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Subsidized R&D collaboration: The causal effect of innovation vouchers on innovation outcomes

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ABSTRACT

We study the causal effect of subsidized R&D collaboration on external collaborations and innovation outcomes of small and medium-sized enterprises (SMEs). In particular, we make use of a randomized controlled trial to analyze the effect of a nationwide innovation voucher scheme in the United Kingdom that grants SMEs across all industries financial support of up to 5,000 GBP for engaging the services of experts, e.g., from universities, research institutes or IP advisors, when pursuing an innovation-related project. Our results show that the innovation voucher program has an immediate, short-term impact on the execution of these innovation projects with positive effects on product and service development, internal processes, and intellectual property protection. However, we also observe that these results fade out quite quickly, i.e., two years after the intervention many effects caused by the innovation voucher program have disappeared. Based on our results, we also provide some practical guidance to further improve the effectiveness of voucher programs.

1. Introduction

It has been well established that R&D is important for economic growth and innovation, and we know that in particular small and medium-sized enterprises (SMEs) can be drivers of this (Audretsch et al., 2006; Haltiwanger et al., 2013; Howell, 2017). One of the reasons is that SMEs are particularly effective in developing radical innovations, which have been associated with value creation and productivity growth (Criscuolo et al., 2012; Hottenrott & Lopes-Bento, 2015; Scherer & others, 1986). To successfully exploit innovation opportunities, firms need the right combination of financial and human capital resources. However, these are two things that are often in short supply in SMEs. Due to their size, they typically lack access to financial resources, have less availability of skills and competencies, and lower absorptive capacity (Ortega-Argilés et al., 2009).

Several policy schemes have been introduced to reduce these company constraints (Czarnitzki & Delanote, 2015; Mina et al., 2021; Santoleri et al., 2020). First, direct R&D subsidies and fiscal incentives for R&D activities (such as tax credits) are meant to alleviate financial constraints. These policy schemes have shown to be partly effective in fostering R&D investments and innovation activities of SMEs. However, there are also some downsides to these schemes such as high administrative burden and limited availability (Hottenrott & Lopes-Bento, 2016; Romero-Jordán et al., 2014). Furthermore, recent research indicates that merely increasing R&D spending without the relevant additional human capital could be suboptimal, because internal capabilities are important drivers of innovation activities and success (Coad et al., 2014). Hence, policy makers have started to encourage external R&D collaborations by providing subsidies for these types of projects to alleviate human capital constraints (Hottenrott & Lopes-Bento, 2014; Kang & Park, 2012; Roesler & Broekel, 2017). However, these subsidized R&D collaborations are typically only available for a few large-scale research consortia (Branstetter & Sakakibara, 2002; Czarnitzki et al., 2007) and thereby do not seem to be the optimal tool to alleviate human capital constraints faced by SMEs. At the same time, alleviating these constraints seems particularly important, since research shows that in today's complex and knowledge-intensive environment the acquisition of missing knowledge and complementary

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resources is key to SMEs' innovation and growth outcomes (Parida et al., 2012; Spithoven et al., 2013).

One way to address this issue is by encouraging SMEs to get the required knowledge from external consultants or specialized knowledge providers. Building on the more general literature on R&D collaborations (e.g., Belderbos, Carree, & Lokshin, 2004; Cassiman & Veugelers, 2002; Leiponen & Helfat, 2010), several recent papers show that this type of collaboration is also highly relevant for SMEs (Hossain & Kauranen, 2016; van de Vrande et al., 2009). The question then arises: what prevents SMEs from accessing these resources that could be potentially beneficial to them? One of the reasons that has been identified in the literature is organizational resistance from managers regarding the use of external knowledge providers (Chapman & Hewitt-Dundas, 2018). Additionally, for many subsidies the administrative burden may be high which is particularly burdensome in a small organization, whereas the results of R&D expenditures are typically uncertain and not immediate (Sala et al., 2016). Moreover, the costs associated with external collaborations, such as communication and monitoring costs, may not outweigh the benefits (van de Vrande et al., 2009). Finally, collaborations with external partners can suffer from other issues, such as SMEs having difficulty articulating their knowledge needs, or the lack the absorptive capacity to use the acquired knowledge effectively (Muscio, 2007). Taken together, these factors can lead to suboptimal behavior by managers of SMEs when it comes to using external knowledge providers for their innovation activities (Bakhshi et al., 2015; Chapman & Hewitt-Dundas, 2018).

