizations, such as universities and other non-for-profit extra-university public research organizations. The institutional arrangement implying a public supply of knowledge however suggests that business firms do not only rely on their own R&D as well as spillovers from internationally available knowledge stocks but also on public knowledge stocks and public R&D expenditures. Again, when ignored, we would expect that the elasticities of domestic business R&D are overestimated. Indeed, we observe the elasticity of business R&D drops significantly when including public knowledge stocks and public R&D (

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Table 8.11). For the full sample, we obtain an estimate of 0.23 as compared to 0.53 in Table 8.8. For the EU, the value drops from 0.62 to 0.38 and for the G7 countries from 0.60 to 0.17, where in the latter case the estimate is not even statistically significant anymore. The estimates for the term including international spillovers does not dramatically change, and to the degree that it does even amplifies somewhat.

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Table 8.11: Regression results for COINT-2
(country fixed effects, no controls, homogenous time trend)

	(1) All	(2) EU	(3) G7
Log BERD	0.22630***	0.38241***	0.17149
	(2.94)	(4.21)	(1.17)
L1: Log business EPO patent stock (ROW)	0.82678***	0.86181***	0.66274***
	(12.08)	(12.02)	(6.83)
Log GOVERD+HERD	0.48790***	0.29472**	0.19309
	(4.28)	(2.24)	(1.28)
L1: Log public EPO patent stock	0.12286***	0.13714***	0.23543***
	(2.98)	(2.78)	(3.37)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	493	319	203
R^2	0.967	0.973	0.982
Number of groups	17	11	7

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The most remarkable result, however, is the importance of the public knowledge. In the full sample, the elasticity of public R&D as measured by the sum of GOVERD and HERD is with 0.49 almost twice as large as the elasticity for business R&D. In addition, to the contemporaneous public R&D investments also the public patent stock contributes to the generation of the business patent stock with an elasticity of 0.12, which is more than half of the size of the BERD elasticity. For the EU the pattern is less tilted towards the public R&D, but also here the public R&D expenditures and the public knowledge stock have a combined effect that is larger than the isolated elasticity of domestic business R&D. For the G7 countries, the results point into the same direction although it should be noted that neither the business nor the public R&D elasticity are significant.

For the core results in

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Table 8.11 we provide a number of robustness checks, which we present in Table 8.12. First, we check whether the inclusion of GDP, student enrollment as a share of the population, and the export-import ratio (in logs) have significant effects. Furthermore, the DOLS estimator includes a number of leads and lags. While all regressions so far included one lead and one lag, here we probe the results with two leads and lags, one lead and two lags, and two leads and one lag. Then we rerun the regressions with no trend and with a heterogeneous trend. Finally, we check whether using R&D employees instead of the R&D expenditures has any influence on the results. Our results indeed are almost unchanged when we use the control variables or when we employ different lead and lag structures. With respect to differences in trends, we obtain the same changes as already discussed for the baseline model in Section 8.8.3.3.1. Some differences however become observable when R&D employees are included as control. First, the business R&D elasticity is with 0.41 significantly higher. In addition, the estimate of the international spillovers is somewhat larger. The effect of public R&D employment instead is small and insignificant. The elasticity of the public knowledge stock remains however significant and with 0.13 almost the same size.

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Table 8.12: Robustness checks for COINT-2

	(1) Controls	(2) Lead 2 Lag 2	(3) Lead 1 Lag 2	(4) Lead 2 Lag 1	(5) No trend	(6) Heterogeneo us trend	(7) R&D employees
Log BERD	0.18107**	0.22751***	0.22826***	0.22737***	0.23653***	0.09546**	
	(2.26)	(2.76)	(2.87)	(2.86)	(2.91)	(1.97)	
Log Business R&D employees							0.40883***
							(6.33)
L1: Log business EPO patent stock (ROW)	0.81890***	0.88515***	0.84584***	0.87509***	0.50503***	0.98865***	0.98973***
	(11.18)	(12.04)	(11.93)	(12.34)	(7.19)	(25.37)	(14.97)
Log GOVERD+HERD	0.40089***	0.53530***	0.53014***	0.49956***	0.36934***	0.28241***	
	(3.22)	(4.38)	(4.49)	(4.24)	(3.58)	(4.28)	
Log Public R&D employees							0.07136
							(0.68)
L1: Log public EPO patent stock	0.15659***	0.11095**	0.11001**	0.12246***	0.11322***	0.00765	0.12666***
	(3.64)	(2.50)	(2.57)	(2.87)	(2.59)	(0.31)	(2.86)
Log share tert. ed. empl.	0.14423						
	(1.55)						
Log GDP	0.04857						
	(0.75)						
Log exports/imports	0.19830						
	(1.43)						
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	No	No	No	Yes	No
year	Yes	Yes	Yes	Yes	No	No	Yes
Observations	435	459	476	476	493	493	464
R^2	0.968	0.969	0.968	0.967	0.965	0.989	0.965
Number of groups	15	17	17	17	17	17	16

