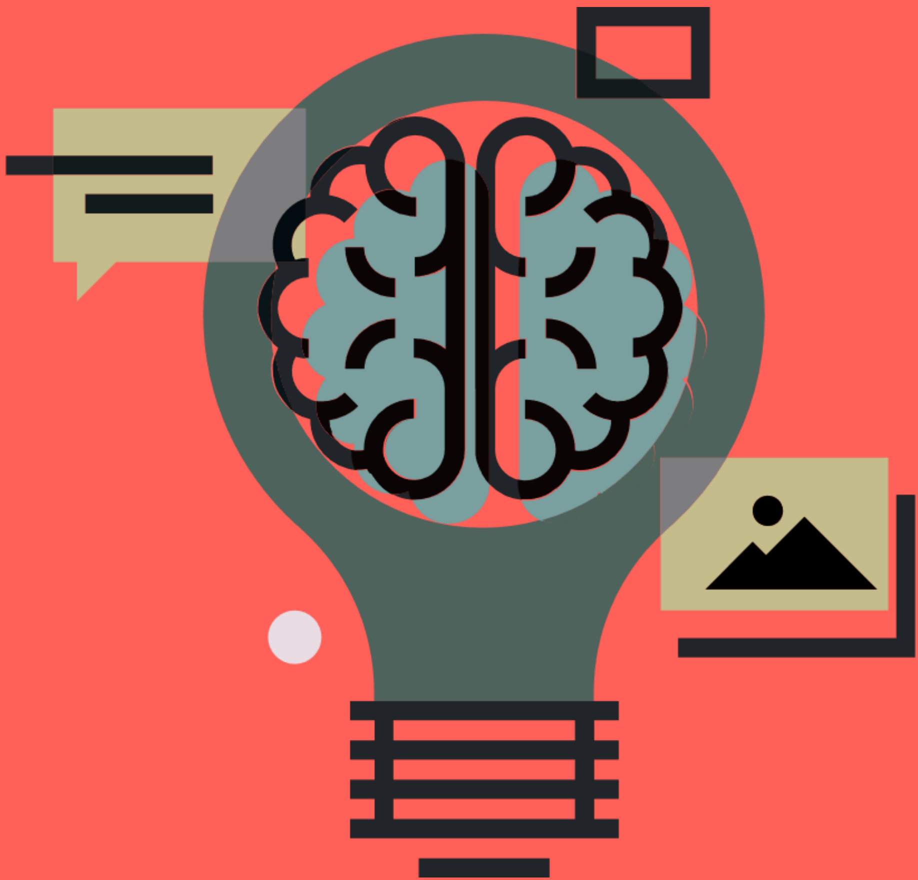

WP 2020:04

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Tillväxtanalys
Myndigheten för tillväxtpolitiska utvärderingar och analyser

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Publicly funded R&D, collaboration and patent activity[1]

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November 6, 2020

Abstract

Publicly supported R&D collaboration is a widespread policy tool to increase national innovation capacity. By combining firm-level data on collaborative and non-collaborative research grants from Sweden's innovation agency, Vinnova, with patent and register data, we investigate the relationship between Vinnova research funding, research collaboration and firm patenting behavior. Using modern matching methods to find control groups and a *difference-in-differences* (DiD) estimator we analyze three questions: Does Vinnova's research grants affect the number of patents the Swedish companies apply? Does support for research collaborations have greater impact than support to individual firms? Do the effects of the research collaboration differ depending on the types of actors involved in the innovation projects? We conclude that Vinnova research grants increase the number of patents filed by the Swedish firms. Our analysis does not give evidence that support for research collaboration have a greater impact than support to individual firms. We also conclude that research collaborations including academia have a larger effect on patent activity than research collaboration between firms.

Keywords: Public R&D subsidies, impact evaluation, R&D collaboration, patents

JEL classification: D22, H25, H81, O25, O31, O32, O34, O38

[1] We are grateful for valuable comments and suggestions from Anders Broström, associate professor, KTH Royal Institute of Technology, and participants at Ratio brown bag seminar. The usual disclaimers apply.

1. Introduction

Governments worldwide have adopted mixes of policy tools like patent laws, R&D grants, low interest loans or tax incentives to strengthen the national innovations and patent activities. By subsidizing private research or protecting innovation governments aim to offset market failures and relieve capital constraints.

Efforts to stimulate the development of cooperative R&D and local networks, particularly between university and industry, have since the late 1970s been a growing part of the innovation policy in many countries (Fornahl et al 2011, Muldur et al 2006). Beside direct subsidies to R&D consortia, governments are investing in science parks, technology districts and informal networks, and are granting antitrust exemptions to firms collaborating in joint research projects (Branstetter and Sakakibara 1998). Accordingly, there are considerable evidence that indicate an increasing number of R&D co-operations, mergers, patent licenses, and alliances in industry and science (Branstetter and Sakakibara 1998; Czarnitzki et al 2007).

While economic theory identifies the market failures that can motivate governmental intervention to promote private R&D investments and cooperation, theory also provide explanations for why policy outcomes may be poor. A large and growing number of evaluation studies of the effectiveness of individual or cooperative research grants show mixed result. A general conclusion is that the details of the support scheme seem vital for an efficient outcome. For that reason, it is important to evaluate Swedish research grants to ensure that the national innovation policy has an appropriate design such that taxpayer's funds are efficiently allocated to generate increased economic growth, productivity and innovation.

Adding to this literature, Growth Analysis analyses the effects of Swedish collaborative and non-collaborative research grants on business innovation output. By combining firm-level data on participation in collaborative and non-collaborative R&D projects funded by Vinnova, Sweden's innovation agency, with patent and register data, we investigate the relationship between Vinnova research funding, research collaboration and firm patenting behavior. In particular, we analyze three questions:

Do Vinnova's research grants affect the number of patents filed by the Swedish companies?

Does support for research collaborations have greater impact than support to individual firms?

Do the effects of the research collaboration differ depending on the types of actors involved in the innovation projects?

The Swedish Agency for Growth Policy Analysis (Growth Analysis) evaluates and analyzes the effects of Swedish innovation policy on the national innovation capacity. This working paper forms part of the evaluation of the Swedish Innovation Agency Vinnova and is included in the framework project *How can the government set up collaboration for increased innovation*. Other evaluation studies published by Growth Analysis include Halvarsson et al. (2018), an evaluation of Vinnova research grants on firm growth; and Balland et al (2020), an analysis of Vinnova research grants on regional diversification.

There are also a few academic studies evaluating Swedish research and innovation support to firms. Ejermo (2018) evaluates publicly funded incubators influence on firm patenting and finds that incubation has a positive innovation effect on some participating individuals, foremost the CEO. Lööf and Broström (2008) examine collaboration and innovation without specific focus on government grants. They find a higher innovation activity for large manufacturing firms that collaborate with universities. In the international research literature, there is a large number of studies evaluating government research and innovation funding. There is also a growing literature on research collaboration and the effects of public research support. A smaller number of studies examine the effects of public research collaboration support on innovation output, and of these, we find a handful studies that focus on patents. Table 1 shows how these studies diverge in terms of method and data. Our study contributes to this literature by examining the effects of Swedish support for research collaboration on firm patent activity. We employ similar method as Czarnitzki et al (2007) and Bellucci and al (2019). However, as our data to some extent are different, we use alternative estimation methods.

The study is structured as following. After the introduction, we summarize the insights from economic theory and the empirical literature regarding research collaboration and public support. The following section presents the institutional background of Swedish innovation policy. Next, we discuss the empirical challenges and outline the econometric approach and data. Finally, we present the estimation results and conclusions.

2. Theoretical background and empirical outlook

2.1 The role of R&D and the rationale for public support

The key role of innovation and technological development for economic growth is acknowledged in various strands of the theoretical growth literature. Solow (1956) identified technological development as the only source of long-term economic growth in the exogenous growth model. In the Schumpeterian growth models as well as in other versions of endogenous growth theory (e.g. Romer, 1990; Aghion and Howitt, 1998; Grossman and Helpman, 1991) it is the process when innovations replace older technologies that drives economic growth. In these models, competitive markets provide incentives for firms to engage in innovative activities by rewarding successful innovators with temporary monopoly rents. Firms' investments in innovation by conducting R&D or other activities add to the economy's stock of knowledge capital. However, theoretical work show that firms tend to underinvest in innovation relative the socially optimal level (Nelson 1959, Arrow 1962, Usher 1964). There is a number of explanations for this and the main argument is the following.