Policy tools that step in and support companies and managers in overcoming these burdens of collaboration could be beneficial for companies, and the increase in innovation seems desirable from a societal perspective. The innovation voucher is a policy tool that aims to do exactly that. The rationale behind this program is that it provides a small, low barrier subsidy that encourages SMEs to collaborate with an external partner on a specific, well-defined innovation project. The additional financial resources in combination with the acquired external knowledge will allow them to experience the benefits of increased knowledge and capabilities, without many of the downsides mentioned above. This policy tool has become popular in recent years and provides a small subsidy of typically 5,000 to 10,000 EUR to acquire knowledge that is not available within the SME (Bakhshi et al., 2015; Sala et al., 2016; Schade & Grigore, 2009).[1] However, to date, relatively little is known about the effectiveness of this policy tool when it comes to innovation outcomes. This paper aims to fill that gap by testing the effectiveness of the innovation voucher program on fostering innovation activities and improving innovation outcomes of SMEs.

To evaluate the effectiveness of the program, we are interested in two types of effects. First, we want to test if the voucher indeed increases collaborations of SMEs with external partners and to what extent this lasts beyond the treatment period. Second, we move beyond the analysis of collaboration activities and estimate the effectiveness of the innovation voucher on innovation outcomes. To this end, we collaborated with Innovation Growth Lab (IGL) and Innovate UK to evaluate a large-scale randomized controlled trial (RCT) that was conducted on a cross-industrial innovation voucher program in 2015 that addressed all SMEs in the United Kingdom (UK). Firms that were awarded the innovation voucher received (up to) 5,000 GBP to conduct an innovation-related project with any type of expert or partner they wanted to collaborate with, as long as they had not worked with them before. Applicants were randomly assigned to the treatment and the control group, where the firms in the treatment group were offered the voucher and the firms in the control group were not. Firms were further tested for eligibility for the voucher (cf Section 3.2. for eligibility criteria). The population of all eligible firms consisted of 1,463 firms (1,107 in the treatment and 356 in the control group). To assess the effects of the innovation voucher program, we collected various outcome measures related to innovation outcomes and activities by means of two surveys. The first survey was conducted one year after the award of the voucher, the second survey two years after the award of the voucher. Our final sample covers 760 observations (from 570 unique firms) that had applied for the voucher in 2015 and replied to one or both of our surveys.

In terms of firms' collaboration activities, we can report a significantly positive effect on the probability of having any external support for innovation activities in the year of the program. However, we do not find evidence for lasting effects on collaboration beyond the very period of the innovation voucher project execution. Furthermore, our results show that being awarded a voucher has a positive effect on project-related innovation outcomes. For example, we find positive effects on product and service development for those firms aiming to conduct respective projects with the innovation voucher, both one and two years after the program as well as a significant improvement of firms' internal processes overall in the first year. Furthermore, the innovation voucher has a positive short-term impact on the number of patent applications for those firms planning to use the innovation voucher for IP-related projects. However, also for these results we observe a high fade out of the policy intervention, i.e., two years after the treatment many differences between the treatment and the control group have disappeared. Finally, beyond these main effects, we were also interested in understanding reasons for non-compliance (i.e., not accepting or redeeming the voucher that was offered). The results show that an important predictor of voucher acceptance seems to be readiness, as indicated by having already chosen an external partner at the time of application. This finding is confirmed by responses to a set of specific questions on this topic at the end of the second survey. These responses further indicate that application process complexity is another important reason for not redeeming the voucher. Hence, our results suggest that innovation voucher redemption rates and successful project implementations could be increased by promoting readiness at the time of application, allowing for longer project execution periods and by further simplifying the administrative process.

With this paper, we make several contributions to the innovation policy literature. First, since there is already some evidence on the effect of innovation vouchers on future collaborations (e.g., Bakshi et al., 2015), the main contribution of our paper lies in understanding if this policy tool and the use of external knowledge providers by SMEs also leads to improved innovation outcomes. Second, endogeneity in the choice to search for and to use external knowledge for innovation activities prevents the estimation of causal impacts of external knowledge acquisition on innovation outcomes. The random assignment of a subsidy that intends to increase collaborations with external partners provides us with the perfect instrument to estimate these effects in a causal way. Furthermore, we extend existing findings on innovation vouchers that are limited to a narrow scope in terms of industry, type of collaboration partner and region (Bakhshi et al., 2015; Cornet et al., 2006) by making use of a large-scale field experiment to test the effectiveness of a nationwide, all-industry program with a broad scope of potential partners. Lastly, our study makes important contributions to the policy debate on how to support innovation activities of SMEs. In this respect, our results also provide guidance on how to increase the effectiveness of innovation voucher programs.