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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8.3.3.3 The relationship between the public knowledge stock and public R&D

The last relationship of interest concerns the one between public knowledge stocks and public R&D. Again including country fixed effects and a homogeneous time trend, the results can be found in Table 8.13. In the overall sample, the elasticity is estimated to be 0.86, which is roughly of the same size as the estimate for the G7 countries (0.91). For the EU the elasticity is however considerably larger and reaches with 1.56 a value which is almost twice as large.

Table 8.13: Regression results for COINT-3 (country fixed effects, controls, homogeneous trend)

	(1) All	(2) EU	(3) G7
Log GOVERD+HERD	0.86763***	1.56705***	0.91253**
	(3.65)	(8.09)	(2.19)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	493	319	203
R^2	0.857	0.924	0.879
Number of groups	17	11	7

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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8.4 Summary

Many authors analyzed the process of knowledge generation - be it at the firm, sector or country level - within the conceptual framework of the knowledge or innovation production function (compare Grilliches and Pakes 1990, Mairesse and Mohnen 2004, Robin and Schubert 2013). This approach suggests the notion of inputs producing outputs known from regular production processes can be directly applied also for the case of knowledge. We have made a case that the public goods nature knowledge suggests a more complicated relationship. On the country level, we have argued the non-rivalry and the non-excludability of knowledge will imply one the hand that international spillovers need to be taken into account. Furthermore, we have argued that not only business R&D but also public R&D and the public knowledge stock will matter as input into knowledge generation in the business sector. Our results largely confirms that important role of both international spillovers (compare Bottazzi and Peri 2007, Deloitte 2017, Bottasso et al. 2015) and public R&D and public knowledge stocks. Our results suggest that indeed both mechanisms are in terms of size of the effects more important than domestic business R&D.

On a conceptual level, our results contribute to the literature by showing that borrowing the production function concept and applying it knowledge related production processes will miss important mechanisms that genuinely result from the public good nature of knowledge. That argument does not invalidate the production function metaphor per se, but it illustrates that a theoretically more grounded specification of the production function will be more complicated than relating inputs of the focal unit to its output. On the econometric level we have argued that neglecting effects attributable either to public research or to international spillovers will imply an overestimation of the effects of domestic business R&D. We found that the upward bias in the elasticity of business R&D can be in the order of more than 400% when both alternative mechanisms are excluded. The implications of such a large bias for policy are tremendous, potentially leading to an dramatic overemphasis of fostering private R&D expenditure at the expense of sustaining a sufficiently high levels public R&D expenditures and investments into public knowledge stocks.

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8.6 Appendix 1. Sector differentiation

8.6.1 By technology field

The results obtained so far only refer to the country level, while differences between sectors have been ignored. It is however quite likely that different sectors show differences in the elasticities of their respective knowledge production functions. Estimating these differences in principle easily possible using the same methods we have used for the country level estimations. Practically, however, the potential to implement the methodologies on the sectoral level is severely limited by several factors. First, while already the country level R&D data contains a substantial number of missing values, the problems is even larger for sector level data. For many countries and sectors the data is not available. Second, in our period the sectoral classification schemes have changed from NACE 1.1 to NACE 2. While on the five-digit level official conversion tables exist, on the two-digit level, which is the highest disaggregation, a direct conversion is possible only for few sectors. That implies only for very few sectors time series consistent over time can be generated, even when the respective time series do not contain missing values. Third, a disaggregation by sector is conceptually meaningless for the question of how public R&D affects the public knowledge stock, since by definition public R&D falls into the public sector. We report the elasticities resulting from the regressions of COINT-1 and COINT-2 in Table 8.14 and Table 8.15 for the few sectors discussed in Section 8.8.2.2 as point of references. We emphasize however that the low quality of the data, in particular as concerns R&D, and the low number of remaining observation, cast considerable doubts on the quality of the estimation results.