Knowledge created by R&D has public good characteristics. Knowledge is non-rival in consumption meaning that an idea can be used by more than one firm at a time, in the present and in the future. Knowledge is also non-excludable in the sense that it could be difficult to prevent an idea from being available to other firms. The non-rival and non-excludable nature of knowledge gives firms the opportunity to free-ride on the R&D efforts of other firms without compensation. Whereas this knowledge spillover effect is socially beneficial, private firms are unable to appropriate all the benefits from their R&D (Griliches 1979; Mansfield et al, 1977; Spence, 1984). This mismatch between social and private benefits is one reason for an underprovision of R&D investments in the economy and a widely used argument for policymakers to justify intervention.

In addition, imperfections on capital markets enhance the public good problem that R&D is associated with and create a finance gap between investments in R&D and other investments (Griliches, 1986; Hall, 2002). To prevent disclosure of the idea to competitors, inventors might be reluctant to reveal details of their research and the likelihood of success to external financers. This information asymmetry when investors have more difficulty distinguishing good projects from bad, may lead to "lemon market" problems as modeled by Akerlof (1970) that might discourage creditors and create a lemons' cost premium to R&D investing. Moreover, there could be additional agency cost on R&D investing if the innovating firm ownership and management of the innovating firm is separated. This could create principal-agent and moral hazard problems if the goals of the two conflict.

This financing gap is exacerbated by the intrinsic characteristics of R&D investments. Most of R&D spending is intangible assets, i.e. the firm's knowledge base, which in general will not be considered as eligible loan collateral. Moreover, there is a high degree of uncertainty associated with R&D output and a long time lag between basic research and commercialization of new products or processes, often in combination with sizeable initial investment. Although these features are not market failures, they increase the cost of external finance.

2.2 The role of R&D collaboration and the rationale for public support

Under some circumstances, the market will provide a solution to the tradeoff between incentives for the socially efficient production and diffusion described above (Branstetter and Sakakibara 1998). Firms can cooperate in R&D to overcome the free-riding problem and improve the appropriability of research returns within the research consortium (e.g. Spence 1984). By sharing their R&D cost and R&D benefits, research consortia can avoid duplication of investments and increase the knowledge diffusion. By cooperating, firms internalize knowledge spillovers and establish a more efficient allocation of knowledge.

In the 1980s, a large theoretical literature developed which analyzed the nature of R&D collaborations and the effects on welfare. In simplistic duopoly models with competing firms, collaborative and non-collaborative R&D levels were compared at different magnitudes of knowledge spillovers at various grades of product market competition (Katz, 1986; d'Aspremont & Jacquemin, 1988; Suzumura, 1992; for more references see e.g. Branstetter and Sakakibara 2002; and Czarnitzki et al, 2007). A general result from the analyses is that total R&D levels decrease with cooperation because of less research investment duplication but increase above non-cooperative R&D levels when spillovers are sufficiently large. However, the effect on social welfare is ambiguous when spillovers are low if R&D collaboration also facilitates product market collusion. Thus R&D collaboration, and as a consequence lower production levels, may generate higher profits for the cooperating firms, while lowering consumer surplus and total welfare, unless lower production levels are compensated by a higher level of R&D. Hence, key to the effect on social welfare is the size of knowledge spillovers.

Although these basic insights would be sustained in a setting with a more heterogeneous, or larger, group of potential beneficiaries, for example universities or other research institutions, other aspects would affect the outcome. Differences in objectives, organizational structure and policies could give coordination problems that lowers the probability for voluntary R&D cooperation. For example, while university researchers wish to publish findings, firms seek to withhold them from competitors (Newberg and Dunn, 2002; Lai and Lu, 2016). And while university researchers would benefit from R&D projects that result in new knowledge to publish in academic journals, private firms tend to be primarily interested in the commercialization of R&D results (Schwartz et al 2012). There are also costs of searching for partners, building up trust and coordinating and monitoring the research network that result in high coordination failure and transaction costs of R&D cooperation (Grimpe and Kaiser, 2010; Hottenrott and Lopes-Bento 2016).

Besides improved appropriability of research outcome and cost and risk sharing, there are other arguments for R&D collaboration. When there are economies of scale and scope in research investments, R&D collaboration could generate private as well as social benefits. There is also a widespread agreement that synergies can arise when partners share complementary skills and assets (e.g. Fornahl et al 2011). In the recent innovation literature, innovation is seen as a process enabled by diverse stakeholders in a dynamic context. This idea of innovations being created within systems rather than within organizations has found empirical support although not often elaborated in mainstream economic modeling.

Notwithstanding the motivation for collaboration i.e. firm internalization of knowledge spillover and improved knowledge allocation or synergy effects, the transaction costs associated with cooperation would be a rationale for publicly supported R&D cooperation.

2.3 Policy considerations

The classical policy solution to the problem with lower than socially optimal private R&D investments would be to subsidize the activity generating positive spillovers. The two main policy tools available to governments are R&D tax policies and direct subsidies of R&D projects.

According to economic theory, firms will undertake privately profitable R&D projects and disregard positive spillover effects in their investment decision. Thus, optimal public policy targets R&D projects that are socially but not privately valuable, since the latter would be financed with private means. However, identifying R&D projects that would not be launched without public support is challenging since all firms will have incentives to apply for public grants. If public support is granted, the firm might then substitute public for private investment. This possible crowding–out effect between public grants and private investment would leave private innovation activities constant (Lerner 2009). Moreover, even if the socially optimal level of R&D investments could be achieved, the problems with insufficient knowledge diffusion would not be overcome, unless spillovers are high (Katz 1986).

Another category of traditional innovation policies aims to correct the lack of appropriation incentives by implementing strongly-enforced patent or other intellectual property rights. The theoretical literature demonstrate that too strict proprietary rights will increase the cost of new knowledge such that the diffusion of new knowledge risks being less than socially optimal (Spence 1984).

A third category of innovation policies takes both deficient appropriation incentives and knowledge diffusion into consideration by encouraging R&D collaboration. Beside direct financial support, the policy approach also includes soft measures such as promoting R&D networks or legal measures such as a permissive anti-trust legislation for R&D joint ventures. However, as already highlighted in the theoretical section, there could be multiple problems associated with this approach, such as opportunism, inefficiency and market power imbalances at the expense of consumers. As argued in Czarnitzki et al (2007), there is a risk that good ideas and promising future technologies will not be developed if publicly funded R&D collaboration programs are the dominating kind of public funding available to innovative firms. A highly innovative firm could be reluctant to collaborate because of fear of disclosing commercial ideas to collaboration partners and may therefore not apply for subsidies.

To conclude, for most innovation policy there is a tradeoff between incentives for the socially efficient knowledge production and the incentives for its socially efficient diffusion (Spence 1984; Branstetter and Sakakibara 1998). The question of whether R&D subsidies, individual or collaboration, lead to additionality effects or crowd out firms' private R&D investment has been subject of a long debate on the effectiveness of direct R&D support.

2.4 Evaluation of R&D collaboration and public support

There exists a large body of studies evaluating the effects of R&D support policies on different aspects of firm performance and innovative activity. The potential effects of public support are searched for on for instance firm growth, productivity, profitability, innovation input and output and collaboration. The results are mixed and vary with time period, country, industry, the empirical approach and type of policy program. Whereas some studies have supported the view that public subsidies have a positive effect on R&D expenditure, investments, value added, and innovation, other studies reveal no improvement in firms' productivity, employment, labor productivity or exports. Recent research on the effects of R&D subsidies on private R&D investment and patenting mostly found a positive relationship. For a recent summary with references, see Bellucci et al (2019), Becker (2015), as well as Zúñiga-Vicente et al (2014).

A growing number of studies evaluate the effects of collaboration on various outcome variables including collaboration itself. In this literature, collaboration is interpreted broadly and translated into variables ranging from networks, clusters, regional proximity, to joint patents, co-authoring of scientific articles and formalized R&D collaborations. The literature on R&D collaboration lack conclusiveness, although there seems to be agreement on the finding of a positive impact on firms' performance (Scandura 2016). Using data from the Community Innovation Survey in Sweden, Lööf and Broström (2008) use a matching technique to produce a comparison group of firms with similar observable characteristics to estimate impact of university collaboration on innovation. They find that large manufacturing firms that collaborate with universities have higher innovation sales and a greater number of patent applications.