The remainder of the paper is structured as follows. In Section 2, we provide an overview of the related literature Section 3. covers the context of the innovation voucher program and the design of the RCT. The data and methods descriptions (Section 4) are followed by the presentation of the results (Section 5). In Section 6, we discuss and conclude.

[1] Innovation voucher programs are widely spread throughout Europe, Australia, Canada, and the US with schemes on the national and regional level. The respective scope of the different programs varies and the subsidies range from 500 EUR to 25,000 EUR.

2. Related literature

In this section, we provide an overview of the related literature. We start by examining the rationale behind public R&D support schemes in general and discuss the potential limitations of these schemes for SMEs (Section 2.1). Next, we focus our attention on the literature on external R&D collaborations (Section 2.2), before considering the innovation voucher as a specific policy tool that aims to improve innovation outcomes by SMEs in Section 2.3.

2.1. Public R&D support

It has been widely acknowledged that SMEs play an important role in innovation activities, technological change and future growth (Cohen et al., 2002; Czarnitzki & Delanote, 2015; Mina et al., 2021; Veugelers et al., 2008). However, because public returns to R&D are potentially higher than the private returns, investment levels in R&D are typically below the social optimum (Veugelers et al., 2008). For SMEs, there are several barriers that prevent them from reaching their full innovation potential. For instance, the most prominent challenges that SMEs face when striving to innovate is accessing the required financial and human capital resources. To alleviate these constraints, increase R&D investment levels, and improve innovation performance, policy makers have implemented a number of public support schemes targeted at all types of firms including SMEs (Canton et al., 2013; Czarnitzki & Hottenrott, 2011; Mina et al., 2021).

With regards to financial constraints, there are two types of policy tools that are most common: direct R&D subsidies and R&D tax credits or fiscal incentives. The literature studying the effects of the former on innovation activities by SMEs mostly deals with larger subsidies aiming at directly relaxing firms' financial constraints. The results from these studies typically show a positive impact of direct R&D subsidies on innovation outcomes, such as patents and new product development (e.g., Czarnitzki & Delanote, 2015; Czarnitzki & Hottenrott, 2011; Howell, 2017; Lerner, 2000) as well as more indirect effects such as SMEs' increased access to long-term debt (Meuleman & De Maeseneire, 2012) and an increased likelihood of future collaborations (Bianchi et al., 2019). While direct R&D subsidies are only available to a small set of selected companies, R&D tax credits or similar types of fiscal incentives are broader policy tools aimed at reducing financial constraints (Bloom et al., 2002; Lokshin & Mohnen, 2012). The main aim of these tools is to lower the user cost of capital for all firms that are targeted by the tax incentive to stimulate investment in R&D by these firms (Cowling, 2016). Several studies have been conducted to evaluate the effectiveness of this policy measure and the findings suggest that there are indeed benefits in terms of higher R&D expenditures and improved innovation outcomes for SMEs (Cappelen et al., 2012; Coad et al., 2014; Czarnitzki et al., 2011).

However, there are also several potential drawbacks to public R&D support. For example, there is the risk of crowding out, i.e., when public spending drives down private spending without increasing the overall amount spent on R&D (Hottenrott & Lopes-Bento, 2014). Furthermore, in the case of R&D tax credits, the scale of the forgone taxes is not trivial. If tax credits are mainly used by large firms to reduce the burden of corporate tax, this could lead to long term inefficiencies and deadweight loss (Cowling, 2016; Romero-Jordán et al., 2014). Finally, recent research indicates that merely increasing R&D spending without adding the appropriate human capital could be ineffective. For example, Coad et al. (2014) found that strategic intent and internal capabilities are important drivers of innovation activities, more so than the R&D tax credit. Hence, besides financial constraints, the other constraint that needs to be alleviated is access to relevant human capital. This is especially important for SMEs because they are disproportionately affected by knowledge constraints (Czarnitzki & Delanote, 2015; Hottenrott & Lopes-Bento, 2014) due to their weaker competencies (Ortega-Argilés et al., 2009) and lower absorptive capacity (Muscio, 2007).