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Table 8.14: Regression results for COINT-1
(country fixed effects, no controls, homogeneous trend)

	(1) Chemicals and pharmaceuticals	(2) Machinery	(3) Electrical equipment	(4) Motorvehicles and trucks	(5) Other transport equipment
Log BERD	0.36424***	0.10652	0.15002**	0.07762	0.07363
	(5.69)	(1.54)	(2.53)	(1.31)	(1.37)
L1: Log public EPO patent stock (ROW)	1.31152***	0.94738***	0.79789**	0.77203***	-5.32567***
	(7.24)	(7.03)	(2.54)	(5.15)	(-13.63)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	336	312	264	264	312
R^2	0.886	0.929	0.924	0.913	0.877
Number of groups	14	13	11	11	13

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Table 8.15: Regression results for COINT-1
(country fixed effects, no controls, homogeneous trend)

	(1) Chemicals and pharmaceuticals	(2) Machinery	(3) Electrical equipment	(4) Motorvehicles and trucks	(5) Other transport equipment
Log BERD	0.18779*	0.06798	0.21618***	0.04205	0.03689
	(1.90)	(1.14)	(2.82)	(0.67)	(0.85)
L1: Log public EPO patent stock (ROW)	1.16704***	1.01978***	0.74101**	0.83533***	-3.20696***
	(5.93)	(8.65)	(2.01)	(6.13)	(-12.28)
Log GOVERD	0.03731	0.03271*	-0.02237	0.06772***	-0.04343**
	(0.96)	(1.85)	(-0.77)	(2.83)	(-1.99)
L1: Log public EPO patent stock	0.12625**	0.16925***	0.14304**	0.10976***	0.12739***
	(2.23)	(4.13)	(2.28)	(3.25)	(4.26)
Country Fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	264	288	192	216	168
R^2	0.916	0.955	0.923	0.937	0.957
Number of groups	11	12	8	9	7

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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8.6.2 By economic sector: evidence from the Mannheim Innovation Panel

In order to deliver a more satisfactory answer to the question of sector-specific knowledge generation input elasticities, we rely on a micro-economic data set of German firms in manufacturing and services industries. These are drawn from the Mannheim Innovation Panel (MIP, 1993-2014) and contain information on firm's innovative activities. The data have been amended with DMPA (German Patent and Trademark Office) patent application information. Crucially, the MIP covers firms in manufacturing as well as service industries, thereby avoiding the limitations inherent to macro-level patent estimation and industry concordance tables.

We estimate the elasticity of knowledge generation to R&D expenditures in a simple Cobb-Douglas style production function taking R&D expenditures, fixed capital, and labour as input factors, and further controlling for firm age, industry sector, and calendar year. We hence estimate:

$$\ln(PAT_{it}) = \beta_1 \ln(R\&D_{it}) + \beta_2 \ln(CAP_{it}) + \beta_3 \ln(EMP_{it}) + \beta_4 \ln(AGE_{it}) + \delta_{it} + \gamma_t + u_{it} \tag{8.8}$$

Where PAT_{it} describes the (depreciating) stock of patent applications of firm i in year t $R\&D_{it}$ R&D expenditures, KAP_{it} the value of assets, and EMP_{it} the number of employees. AGE_{it} represents the years since the firm's foundation, δ_{it} represent sector fixed effects (20 broad industries), and γ_t captures year effects. u_{it} is the error term. Table 8.16 shows summary statistics.