A sub-group of this literature evaluates the effects of publicly funded R&D cooperation between firms or between firms and universities. There is little empirical evidence on the causal effects of R&D subsidies on the performance of collaborating firms and the present evaluation studies find mixed results (Cunningham and Gök, 2012; Bruhn and McKenzie, 2017; Scandura, 2016). Some recent examples include the Swedish study by Halvarsson et al (2018) that analyses subsidized R&D collaboration on small firm growth. They find that the results depend on group composition and program design, with some general growth effects but no specific outcome from collaboration programs.

Just a few empirical analyses, we find 10, analyze the effect of public R&D collaboration grants on innovation output measured by firm patenting. Table 1 summarize context, empirical approach and results. Parallel to the other evaluation literature, these studies display a range of methodological approaches with a preference towards data-driven models such as matching and difference-in-difference (DiD). Effects of collaboration is estimated either as a natural experiment (Bellucci et al 2019), in separate estimations (Schwarz et al 2012) or by a dummy approach (e.g. Cappelen et al 2008; Czarnitzki and Fier 2007; Fornahl et al 2011). The majority of results seem to indicate a weakly positive association between publicly funded R&D cooperation and firm patenting, although the specific setting varies. For instance, Czarnitzki et al (2007) show that R&D collaboration with and without R&D subsidies yield positive effects on patenting in Finland, but less pronounced result in Germany. In a study on the Norwegian R&D tax credits scheme, Cappelen et al (2008) demonstrate that collaborating firms are more likely to patent but that the tax scheme itself has no effect. Kang et al (2012) investigate governmental R&D support in the Korean biotech industry and find that collaboration with international firms in particular has positive effects on firms' patenting outcome. Also in Germany are large-firm involvement in subsidized R&D cooperation projects positively associated with the number of patent applications (Schwarz et al 2012). Conversely, no significant effects on patenting are observed for university partnership, project size, spatial proximity between cooperation partners or prior cooperation experiences. Finally, whereas the most recent study to date, Bellucci et al (2019), find positive effects on patenting from individual research subsidies, collaborative subsidies have no effect.

Table 1 Evaluation of publicly funded R&D collaboration and firm patenting

Author(s)	Outcome variable	Measure of treatment	Estimation method/empirical approach	Control group	Main result
Bellucci et al (2019) Italy, 2005-2008	Patent applications (count), R&D spending/sales, tangible vs intangible investments, hiring of new R&D personnel	Separate estimations for collaborative and non-collaborative R&D support, public funding dummy	DID, kernel PSM, FE	Control group from same region meeting subsidy program criteria and not benefiting from other R&D subsidies.	Mixed. Positive medium-term effects from individual subsidies on patents, some positive effects on R&D expenditure, tangible investments and wages. Less effects from collaborative subsidies and no effects on patenting
Branstetter et al (2002), Japan, 1980-1992	Patent application (count)	Treatment dummy for government sponsored R&D	FE negative binomial linear (DiD),	Nonparticipating firms	Consortium design important for positive effect. Consortium engaged in basic rather than applied R&D seem to give more impact.
Bruhn et al (2017), Poland, 2012, 2013	Patent applications	Only research consortium in sample	Regression Discontinuity	Unfunded applications	Positive impact of R&D subsidies on patent applications. Positive impact on collaboration, i.e. joint publications, within consortia
Cappelen et al (2008), Norway, 1999-2001, 2002-2004	Patent applications (binary)	Three treatment dummies: R&D tax credit, R&D cooperation and an interaction dummy	CDM	Firms included in the annual R&D survey	Tax credit no contribution to patenting. Collaborating firm more likely to innovate.
Chai & Shih (2014), Denmark, 2005-2010	Granted patents (count)	Only research consortiums in the sample Treatment dummy for funding	DiD, RE and FE panel reg, quasi-maximum likelihood poisson models with cluster-robust standard errors	Matched control group of firms that applied for funding and selected to the second round but ultimately did not receive funding	No effect on granted patents but improvements in firm's survival and employment, and increases in the number of peer-reviewed publications, collaborations with academic researchers and publication forward citations.
Czarnitzki & Fier (2003) Germany 1992, 1996, 2000	Granted patents (binary, count)	Three treatment dummies: R&D subsidy with collaboration, subsidy without collaboration, collaboration without subsidy	Negative binomial for patent grants. Two PSM:s: collaboration with non-collaboration, then subsidized collaboration with non-subsidied	Firms included in the annual R&D survey	Collaborating firms are more likely to patent than non-collaborating firms. Firms in publicly funded networks are more likely to apply for a patent than firms in private networks.
Czarnitzki et al (2007) Finland, Germany, 1996, 2000	Patent (binary, count),	Treatment dummies: Public R&D funding and collaboration	PSM, nearest neighbor	Firms included in the annual R&D survey	Collaboration with and without subsidies have a positive impact on patent activity in Finland.
Forndahl et al (2011), German biotech, 1992-2004	Patent intensity	Treatment dummy for collaboration and non-collaboration R&D subsidy	Neg.binominal panel regression	Firms in the German biotech industry	R&D subsidies granted to joint R&D projects enhance performance but little evidence of positive effects of subsidies to single firms
Kang et al (2012), Korea biotech, 2005-2007	Patent applications (count)	Gov. R&D support, upstream and downstream collaborations	Stepwise Structural equations model (path model), RE linear regression	Industry survey data	Gov R&D support has a strong direct effect on firm patenting. International firm collaboration had a positive significant effect on firms' patenting outcome.
Schwarz et al (2012), Germany 2000-2006	Patent applications (count), publications (count)	Separate estimations for inter-firm and academic-industry cooperation types	Negative binomial regression	Participants in R&D cooperation project funded by Development Bank of Saxony.	Projects with large firms more successful wrt patenting, esp. for inter-firm cooperation. No such relationship for academic partners. Positive effect of project amount on patents in particular. No effect from spatial proximity, number of partners or prior cooperation.

To summarize, although economic theory offers a motivation for governmental intervention to promote additional private R&D investments and cooperation, the literature does not provide any clear indication of the preference between individual and collaborative R&D support programs. As stated in Bellucci et al (2019), R&D programs that involve collaboration can in theory produce better or worse results than individual research projects, depending on whether synergy and spillover benefits exceed the coordination and free-riding costs. The theoretical and empirical literature alike suggests that the policy instruments need to be well-designed and well-implemented.

3. Institutional background of Swedish publicly funded innovation cooperation

3.1 The Swedish policy context, the innovative firms and the R&D collaborations

This study considers R&D projects funded by Sweden's innovation agency, Vinnova, between 2010 and 2012. This is a period preceded by significant changes in the Swedish innovation policy. After a long period, 1970-1990, with slow economic growth and a large national economic crisis in the early 1990s, economic growth was acknowledged as a specific policy area. In the beginning of the 2000s, two growth policy fields emerged, national innovation policy and regional growth policy, and two corresponding governmental agencies were established to apply the policy, The Swedish Agency for Economic and Regional Growth (Tillväxtverket), and Vinnova. During this phase, as in most countries, the role of collaboration became a priority, along with a greater role for academic and business partnership (Tillväxtanalys 2020).

Among the OECD countries, Sweden rate as number five in terms of R&D expenditure, both overall and business sector, as a percentage of GDP as well as per capita (The Swedish Research Barometer 2019). Total expenditure and personnel allocated to R&D in Sweden has increased over the past fifteen years, in particularly R&D expenditures in the business sector (SCB 2017, 2018, 2019). In 2017, the business enterprise sector accounted for SEK 110.9 billion, which corresponds to 71 percent of total Swedish R&D expenditure. The higher education sector R&D expenditure amounted to SEK 38.8 billion, compared to government sector R&D expenditure of SEK 5.6 billion. The funding of the business sector FoU is mainly by self-financing and less than five percent of business R&D (SEK 5.3 billion) is funded by the public sector. Likewise is the share of business funding of public sector research minor, corresponding to 3.4 percent of total R&D expenditure (SEK 1.3 billion). Thus, these register data seem to indicate that the academic and business collaboration in Sweden is marginal.