2.2. External R&D collaboration

One way to resolve human capital constraints for innovation activities is by encouraging firms to find the relevant knowledge outside of their organization, for example through external R&D collaborations (Hottenrott & Lopes-Bento, 2016). The rationale behind fostering external collaboration is that successful innovation depends on accessing new knowledge by expanding the knowledge, skills and capabilities of the own firm. When searching for knowledge, firms tend to search in close proximity, both in terms of geographical location as well as in terms of technological expertise (Wagner et al., 2014). However, when it comes to innovation activities, there is a clear benefit from tapping into larger and broader pools of knowledge (Leiponen & Helfat, 2010). Furthermore, since new knowledge is constantly being generated by different actors in the economy, it no longer seems possible to have all the required knowledge in-house (van de Vrande et al., 2009). Therefore, SMEs need to capitalize on external knowledge and collaborate with various types of partners to create and commercialize new innovations (Haus-Reve et al., 2019). Bringing in external partners can be useful to enhance R&D productivity and to be able to better exploit existing resources, as they can serve as novel sources of ideas, ensure fast access to resources, and enhance knowledge transfer (Hottenrott & Lopes-Bento, 2016; Tether & Tajar, 2008).

However, so far most of the policy tools in this context were targeted at fostering R&D collaborations in the form of larger research consortia, where SMEs typically only played a minor role (Branstetter & Sakakibara, 2002; Czarnitzki et al., 2007). Only more recently, the research on open innovation and external knowledge collaborations has expanded to include multiple industries and different types of collaboration (Haus-Reve et al., 2019; Mina et al., 2014; Tether & Tajar, 2008). Overall, there is quite some evidence that shows that technology acquisition, R&D collaboration and the adoption of open innovation practices are positively related to SMEs' innovation outcomes, in terms of product or service innovation, patenting activity, and process innovation (Czarnitzki & Delanote, 2015; Hossain & Kauranen, 2016; Parida et al., 2012). For example, research has shown that collaboration with external partners has a more positive influence on launching new products and services for SMEs as compared to large firms (Spithoven et al., 2013). These partners also help SMEs to capture the value of their inventions by generating sales from them (Czarnitzki & Delanote, 2015; Tether & Tajar, 2008; van de Vrande et al., 2009).

Besides these benefits, there are also a number of drawbacks of external R&D collaboration for SMEs (Hottenrott & Lopes-Bento, 2016). First, there is the issue defining the knowledge requirements and searching for the right partner (Hossain & Kauranen, 2016). Second, since trust is important for successful collaboration (Chapman & Hewitt-Dundas, 2018), resistance within the firm to use external sources could hinder successful access and use of relevant knowledge. Moreover, once the correct partner has been found, it is important to have sufficient absorptive capacity within the firm to use the external knowledge effectively which may be more challenging for SMEs (Muscio, 2007). Furthermore, working together with external partners can lead to coordination cost and requires more monitoring. The more complex the project, the higher these costs will be (Leiponen & Helfat, 2010), which could be problematic for smaller firms with limited available resources (van de Vrande et al., 2009). Finally, since collaborating with external partners on R&D activities requires some disclosure of knowledge, there is always the risk of idea expropriation (Laursen & Salter, 2014). Even though intellectual property (IP) protection seems at least as important for SMEs as for larger firms, research shows that SMEs are more selective about what IP they protect (Spithoven et al., 2013).

Besides the drawbacks for external collaboration itself, there are also some concerns with respect to public support schemes for R&D collaborations in general. One drawback that has been mentioned in relation to large-scale R&D subsidies is the high administrative burden (Branstetter & Sakakibara, 2002). Applying for large subsidy programs typically involves a long, sometimes complicated process for which SMEs lack the resources and expertise, making these schemes unattractive to them (Czarnitzki et al., 2007). Furthermore, also in this case there is the risk of crowding out, i.e., if all attention and resources are spent on one particular project at the expense of other potentially promising projects this can be inefficient. Because SMEs are more resource constrained than larger firms, they must think even more carefully how time and money is spent (Hottenrott & Lopes-Bento, 2016).