Table 8.16: Mannheim Innovation Panel summary statistics

	Total					Manufacturing		Services	
	mean	sd	min	median	max	mean	sd	mean	sd
$\ln(PAT_{it})$	0.360	0.900	0	0	9.708	0.492	1.03	0.096	0.450
$\ln(R\&D_{it})$	0.203	0.592	0	0	8.629	0.266	0.675	0.077	0.341
$\ln(EMP_{it})$	3.956	1.614	0	3.829	13.145	4.219	1.589	3.427	1.533
$\ln(CAP_{it})$	1.271	1.464	0	0.704	10.127	1.481	1.483	0.850	1.328
$\ln(AGE_{it})$	2.947	0.994	0	2.890	5.371	2.975	1.059	2.889	0.848
Observations	42905					28613		14292	

Notes: Amounts in mio. real 2010 EUR

Figure 8.5 describes the relationship between $\ln(R\&D_{it})$ and $\ln(PAT_{it})$ for respectively manufacturing and service firms. The slope of the fit line represents the elasticity of knowledge stock to R&D investment, and is larger for manufacturing firms (0.963) than for service firms (0.704).

Tables 8.17 and 8.18 further support this through econometric models. Table 8.17 shows the results for manufacturing firms. The estimated elasticity of R&D with regard to knowledge stocks is statistically highly significant and large, at 0.963. It drops down to 0.909 once sector and year effects are controlled for (model 2), and further slinks down

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to 0.715 once labor and capital are included in the model (model 3). Labor inputs also show a positive relationship with knowledge production, at an elasticity of 0.139. Model 4, lastly, further includes firm age. Whereas knowledge stocks do increase significantly with the age of the firm, the R&D elasticity estimate is not strongly affected and stays at 0.713.

Table 8.18 shows the regression results for services firms. The estimated elasticity of R&D with regard to knowledge stock starts off lower than that found for manufacturing (0.704, column 1). Inclusion of sector and year controls reduced the coefficient to 0.652 (model 2). Including labour and capital does not result in a significant drop of the coefficient (0.646, model 4). Further including firm age does not affect the main coefficient in any significant way (0.647, model 4).