The latest survey on innovation activities in Swedish firms provides a more detailed outlook. The Community Innovation Survey 2016-2018 (Statistics Sweden 2020) shows that 55 percent of Swedish enterprises conduct innovation activities. This share ranges from 53 to 76 percent depending on firm size class, with larger firms being more innovative than smaller. There are also differences between industries; besides scientific research and development (NACE 72), the information and communication enterprises as well as manufacturers of computer, electronic and optical products are particularly innovative. Among the innovative firms 11 percent state that they cooperated with other parties, this share significantly increasing to 35 percent for large enterprises with 250 or more employees. Firms collaborate in innovation largely with private partners, such as clients, customers and suppliers, than with public partners. The share of firms that cooperated on innovation with universities or other higher education institutions are ranging from three percent of firms with 10-49 employees, nine percent of firms with 50-249 employees to 24 percent of firms with 250 or more employees. Similarly, it is more common for larger firms to receive external funding for their innovation activities; 20 percent of enterprises with 250 or more employees received external funding for their innovation activities, whereas 11 percent of firms with 50-249 employees and 8 percent of firms with 10-49 employees received external funding. The source of external funding was most commonly governmental support and tax credits, EU-funding such as Horizon 2020 or regional and local support. In comparison, the Swedish share of public funding of innovative enterprises for innovation activities is among the five lowest in the European Union.[2] However, the share of innovative firms engaged in innovation cooperation in general or with specific cooperation partners do not significantly divert from the EU average with one exception. Although still considerable below Finland, Sweden is one of five countries in Europe with the highest share of large firms cooperating with universities or other higher education institutions.[3]

3.2 Sweden's innovation agency, Vinnova, and the supported firms

Vinnova, founded in 2001, is mainly responsible for promoting applied R&D and business innovation by providing early stage financing. In a wide range of programs with varying industry, R&D stage or area focus, Vinnova is offering grant support to single companies or collaborative R&D projects. During our study period, Vinnova funded almost 1400 projects each year, allocating on average 2.14 billion SEK amounting to a little more than five percent of the public R&D expenditures. With co-funding requirements, either in financial or in-kind contributions, the programs amounted to 4.5 billion SEK yearly.

A range of organizations, including private firms (2,402), colleges and universities (48), research institutes (36), miscellaneous public actors (350), and others (289) participated in the research projects during the period. On average, each project had three participants, but one fifth of the programs had only one participant on average and two thirds of the programs had only one participant in median. Universities or research institutes participated in 53 percent of the funded research projects, out of which 43 percent involved business collaborations. Altogether, 38 percent of the funded research projects had more than one participant. Eight percent of the R&D collaboration projects included only private firms. A breakdown of the total number of projects supported by Vinnova in the ten main programs over the period 2010-2012 is provided in Halvarsson et al (2018). Table 2 summarizes the share of innovative firms, the share of firms involved in R&D collaboration and the share of firms with external R&D funding among firms

[2] Product and/or process innovative enterprises that received public funding for innovation activities by source of founding, NACE Rev. 2 activity and size class [inn_cis10_pub]

[3] Product and/or process innovative enterprises engaged in co-operation by co-operation partner, NACE Rev. 2 activity and size class [inn_cis10_coop]

participating in the Vinnova funded R&D programs 2010-2012 compared to the Swedish corporate population in general (Statistics Sweden 2020).

Table 2 Comparison of firms in CIS 2016-2017 and firms in Vinnova programs 2010-2012

Variable	The Community Innovation Survey 2016-2017	Firms participating in the Vinnova funded R&D projects 2010-2012
Involved in innovation, %	55	100
Innovation collaboration, among innovative firms, %	11	72
Innovation collaboration with universities, among innovative firms, %	5	46
External funding (whereof governmental), among innovative firms, %	9 (4)	100

The private firms participating in the Vinnova funded R&D projects correspond to 0.7 percent of all companies in the firm-level data from Swedish official business register. Persons employed in the Vinnova firms represent 15.4 percent of the employees in the private business sector and 10.4 percent of the labor force. In terms of total value-added and share of GDP, the Vinnova firms' share correspond to 23 percent of the corporate sector and 12 percent of GDP respectively. Comparing Vinnova firm technology and knowledge intensity[4] with the Swedish corporate population, the supported firms are overrepresented in all technology levels of the category Manufacturing as well as in the category High-tech knowledge intensive services. The Vinnova firms are underrepresented in categories Less knowledge-intensive market services and Construction.

During our study period 2010-2012, 13 000 patent applications were filed in Sweden.[5] Half of the applications were owned by Vinnova organisations; the vast majority by firms and a modest share university patenting. Out of 1864 patenting firms, were 23.3 percent Vinnova firms, which suggest that a few firms were involved in several patent applications. Indeed, ten firms own 70 percent of all Vinnova patent applications during the period, with the top assignee alone holding 41.3 percent of the Vinnova patents and 21 percent of all patent applications. Vinnova firms with less than 250 employees owned 880 patent applications, amounting to 13.7 percent of the total number of Vinnova patent applications.

To conclude, the firms that participate in Vinnova programs are larger, both in term of persons employed and value-added, than the Swedish corporate population generally. Vinnova firms also appear more innovative in terms of propensity to patent compared to corporate sector average. In addition, a larger share of program participants are involved in R&D collaboration than the innovative firms' national average. Evidently, the causal relationships are still undetermined from these statistical facts.

[4] Eurostat high tech sector categories based on NACE Rev. 2

[5] Patent applications of the types SE, EP and WO

4. Econometric methodology and data

4.1 Empirical challenges

If public policies were implemented as natural experiments, targeting a random sample of the population, evaluation of the impact would be achieved by a straightforward comparison of outcomes. For practical, political or ethical reasons, this is seldom the case. The econometric problems facing researchers seeking to measure the impact of government innovation policy on firm performance are well-known, including issues of sample selection, causality and unmeasured heterogeneity of participating firms (Klette et al 2000; Cerulli 2010). When estimating the effect on innovation output measured as patenting as in this study, receiving or searching for funding, enter a R&D collaboration or applying for patents could all be subject to possible selection bias (Czarnitzki et al 2007). Participants in public measures could differ from non-participants in important characteristics (see Heckman et al. 1999; Heckman et al. 1997, for surveys). Firstly, R&D consortia that are granted public support are evaluated according to some criteria related to project quality. Accordingly, R&D consortia with a lower probability of future success will be systematically rejected in the selection process (Schwartz 2012). Secondly, it is reasonable to believe that primarily firms with strong R&D capabilities will apply for public R&D collaboration grants. Branstetter and Sakakibara (2003) argue that the same kind of innovative firms also are more inclined to participate in R&D partnership. Unless there is information on the attributes of the rejected projects or of these non-collaborating, non-funded firms, the estimated effects of public support on innovation performance risk being positively biased.

Evaluation studies employ various estimation strategies to identify treatment effects when the available observations on individuals or firms are subject to such selection bias or endogeneity problems. Typically, the literature on R&D subsidies to firms relies on the DiD estimator, selection models, instrumental variable estimations (Branstetter et al 1998; Azoulay et al 2019; Cerulli 2010), matching methods (Branstetter and Sakakibara 2002), or a combination of approaches. Researchers with access to innovation agency data on R&D project rankings have employed regression discontinuity designs to reduce the selection bias (Bruhn and McKenzie 2017; Bronzini and Piselli 2016; Howell 2017).

In addition to selecting identification strategy, researchers also need to decide what empirical model to estimate. The empirical literature often discusses innovation in the context of a "knowledge production function", which describes the relationship between various innovation inputs, and innovation output (Griliches 1990). The "knowledge production function" is sometimes estimated in a structural model such as the CDM model (Crépon, Duguet and Mairesse 1998), a frequent framework in the empirical literature on innovation and productivity (Lööf et al 2017). However, in many studies the equation of innovation and patenting behavior serve merely as an illustration to how innovation output may be associated with various innovation inputs. The results from these estimations are open to a number of interpretations (Branstetter et al 1998).

All empirical models and econometric approaches are conditional on different sets of assumptions and have different benefits and shortcomings. Therefore, policy implementation and data availability determines the choice of empirical evaluation method.

4.2 Methodological approach

We will rely on a quasi-experimental research design to manage the non-randomly selected sample described above. As our database (described in the following subsection) consists of panel data with observations before and after the R&D subsidy was granted, we will apply a matching approach in combination with a DiD estimator. The details of our methodology are elaborated in the following sections.

4.2.1 Matching procedure

Matching methods are data preprocessing algorithms that can be used in this context to compare publicly subsidized firms with a control group of comparable firms engaged in R&D projects that are not enrolled in public research programs (Branstetter and Sakakibara 2002). Ideally, the control group should reflect developments in the treated group in absence of the intervention, i.e. the so-called counterfactual outcome. After preprocessing, an estimator of choice is applied to the data to draw causal inference.