2.3. Innovation voucher as a policy tool

To attenuate some of the drawbacks described above, policy makers have become increasingly interested in small innovation subsidies for SMEs called innovation vouchers, as an alternative to the more formalized and long-term subsidized R&D collaborations. The rationale behind these vouchers is to encourage and subsidize external collaborations by SMEs on a specific innovation project. For example, one of the objectives of this policy scheme is to reduce the behavioral failure of managers when it comes to the use of external knowledge (Bakhshi et al., 2015; Chapman & Hewitt-Dundas, 2018). That is, it tries to overcome organizational resistance from managers by encouraging them to find the knowledge or expertise they need to execute a specific innovation project externally and to collaborate with an external partner that they have not worked with before. Moreover, while the main aim of these vouchers is not to remove financial constraints, receiving 5,000 GBP of public funding in one R&D year could still be an important resource that helps SMEs to undertake an innovation project that they would not have done otherwise. Furthermore, the increase in relevant knowledge and capabilities through the collaboration with external experts that are new to the firm should lead to fresh ideas and more successful innovation outcomes for this specific project. This could encourage SMEs to draw on external knowledge providers more easily in the future (Bakhshi et al., 2015). Finally, instead of having a complex application process to obtain the subsidy, the administrative process to apply for the innovation voucher is typically very straight forward and short, as to not discourage SMEs from applying for this subsidy.

Based on the objectives and the design of the innovation voucher as a policy tool, several effects can be expected. In terms of collaboration between SMEs and external knowledge providers, there are likely to be some first order effects because of the direct financial incentive provided by the program to search for the support of an external expert. Recent studies that have looked at how innovation vouchers influence behavioral outcomes, in terms of attitudes towards external knowledge providers and the number of projects conducted with external partners, show that being awarded an innovation voucher leads to a short term increase in external collaborations for innovation activities among SMEs (Cornet et al., 2006; Chapman & Hewitt-Dundas, 2018). Furthermore, there are reasons to believe that receiving an innovation voucher will also lead to improved innovation outcomes. Indeed, some preliminary evidence on the positive impact of a small innovation subsidy (called creative credits) on innovation outcomes has already been documented in the paper by Bakhshi et al. (2015). This paper primarily discussed the merits of experimental methods to policy evaluation for industrial and innovation policy. As an example of an experimental approach, the authors examined a small scale (N=150) regional program that provided firms in the treatment group with a small (4,000 GBP) subsidy intended to stimulate partnerships between SMEs and very specific types of knowledge providers (i.e., creative service providers) around Manchester City (United Kingdom). In terms of innovation output, Bakhshi and colleagues found that firms in the treatment group are more likely to have product, service, or process innovations, or new to market innovations one year after being awarded the voucher.

The aim of our study is to extend this evidence by investigating whether innovation vouchers can stimulate innovation outcomes on a broader scale. As discussed above, the effectiveness of the innovation voucher relies on two complementary components: external collaboration and financial support. On the one hand, the focus of the tool has been on resolving human capital constraints. On the other hand, especially for SMEs, the additional financial resources may help them to push forward the development of a particular innovation activity or project. Hence, the observed effects in terms of innovation outcomes may be due to the additional funding and/or the collaborative element of the grant.

3. Context and RCT design

3.1. Context and program

The innovation subsidy that is analyzed in this study is called “Innovation Vouchers Programme”. It was established by Innovate UK, the UK government’s national innovation agency and part of the UK Research and Innovation organization, in 2012 with an annual budget of 4 million GBP. The program provided up to 5,000 GBP to enable innovative small and medium-sized businesses to engage the services of experts they had not worked with before to gain new knowledge that could help their business to innovate and grow. In the 10 rounds that were conducted before our study, over 6,600 firms applied for a voucher with the result of over 3,100 subsidies being awarded. Of those, nearly 2,000 vouchers were redeemed. The innovation voucher program was discontinued in 2016 for several reasons (e.g., strategic considerations, high administrative burden as well as budgetary cuts led to the decision of stopping the program to focus on other areas).

The innovation voucher’s logic chain (developed by Innovate UK) was based on the rationale that the different elements would lead to the persistence of the impact of the voucher over time. This rationale can be summarized as follows: First, it aimed to stimulate SMEs to work with external knowledge providers by incentivizing a first contact. Second, collaboration with external experts was presumed to result in enhanced knowledge and capabilities of SMEs, which in turn should lead to more innovation outcomes. Finally, the goal of the voucher was to stimulate ongoing collaborations with the new knowledge base beyond the expiry of the voucher (see Table A.1 in the Appendix for more details). To this end, the governmental initiative granted SMEs from all sectors financial support of up to 5,000 GBP for engaging the services of experts from the public or private sector for pursuing a particular innovation-related project within the firm. Given the relatively small amount of support, the scheme was mainly targeted at small-scale projects, for example leading to an improved IP protection and product, service, or process development, rather than breakthrough innovations.