Figure 8.5: R&D expenditures versus Patent stock, manufacturing versus services

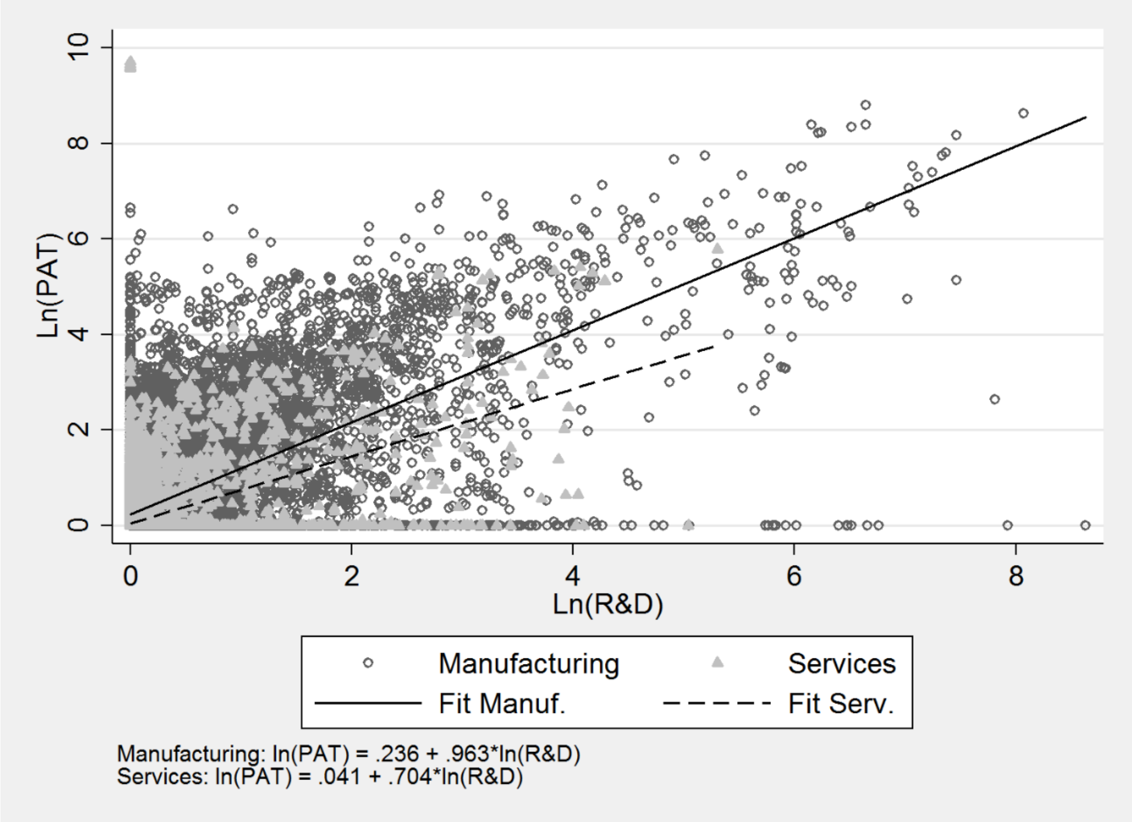

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Table 8.17: Regressions: Manufacturing firms

Dependent: $\ln(PAT_{it})$	(1)	(2)	(3)	(4)
$\ln(R\&D_{it})$	0.963***	0.909***	0.715***	0.713***
	(0.034)	(0.035)	(0.037)	(0.037)
$\ln(EMP_{it})$			0.139***	0.126***
			(0.009)	(0.009)
$\ln(CAP_{it})$			0.012	0.012
			(0.010)	(0.010)
$\ln(AGE_{it})$				0.087***
				(0.010)
Constant	0.236***	0.048**	-0.604***	-0.773***
	(0.009)	(0.024)	(0.039)	(0.045)
Year F.E.	NO	YES	YES	YES
Sector F.E.	NO	YES	YES	YES
Observations	28613	28613	28613	28613
R-Squared	0.399	0.43	0.463	0.47

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

Table 8.18: Regressions: Services firms

Dependent: $\ln(PAT_{it})$	(1)	(2)	(3)	(4)
$\ln(R\&D_{it})$	0.704***	0.652***	0.646***	0.647***
	(0.069)	(0.067)	(0.068)	(0.068)
$\ln(EMP_{it})$			-0.005	-0.005
			(0.004)	(0.004)
$\ln(CAP_{it})$			0.013***	0.012***
			(0.006)	(0.005)
$\ln(AGE_{it})$				0.007***
				(0.009)
Constant	0.041***	0.157	0.145	0.134
	(0.005)	(0.140)	(0.137)	(0.138)
Year F.E.	NO	YES	YES	YES
Sector F.E.	NO	YES	YES	YES
Observations	14292	14292	14292	14292
R-Squared	0.284	0.43	0.463	0.47

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

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8.7 Appendix 2: The diffusion and adoption parameters (P4, P5)

Estimating the diffusion and adoption parameters requires the existence of data giving information on the long-term adoption of technologies. Aggregate macro-economic time-series do not generally exist. Authors have therefore resorted to specialized and/or survey based datasets. Estimates of P4, i.e. the average adoption lag per country have been determined by Comin and Mestieri (2016) based on the Cross-country Historical Adoption of Technology (CHAT) dataset covering the diffusion of 104 technologies in 161 countries over the last 200 years (Comin and Hobijn 2009). Parameter P4 can be reused from Comin and Mestieri (2016). Estimating P5 is due to a lack of data only estimable indirectly. Anzoategui et al. (2016) determine P5, i.e. the elasticity of private adoption with respect to private adoption investment to be 0.925 and thus exhibit slight decreasing returns to scale. It should be noted that the parameter has not been determined by a structural economic model due to the lack of data. Rather, the parameter was chosen so that the simulation results of structural model described in Anzoategui et al. (2016) are consistent with the observed R&D intensities (R&D as share of GDP in the US after 1970). In the absence of sector-level country or sector level data on private diffusion investments, we still propose using the already derived estimator. An alternative would be to exploit the Fraunhofer dataset (see previous Chapter). Although this strategy would lead an econometrically validated estimate, it should be noted that the Fraunhofer dataset can only deliver information on the elasticity of public adoption investments but not private ones. In that respect, there is a risk that we, potentially unduly, equate the public and the private adoption elasticity. While this option may be discussed, possibly also as a robustness check, the preferred solution is to use the already existing estimate of 0.925.

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