There are several matching techniques available in the literature, e.g., propensity score matching (PSM) (Rosenbaum and Rubin 1985), coarsened exact matching (CEM) (Blackwell et al. 2009), and the Mahalanobis distance (Mahalanobis 1936; Rubin 1980). CEM has the advantage over other matching methods of being non-parametric, more transparent, dealing with common support by construction and reducing the sensitivity to measurement error (Iacus et al. 2012). However, CEM may result in unwarranted loss of observations when matching is too exact. Conversely, matching can become imprecise if less strict restrictions are applied, resulting in larger dissimilarities between firms and thus less comparable treatment and control groups. We use a combination of coarsened exact matching (CEM) and nearest neighbors algorithm based on Mahalanobis distance to generate comparable groups in terms of observable characteristics while keeping a sufficient number of observations.

As summarized in an earlier section, matching methods have recently been applied by Czarnitzki et al (2007) and Bellucci et al (2019) to evaluate R&D collaboration support in Germany and Finland respectively Italy. While our study has benefitted from following the approaches of Czarnitzki et al and Bellucci et al, our data are to some extent different and consequently also our preferred estimation method. Czarnitzki et al use the richness of the CIS survey data to recognize the details of firm R&D collaborations and Bellucci et al the parallel implementation of a cooperative and non-cooperative R&D grants to identify the collaboration effect. Our study exploits the panel structure of the R&D collaboration grant data, which is linked to a longer panel of firm-level register and patent data (our data sources are described in more detail in the section below). In addition, whereas Czarnitzki et al and Bellucci et al use PSM to derive a comparable control group, we employ coarsened exact matching (CEM), which as argued above has some advantages over traditional matching methods.

The basic idea of CEM is to divide (coarsen) each variable into categories (bins) and then match and group similar observations into the corresponding strata (see Blackwell et al. 2009; Iacus et al. 2012). The variables utilized in the matching process, should matter for the probability of being selected, or self-selected, into a Vinnova program. Moreover, the matching variables should be relevant for future patenting. In this setting, it could be theoretically motivated to include the variables in a knowledge or patent production function in the matching process.

The values of coarsened variables, i.e. the category range, are manually defined based on the measurement scale of each variable. There is a trade-off between the number of matching variables and the strictness of the coarsened values on one hand, and the number of matches and match quality on the other. In our matching algorithm, firstly, we select a relatively large number of coarsened variables (firm size, profitability, debt ratio, industry, year, legal form and recent patent output), but let the coarsened values be less strict. In a second step, we select the closest matches for each treated firm in each strata with the Mahalanobis distance metric. The approach is described in more detail below.

Table 3 summarizes the variables and the coarsened values. The empirical literature has guided us to select the following matching variables: firm size measured as the number of employees and firm age, defined as the age of the firm at the point of entering a Vinnova program (e.g. Engel et al 2016; Hottenrott et al 2013; Nishimura et al 2011; Scandura 2016). The number of patent applications during three years before the funding decision describes patent intensity prior to the funding period. Czarnitzki et al (2007) argue that the variables size, age and patent intensity are central indicators of firm capacity and capabilities to innovate. These characteristics are important in the selection process of Vinnova to pick winners, as well as for firm drive to apply for patents. In addition, we control for patent propensity by including an industry dummy. The likelihood to apply for Vinnova funding could depend on the firms' financial situation. We measure this through two variables indicating firm financial constraints (Bellucci et al 2019, Lööf and Broström 2008). First, the debt ratio, measured as the ratio of equity over the total amount of capital and, secondly, profitability, measured as gross operating margin over value added. We partly follow Czarnitzki et al (2007) and argue that industry dummy, size and patent intensity are important variables driving selection into R&D collaboration. Finally, a time dummy reflects changes over time.

Table 3 Matching variables

Coarsened variable	Defined as	Coarsened value
Industry	Two-digit NACE Rev.2	exact
Year	Calendar year	exact
Size	Number of employees	Solo (0-1); micro (2—9); small (10-49); medium (50-249), large (250-999), Very large 1000+
Age group	Age at year of treatment	New (0-2 yrs), young (3-5 yrs), established (6+ yrs)
Profitability	Gross operating margin/value added	<-0.02; -0.02-0.02; 0.02-0.1; 0.1-0.3; 0.3+
Debt ratio	Equity/total assets	<0; 0-0.50; 0.50+
Patent activity	Number of patents over the three years prior to treatment	0; 1; 2-3; 3-9; 10-30; 30+ patents in total over three years

The CEM matching process assigns each observation to a strata, where all observations belong to the same combination of bins. A treated firm and a control firm are considered matched if they belong to the same strata. We retained the observations in strata with at least one treated and one control observation and removed the remaining strata from the sample. See Table 4 for a summary of matched and unmatched observations in the matching processes.

The number of matches varies widely between different strata. Some strata contain dozens of control firms, whereas others contain very few or none. To maximize statistical power, Iacus et al. (2012) recommend keeping as many matched control observations as possible and assign the treated and control groups equal weights in the further analysis. However, if the matching bins are broad and there are many matches in the strata, then the quality of the control group could be improved by selecting the best matches within each strata. In our analysis, we prefer to exchange some statistical power for a closer match. For each treated firm we calculate the Mahalanobis distance based on recent patent output and firm size, and then select the five firms matched in the same strata closest to the treated firm. Weights were used to ensure that the treated and control groups are given equal weight in the regressions. Each treated firm was assigned a weight of one, and its controls were assigned weights such that they summarized to one.

Selection with replacement was employed, which means that one control firm can be matched to several treated firms. Once this occurs, a copy of the control firm is created with a new firm ID. Since matching on year is exact, a treated firm cannot be matched to more than one observation of the same control firm. However, different generations of a control firm can be matched with multiple treated firms in different strata. Matching without such replacement would have impaired the efforts to match as many treated firms as possible.

4.2.2 Estimation method

After preprocessing data with CEM, we use a DiD framework to estimate the effects on patenting of participating in a Vinnova program, some involving R&D collaboration. Identifying t as the first year of project participation[6], we follow firms over a 7-year period, starting from two years prior to treatment (t-2) to four years after (t+4). Since literature show that the full effect of a subsidy may be distributed over several years (Klette and Møen 2012), patent performance in the post treatment period is estimated over the short term (year t to t+2) and the long term (year t+3 to t+4). The pre-treatment period, to which the firms are compared, includes the two years prior to treatment (t-2 and t-1).

We use the following regression model to estimate the difference in differences between the treated and control groups, over the course of the three time periods which we have defined:

$$
\begin{aligned}
no\_of\_applications_{i,t} \\
&= \beta_0 + \beta_1 treated_{i,t} + \beta_2 post\_short_{i,t} + \beta_3 post\_long_{i,t} + \beta_4 DiD\_short_{i,t} \\
&+ \beta_5 DiD\_long_{i,t} + \mu_t + \varepsilon_{i,t}
\end{aligned}
$$

Where *no_of_applications* is the dependent variable, indicating the number of patent applications submitted by the firm during the year; *treated* is a dummy variable equal to one for all observations of treated (Vinnova) firms, and zero otherwise; *post_short* is a dummy =1 for all firms during the short term period (t to t+2); *post_long* is a dummy =1 for all firms during the long term period (t+3 to t+4); *DiD_short* is a dummy =1 in the short term period for treated firms only[7]; and *DiD_long* is a dummy =1 in the long term

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[6] Regardless of how many years the project lasted, or whether the firm joined other projects in subsequent years.

[7] The same variable can be derived by multiplying the variables *post_short* and *treated*, thus *DiD_short* = *post_short*treated*.

period for treated firms only[8]; and μ represents year fixed effects. The betas represent the estimated coefficients for the explanatory variables; β_0 is the constant; ε is the error term; and *i,t* indicates firm *i* in year *t*.

To examine our research questions, we estimate the main model five times: 1) All treated firms are compared to their matched control firms in a DiD framework and similarly for the sub-samples 2) only firms that collaborate, 3) only firms that only collaborate with other firms, 4) only firms that collaborate with universities or research institutions and 5) only firms that do not collaborate. This gives detailed results for our different sub-groups but as additional exploration of heterogeneity in treatment, we make similar comparison among Vinnova firms, only. In this analysis, we perform three DiD estimations consisting of: 1) Collaboration vs. no collaboration, 2) Only firm collaboration vs. other collaboration and 3) University or research institute collaboration vs. other collaboration.