At the time of the intervention, there were many different types of support mechanisms available for SMEs through Innovate UK. These ranged from interventions that help firms to find the right partner, gain access to expertise or equipment, providing financial loans and grants as well as connecting firms with investors. The innovation voucher program combined a small amount of public funding with the obligation to find expert advice or external knowledge for a specific business challenge. These elements distinguished the program from other support programs in several ways. For example, the scope of the projects that was conducted within the program was quite small and focused, e.g., improving the design of a product, identifying suitable materials for production, advice on how to file a patent, or how to commercialize an existing patent. Furthermore, the amount that was available through the innovation voucher program was much smaller compared to other funding schemes. Data on other Innovate UK R&D grant applications of the firms in our sample in the same time period shows that only approximately 1% of these grants were smaller than 20,000 GBP and the average amount of funding sought was 200,000 GBP. Finally, based on the findings from Coad et al. (2014), the combination of financial and human capital resources could be an important determinant in the success of the program.

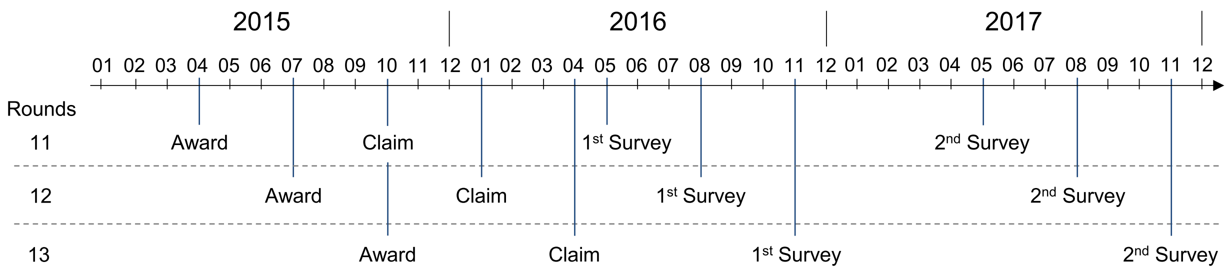

Fig. 1. Timeline of the RCT

3.2. Design of the RCT

To analyze the effectiveness of the program we used the randomized allocation of the voucher for three application rounds in 2015. The vouchers in these rounds were awarded in April, July, and October of 2015, respectively. We examine the year 2015 because the application rounds before and after this time period were targeted at specific themes, such as energy, water, or cyber-security, and at specific geographical areas, which to that date had relatively low levels of private sector innovation and growth. This focus led to an insufficient number of applicants in these rounds to be able to run a proper randomization process. An RCT proposal was written for rounds 11-13. To ensure a large enough number of applicants, these rounds were made available to SMEs from all sectors and without any restrictions on the innovation project.

There were four main stages for participation in the innovation voucher program: (1) application, (2) lottery and eligibility checks, (3) voucher claim, and (4) final payment. In the initial application stage, firms indicated the specific innovation project that they wanted to pursue with external help. If already available, the applicants further proposed a certain external partner that they anticipated working with and assessed the potential impact of the innovation project on their business. In addition, firms answered a questionnaire, which included baseline firm characteristics, past innovation-related activities as well as plans on future activities. In the second step, a lottery was run. The randomization was conducted within the financial restrictions of the overall budget of the innovation voucher program. As such, the lottery could produce as many offers as were needed to ultimately meet the budget. The selected firms were then reviewed by three independent reviewers who checked for certain eligibility criteria. The eligibility criteria for the program required an applicant to be located in the UK and to be a start-up, micro (<10 employees), small (10-49 employees), or medium-sized (50-249 employees) business. Furthermore, the applicant should require help from a specialist to execute a specific innovation project or meet a certain business challenge. Firms were only eligible for the innovation voucher if they had not worked with the chosen external partner before the program. Finally, applicants were not considered if they had previously received an innovation voucher from Innovate UK. To obtain a control group that was comparable to the firms in the treatment group, businesses that did not succeed during the lottery were also subjected to the eligibility check. Reviewers did not know whether a firm had passed the lottery or not. After the review process, a due diligence check with an optional personal credit check was conducted for the firms in the treatment group.[2] An innovation voucher was offered if the applicant passed the lottery and all outlined checks. The third step included the process of claiming the innovation voucher. Applicants had 10 days to accept their offer and up to 6 months to complete the proposed project. After the work was completed, the applicant uploaded a claim form. Finally, the claim was reviewed by a program official with the result of issuing the payment of an amount of up to 5,000 GPB in case of approval.