4.3 Data

4.3.1 Data sources

The empirical analysis is based on three data sources. Our data on R&D projects were provided by VINNOVA, covering complete datasets for 4133 subsidized R&D projects within the funding period 2010-2012. Besides basic information, such as main and subprogram, the decision date and the total amount of project funding, the data set includes information on the partners involved in each R&D project, such as share of funding respectively co-funding, geographical location and project leader. There is substantial heterogeneity across projects in terms of mix of participants; overall 3086 organizations are participating in 1566 R&D cooperation projects and 2567 non-cooperative R&D projects.

The firms in the Vinnova database is linked to Statistics Sweden registry data, including balance sheet data on Swedish companies. Data on firms' yearly patenting activities were collected from PATSTAT, the European Patent Office (EPO) database. Our dataset contains the three types of patent applications that are valid in Sweden, i.e. Swedish (SE) patents filed under the Swedish Intellectual Property Office (PRV), European (EP) patents filed under the European Patent Office (EPO) and World (WO) patents filed under the Patent Cooperation Treaty (PCT). The PatLink dataset provided by the research institute Swedish House of Finance allowed us to link the PATSTAT data to unique firm identifiers, which in turn enabled linking the patent data to subsidy and registry data.

4.3.2 Outcome variables

To assess the effects of public subsidies and R&D collaboration on innovation output we use the number of firm patent applications as outcome variable. Firm patenting is an often used indicator of innovation in practical evaluation (in the related literature, see e.g. Bellucci et al 2019; Fornahl et al 2011; Schwarz et al 2012). There are well-known methodological problems with this measure, since patenting activities are highly industry-dependent and not all inventions are patented (Griliches 1990). It is for instance argued that smaller firms tend to avoid patent registration since the costs often exceed

[8] The same variable can be derived by multiplying the variables *post_short* and *treated*, thus *DiD_short* = *post_short**treated*.

innovation value (Cohen and Lemley 2001). Nevertheless, patents show a strong relationship to technological development and the national patent databases are often available as well as rich (Cadil et al 2018).

As noted earlier, the descriptive statistics of the outcome variable indicate that the largest firms in our dataset are major outliers in terms of patenting activity. Out of firms with at least one patent during 2002-2017, the average number of patents held is more than seven but the median is one. We therefore reduced the sample to firms with maximum 10 patents per year. We measure patent activity as the number of patent applications that a firm files during a year. All patents are weighted as one, regardless of the number of co-applicants on the patent.

4.3.3 Treatment variables

The main question of this analysis is whether the number of patent applications increase when firms receive public funding and participate in publicly induced R&D cooperation. The treatment variables for public funding is created as a dummy variable for firms that were part of a Vinnova project during 2010-2012. Correspondingly, R&D collaboration is described by a dummy variable for all firms participating in a project with more than one organization. We also create two dummy variables to qualify the R&D collaborations, with one dummy indicating if one of the participants in the R&D cooperative project is one or more universities or research institutes, and a second dummy indicating if the R&D partners are private firms only.

It is however more challenging to identify the effect of R&D cooperation since we lack information on non-funded collaborative research. According to the Community Innovation Survey 2016-2018, as described above, the share of innovative firms performing collaborative research are on average six percent of all firms in Sweden. Furthermore, nine percent of the innovative firms stated in the survey that they have received economic support for innovation activities, which correspond to five percent of all Swedish firms. From these statistics, a modest guess is that the share of firms involved in R&D collaborating are lower in the control group than in the treated group. If this is the case, it will be possible to compare cooperative and non-cooperative R&D projects with respectively control group, and say something about the effect of R&D collaboration. In addition, we will assess the effect of R&D collaboration by comparing the outcomes of cooperative and non-cooperative R&D projects within the treated group of Vinnova-funded firms only.

4.4 Descriptive statistics

Based on CEM and Mahalanobis distance matching, we matched the five closest non-funded firm to each of the Vinnova funded firms according to sampling with replacement.[9] The result of the matching procedure is outlined in Table 4, comparing the funded firms to the unfunded firms in the control group, before and after matching, during the period before treatment, i.e. t-1.

[9] Some stratas have less than 5 neighbours after the CEM procedure, we use less than 5 neighbours when this is the case.

Table 4 Summary statistics of the treated and control groups before and after the matching procedure

Variable Mean (sd)	Treated unmatched	Control unmatched	Treated matched	Control matched
Patent intensity the last three years (count)	1.186 (19.57)	0.004 (0.151)	0.0602 (0.270)	0.0617 (0.336)
Size (employees)	224.5 (947.6)	10.80 (75.99)	31.15 (45.62)	30.09 (47.58)
Age (three groups)	2.552 (0.750)	2.234 (0.833)	2.521 (0.776)	2.551 (0.647)
Debt ratio	0.346 (0.253)	0.332 (0.269)	0.356 (0.248)	0.326 (0.219)
Profitability	0.206 (0.353)	0.170 (0.275)	0.193 (0.348)	0.195 (0.290)
Observations	1760	2983038	1306	6255

In Table 4, we observe that the funded firms are on average considerably larger and applied for more patents the three years preceding entering the Vinnova program compared to the control firm population. After the matching procedure was applied, the mean values of the variables barely differ between groups, which underlines that our procedure generates comparable groups based on observable characteristics. The funded firms that were not matched to comparable control firms are not included in the final sample. In addition to pre-treatment similarities in firm characteristics, it is important to find similar pre-treatment trends in the outcome variable. Figure 1 shows the average number of yearly patent applications two years before to four years after treatment year, for the treated and control groups.

Figure 1 Development of patent activity over time

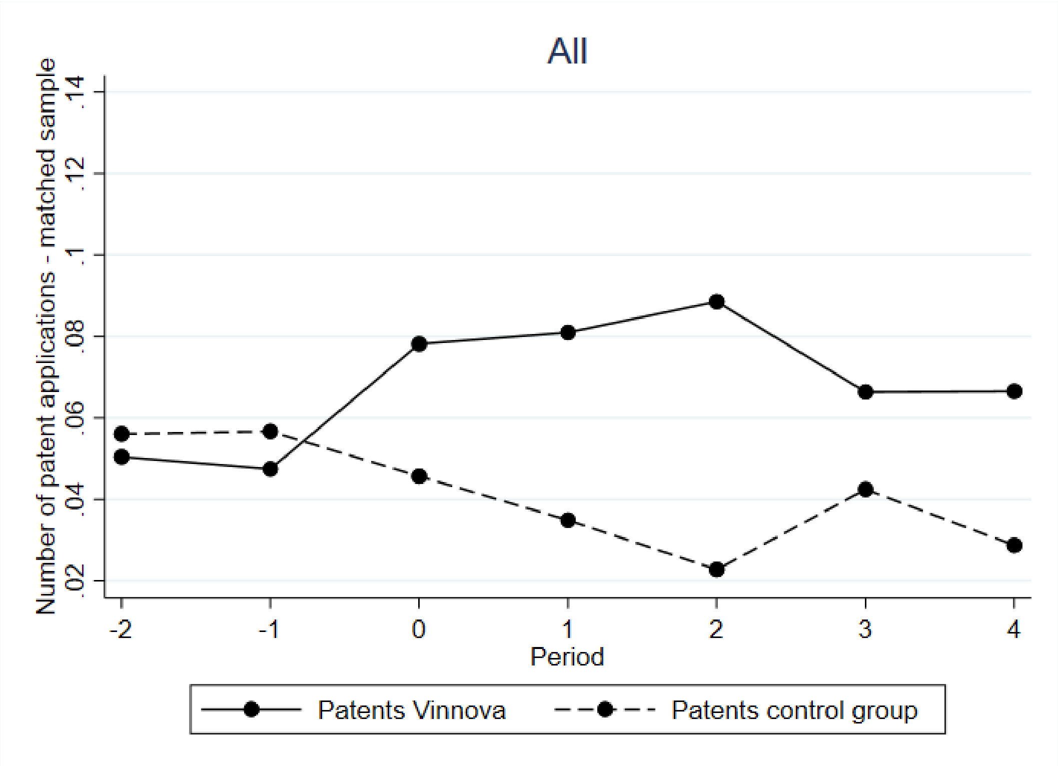

Figure 1 indicates that the groups have a similar trend and level in the average number of patent applications during the pre-treatment period, t-2 to t-1. By assumption, similar pretreatment trends make it more plausible that any deviations of patent applications between the groups after period t-1 can be attributed to participation in a Vinnova program and therefore our DiD estimates are more likely to be causal. However, a discussion of potential caveats will be provided below.[10]

4.5 Estimation results

This section addresses three research questions: (1) Do Vinnova's research grants affect the number of patents filed by the Swedish companies?; (2) Does support for research collaboration have greater impact than support to individual firms?; (3) Do the effects of the research collaboration differ depending on the types of actors involved in the innovation projects?