4. Data and methodology

4.1. Data and sample

In order to evaluate the voucher's effectiveness, we collected data from three sources: (1) Innovate UK, (2) Companies House API, and (3) two surveys. Innovate UK provided us with several types of information. First, they gave us information on the firms that applied for the innovation voucher program, covering all details from the application form. They also informed us on the allocation of firms into the treatment and the control group in the respective rounds, including information on whether firms passed the eligibility checks. Finally, they provided us with data on all other Innovate UK R&D grant applications of the firms in our sample before (between 2010-2014), during (in 2015) and after (2016-2021) the innovation voucher program.

The second data source that we used is the Companies House API.[3] In the application form, not all companies provided their address. Yet, we wanted to control for companies' main location in our randomization and response bias checks as well as in our main analyses. In order to include those companies with missing addresses in our analyses, we used the developer hub of the Companies House API to match this information to our data. With this approach, we were also able to obtain information on the industry in which a company is active, in a well-structured manner according to the "Standard Industrial Classification" (SIC). For most firms (N=1595, 74.2%), we were able to pull the data directly, using the company's unique Companies House Number. For the other firms, we first tried to match them using the company name and their postcode, this was successful for 134 additional firms. For the remaining firms we used a fuzzy matching algorithm that matched the company with the closest possible string distance between the names. This was successful for 357 additional firms (16.6% of our sample). For 63 firms we were unable to find a match and used the available information from the application form (in our final sample location information is missing for 17 firms).

As a final source of data, we designed a questionnaire measuring the firms' innovation activity and outcomes as well as collaborations and business outcomes (cf. Online Appendix 2). The logic chain described in Section 3.1 included both immediate as well as lasting effects of the innovation voucher program. Hence, all applicants of the innovation voucher scheme in 2015 were contacted twice. For each application round, the first survey was conducted one year after the voucher's award and the second survey was conducted two years after (cf Fig. 1.).

Firms were first contacted via an online survey (Computer-assisted web interviewing, CAWI) with follow-up phone calls (Computer-assisted telephone interviewing, CATI) in each of the two survey rounds. Firms were contacted by an independent research organization. They were

[2] For legal reasons, firms in the control group could not be subjected to a due diligence check. In our estimations, we will therefore compare the treatment and the control group based on the lottery and the eligibility check.

[3] https://developer.company-information.service.gov.uk/

Table 1
Sample composition

	Total	Treatm. (T)	Control (C)	T-C
Total	1,463	1,107	356	
Survey 1 (year 1 after award)	459	364	95	
Response rate	*31%*	*33%*	*27%*	*6%***
Survey 2 (year 2 after award)	301	240	61	
Response rate	*21%*	*22%*	*17%*	*5%**
Total observations: Survey 1 & Survey 2	760	604	156	
Unique firms: Survey 1 or Survey 2	570	447	123	
Response rate	*39%*	*40%*	*35%*	*5%**

** $p<0.01$
* $p<0.05$
* $p<0.1$. (Pearson Chi^2 test).

told that they are being surveyed in order to learn more about the innovation activities and needs of UK firms. Hence, in order to prevent any biased responses or behavior, the survey participants were not informed about the objective of evaluating the innovation voucher scheme.

For the analyses, we focus on the group of companies, which passed the program eligibility check. Firms that did not pass the eligibility checks were not included in our analyses, because these were not the firms that were intended to be treated by the innovation voucher scheme Table 1. shows the resulting sample composition. Overall, 2,149 firms applied for the program of which 1,463 firms were eligible to the voucher. These eligible firms were divided into the treatment (1,107 firms) and the control (356 firms) group depending on whether they passed the lottery. It is important to note that the imbalance between the two groups is not the result of any selection bias, but rather due to the fact that the randomization was done within the budgetary boundaries of the innovation voucher program. This meant that firms were randomly assigned to the treatment group, until the budget of the program was fulfilled. Hence, the share of firms assigned to the control group is related to the number of applicants in a certain round, but not due to non-random attrition of firms from this group. However, especially in the survey in year two, the small sample size in the control group could affect the power of our statistical test, making it more difficult to find a significant effect of the treatment. We will take this into account when discussing our results.