First, we analyze all three questions in a traditional DiD approach by comparing Vinnova firms with control groups of nonfunded firms. Next, we address question 2 and 3 in a reduced setup by comparing different groups of Vinnova firms. Finally, we discuss the robustness of the results.

4.5.1 Estimated effects on patent applications with control group

The results from the DiD estimations are summarized in Table 5. The table shows the average effect of the research grant in the short and long terms, i.e. DiD short and DiD long, compared to each matched control group. Year fixed effect is included as a control variable to handle cyclical factors that may affect the number of patents. Column (1) includes all Vinnova funded firms, column (2) displays the results for collaborating firms, columns (3) and (4) show the results for research partnerships with private firms only and research consortia with at least one university or research institute, respectively. The last column (5) shows results for individual research projects, i.e. firms that are funded by Vinnova but not involved in research collaboration.

Table 5 DiD estimated effects on patent applications of Vinnova research grants

	(1)	(2)	(3)	(4)	(5)
Variables	All	Collaboration	Only firm collaboration	University collaboration	No collaboration
Treated	-0.008	-0.003	-0.017	-0.002	-0.021
	(0.013)	(0.012)	(0.016)	(0.017)	(0.030)
Post short	-0.002	0.013	-0.025*	0.014	-0.043**
	(0.010)	(0.010)	(0.015)	(0.012)	(0.022)
Post Long	0.017	0.032**	0.004	0.033**	-0.024
	(0.014)	(0.014)	(0.043)	(0.017)	(0.031)
DiD short	0.055***	0.038***	0.010	0.051***	0.099***
	(0.013)	(0.012)	(0.020)	(0.015)	(0.033)
DiD long	0.038**	0.033**	-0.007	0.041*	0.051
	(0.016)	(0.017)	(0.024)	(0.022)	(0.035)
Observations	48,052	35,553	3,807	25,128	12,499
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In column (1), we can observe a positive and significant estimated effect on the number of patents applications for firms that received Vinnova research grants compared to the control group. This effect is largest in the short run (0-2 years). It diminishes slightly over

[10] Similar graphs for treated firms with and without research collaboration are presented in the appendix.

the long-run (3-4 years), but remains significant, which indicates that the treated firms were able to sustain a higher level of innovation output.

Figure 1 Development of patent activity over time

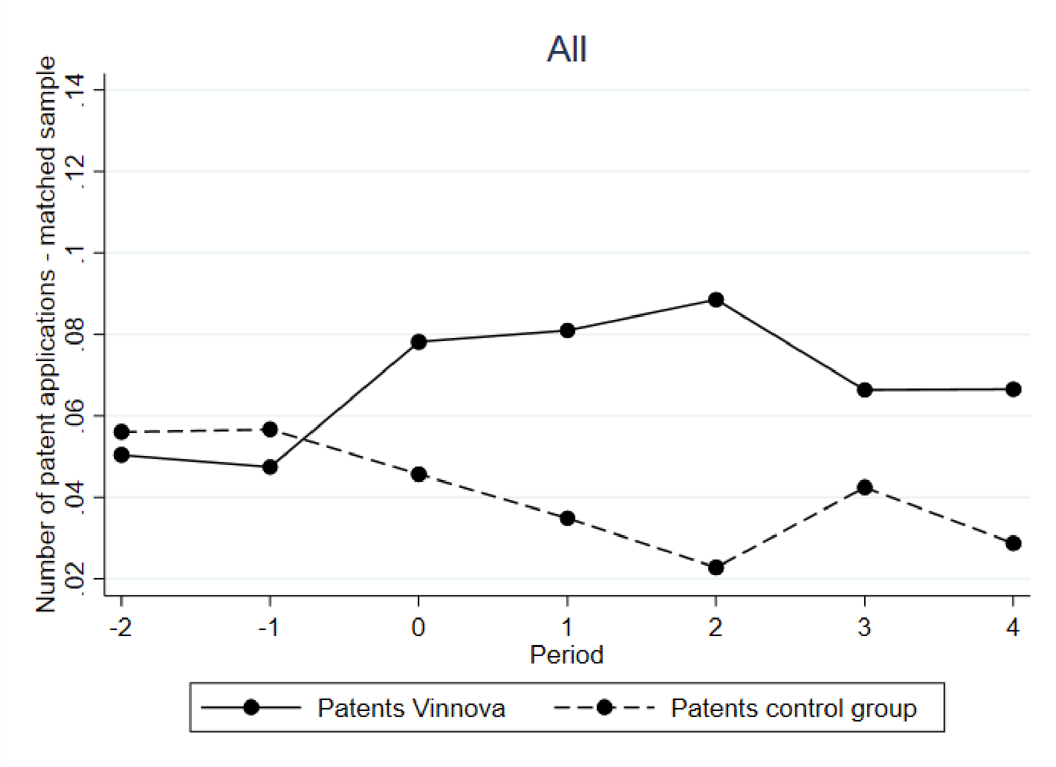

Figure 1 seems to suggest that the effect in part is driven by a decrease in patent activity in the control group. However, this negative trend in the control group disappears in the regression results, likely because year fixed effects are included.

Next, collaborating and non-collaborating Vinnova firms are separated into two groups and analyzed in columns (2) and (5) respectively. In the analysis, we find that individual firms as well as firms in research partnerships increase the number of patent applications after being awarded research grants compared to control firms. No large differences can be observed between collaborative and non-collaborative research programs, although the latter exhibit larger estimated effects (insignificant in the long run). The large short-run effect for the non-collaborating firms seems partly to be driven by poor performance of the control group.

In column (4), we specifically examine research consortia with at least one university or research institute partner. The positive relation between Vinnova funding and the number of patent applications is stable. However, research partnerships between private firms in column (3) do not show corresponding positive effect. The results rather seem to indicate that the positive effects of Vinnova funding are not driven by firm research collaboration.

To summarize the findings of the analysis with matched control groups, we find a positive effect of project participation for all Vinnova firms, which is sustained over the long-run. The results apply for individual research projects as well as research collaboration, with the exception of research collaboration with private firm partners. The long-term estimated effects are in general weaker than the short-term effects. Further exploration of the effects of collaboration on the number of patents follows below.

4.5.2 Estimated effects on patent applications without control group

Next, we examine research collaboration by comparing sub-samples of Vinnova firms directly, without matched control group. This supplements the results from the previous section, although we must be cautious about drawing any conclusions about causality from these comparisons. For example, if one sub-group greatly increased its patenting, while another did not, we could still estimate insignificant effects for both groups if their respective control firms followed the same trajectories. Comparing the treated groups with each other would reveal such differences. They could also be starting from different levels of patent intensity pretreatment.

The results are presented in Table 6. In column (1), we compare collaborating with non-collaborating Vinnova firms and find no short or long term differences in patent activity between groups. These results are in line with the two separate estimations with matched control group in the previous section, in Table 5 column (2) and (5). Thus, the analysis does not confirm that promoting research collaboration generates a larger effect than research support to individual firms. . We may also note that the negative and significant coefficient on *Treated* in column (1) indicates that the firms in the collaborating group applied for fewer patents on average prior to treatment, compared to the non-collaborating firms.

In column (2), we compare firm research partnerships with other collaborating Vinnova firms. Also this analysis confirms the results from the matched regressions in the previous section, Table 5 column (3). Research collaboration with other private firms was associated with a decrease patent activity compared to other research collaborations. Column (3) shows that firms collaborating with universities or research institutes increased their patenting more in the short run, compared to firms engaged in other types of collaboration.

Table 6 Comparison of Vinnova firms

Variables	(1) Collaboration vs. No collaboration	(2) Firm collaboration vs. other collaboration	(3) University or institution collaboration vs. other collaboration
Treated	-0.042**	-0.003	0.017
	(0.017)	(0.015)	(0.012)
Post short	0.046**	0.033***	0.006
	(0.021)	(0.009)	(0.010)
Post Long	0.005	0.025*	0.018
	(0.021)	(0.013)	(0.014)
DiD short	-0.017	-0.037**	0.032**
	(0.023)	(0.019)	(0.015)
DiD long	0.017	-0.027	0.006
	(0.024)	(0.021)	(0.021)
Observations	8,521	6,285	6,285
Year FE	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.5.3 Robustness

As we discussed in the Empirical challenges section, the firms participating in Vinnova research programs are not a random sample and their post-program patent activity could be altered for reasons unrelated to the research support. As described in the Methodological approach section, this study handles this by a combination of modern matching methods on observable characteristics, using matching variables well-motivated in the empirical literature on innovation output.

However, problems can remain and therefore, we have performed various alternative regressions to confirm the robustness of the results. Since some firms in the control group may never apply for patents, we re-run the main regressions with the requirement that all firms had filed at least one patent application during the three-year period prior treatment. In other regressions, we controlled for additional heterogeneity between firms by adding various control variables (age, size, industry, debt ratio, profitability), singled out as important in the evaluation literature. Moreover, to control for potential problems with outliers, we tested robustness using two alternative outcome variables; (1) a dummy variable if the firm has at least one patent, and (2), a dummy variable if a firm has more patents during the post-treatment period compared to the pre-treatment period. Finally, we estimated the regressions with different estimators. All different specifications and tests gave qualitatively similar and consistent results. Therefore, we have chosen to present the most basic specifications in the paper.

5. Concluding discussion

In this paper, we investigate whether collaborative research grants promote innovation. This by evaluating the effects of Vinnova research programs during the period 2010-2012 on Swedish firms' patent applications. In the study, we examine if public funding of research collaborations give larger estimated effects than support to individual firms. We also analyze if the effects of research grants depend on the type of collaborating actors in the research consortium.

Given the policy context with firms being ranked and picked by Vinnova, and the available data, including a rich dataset over Vinnova research projects and panel data over firms and patents, we employ a matching procedure and difference-in-difference (DiD) estimators. We are well-aware of the empirical challenges and the standard critique regarding causal interpretation of the results from this kind of matching approach to evaluate policy output. When selecting empirical method, we have closely studied method developments and followed the recent evaluation literature to find the most appropriate approach.

However, more importantly, the results indicate complete stability across specifications. We find that the Vinnova funded firms significantly increase the number of patent applications compared to the control firms. The short term estimated effect is stronger than the long term estimated effect in all specifications. We find no significant difference between collaborating and non-collaborating research projects; both groups increase patent activity. We can also observe that this positive estimated effect on patent applications is not driven by research partnerships among private firms. In fact, in our estimates firm research collaboration gives no effect on patent activity. Conversely, research collaboration involving universities and research institutes seem successful compared to other types of research collaboration in terms of firm innovation output.

Therefore, we conclude that Vinnova R&D programs increase the number of patents filed by the Swedish firms. Our analysis does not give evidence that support to research collaboration have a greater impact than support to individual firms. We also conclude that research collaborations including academia have a larger effect on patent activity than research collaboration between firms.

The literature on collaborative research present mixed results and the results from this study will unfortunately not contribute to larger coherence. Our findings are however partly consistent with the studies closest to ours, Lööf and Broström (2008), Czarnitzki et al (2007) and Bellucci et al (2019). In line with our findings, Czarnitzky et al and Bellucci et al find no specific positive effects from research collaboration on firm patenting. Using Swedish data, Lööf and Broström also find a positive effect on patenting for university-industry collaborating, at least when large firms are participating.

Although our findings are robust, we need to be careful when drawing policy recommendations. First, it should be underlined that a positive effect on the number of firm patent applications does not necessarily imply that the research grants are efficient and welfare enhancing. The theoretical and empirical literature alike provide both motives and reasons for policy failure. Above all, the policy cost could exceed the welfare gain. The estimated effects are however an indication of the empirical importance of the Vinnova research programs.

Second, there are alternative theoretical arguments for research collaboration. The ideas of synergy and interaction effects generated from shared and complementary competences and infrastructure would be an argument for university-industry collaboration. Firm research partnerships can be motivated by the opportunity to share investment costs and research results. Vinnova provides support for both types of research collaboration. Our evidence suggests that research collaborations with firms do not increase the number of patent applications. This result does however not necessarily imply that Vinnova should focus on university-industry collaboration. The reason behind a smaller number of patent application from research partnership involving firms only, could for example be a consequence of a lower necessity to protect the innovation, since the innovation already is shared and disclosed.

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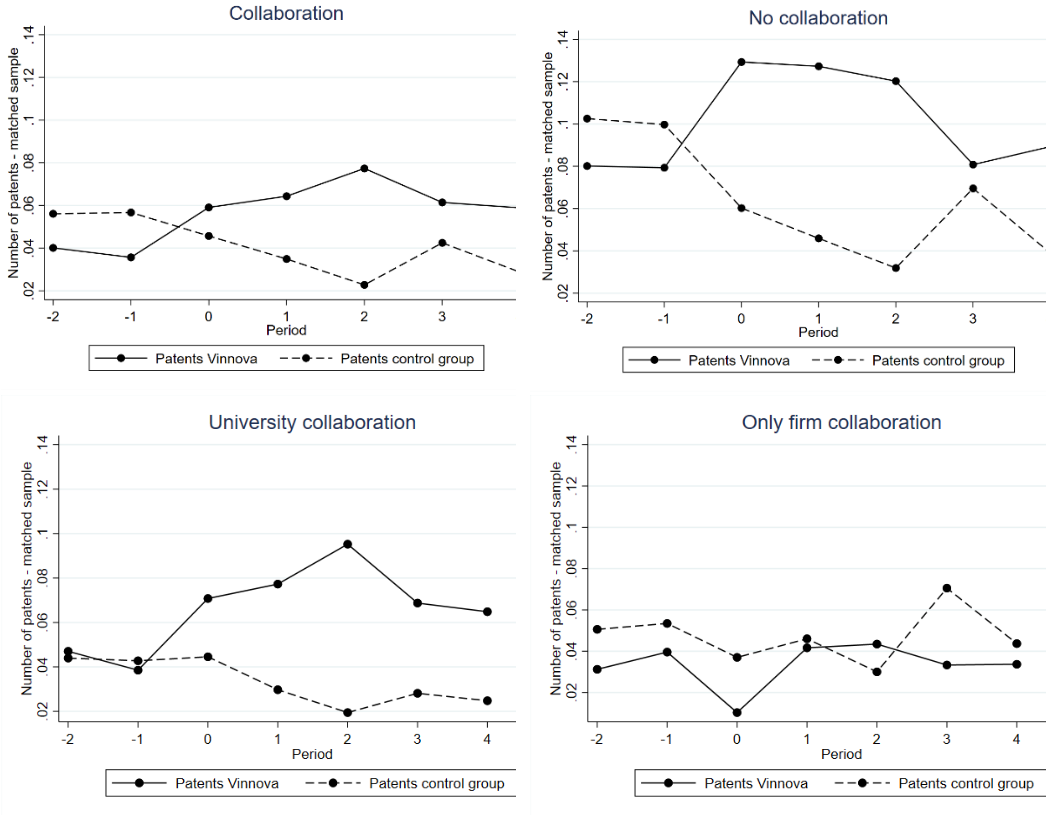
Appendix

Figure 2 Development of patent activity over time for four sub-groups of Vinnova firms



Tillväxtanalys har regeringens uppdrag att analysera och utvärdera statens insatser för att stärka Sveriges tillväxt och näringslivsutveckling. Genom vår kunskap bidrar vi till att effektivisera, ompröva och utveckla tillväxtpolitiken samt genomförandet av Agenda 2030.

I vårt arbete fokuserar vi särskilt på hur staten kan främja Sveriges innovationsförmåga, på investeringar som stärker innovationsförmågan och på landets förmåga till strukturomvandling. Dessa faktorer är avgörande för tillväxten i en öppen och kunskapsbaserad ekonomi som Sverige. Våra analyser och utvärderingar är framåtblickande och systemutvecklande. De är baserade på vetenskap och beprövad erfarenhet.

Sakkunniga medarbetare, unika databaser och utvecklade samarbeten på nationell och internationell nivå är viktiga tillgångar i vårt arbete. Genom en bred dialog blir vårt arbete relevant och förankras hos dem som berörs.

Tillväxtanalys finns i Östersund (huvudkontor) och Stockholm.

Den kunskap vi tar fram tillgängliggör vi på www.tillvaxtanalys.se. Anmäl dig gärna till vårt nyhetsbrev för att hålla dig uppdaterad om våra pågående och planerade kunskapsprojekt. Du kan även följa oss på Twitter, Facebook och LinkedIn.

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