Table 1 also presents data on the number of respondents for the two survey rounds. A total number of 459 firms participated in the first survey that was conducted one year after the subsidy was awarded. This equals an overall response rate of 31%. In the treatment group the response rate is 33% (364 firms) and 6 percentage points higher than in the control group (27%, 95 firms). The second survey round is characterized by a lower response rate than the first survey round (21%, 301 firms). Again, the treatment group (22%, 240 firms) has a 5 percentage points higher response rate than the control group (17%, 61 firms). Overall, the total number of observations amounts to 760 for both surveys. As 190 firms responded to both survey rounds, the number of unique firms sums up to 570 businesses (treatment: 447, control: 123). In Section 4.2, we elaborate on whether the lower response rate by firms in the control group as compared to the treatment group is also likely to result in biases, in particular if it leads to significant differences between treatment and control group in the survey sample.

Table 2 shows some background characteristics of the firms in our survey sample. In part A of Table 2, we present the industry structure of our survey respondents, for the treatment and control group separately. We elicited a firm's principal industry based on the International Standard Industrial Classification (ISIC) and observe that in both groups, about 70% of all survey respondents indicated their principal activities as services (treatment: 71.14%; control: 69.92%). In part B, we present the firm size distribution at the time of application, as measured by the number of employees. The majority of our survey respondents reported

Table 2
Summary statistics of survey sample

A. Industry classification	Total surveys 1 & 2 Treatment	Control	Unique firms Treatment	Control	Unique firms in % Treatment	Control
Manufacturing and other non-service industries						
Manufacturing	127	44	97	33	21.70 %	26.83 %
Construction	18	2	13	1	2.91 %	0.81 %
Waste and recycling	14	1	8	1	1.79 %	0.81 %
Agriculture, forestry, and fishing	10	2	8	1	1.79 %	0.81 %
Others	5	1	3	1	0.67 %	0.81 %
Total manufacturing and other non-service industries	174	50	129	37	28.86 %	30.08 %
Service industries						
Professional, scientific, and technical services	175	42	124	32	27.74%	26.02%
Information and communication services	117	26	91	21	20.36%	17.07%
Retail and wholesale services	48	21	35	18	7.83%	14.63%
Human health services	18	7	11	5	2.46%	4.07%
Administrative services	19	3	15	3	3.36%	2.44%
Others	53	7	42	7	9.40%	5.69%
Total service industries	430	106	318	86	71.14%	69.92%
B. Firm size	Total surveys 1 & 2 Treatment	Control	Unique firms Treatment	Control	Unique firms in % Treatment	Control
No employees	37	8	27	7	6.04%	5.69%
1-10 employees	506	129	372	103	83.22%	83.74%
11-50 employees	47	16	37	11	8.28%	8.94%
> 50 employees	14	3	11	2	2.46%	1.63%
Total	604	156	447	123	100%	100%
C. Project goal	Total surveys 1 & 2 Treatment	Control	Unique firms Treatment	Control	Unique firms in % Treatment	Control
Products and services	296	83	219	65	48.99%	52.85%
IP	113	21	84	18	18.79%	14.63%
Sales and marketing	104	23	76	19	17.00%	15.45%
Conceptual	47	27	35	19	7.83%	15.45%
Internal processes	44	2	33	2	7.38%	1.63%
Total	604	156	447	123	100%	100%

to have 1-10 employees (treatment: 83.22%, control: 83.74%). About 6% of the observations refer to firms not having any employees (treatment: 6.04%, control: 5.69%), whereas about 2% indicated that they had more than 50 employees (treatment: 2.46%, control: 1.63%).

4.2. Randomization check and response bias

4.2.1. Randomization check

An important assumption underlying the internal validity of our estimation of the treatment effect is the random assignment to the treatment and the control group. In this section, we therefore test whether firms have been randomly assigned to the treatment and the control group based on firm characteristics from the application form, i. e., information about the companies at the date of application. In particular, we use the following information about the companies: the number of employees, the balance sheet total in GBP, turnover in GBP, the company's (main) location according to the Nomenclature of Territorial Units for Statistics 1 (NUTS 1), the company's industry according to the Standard Industry Classification (SIC), as well as binary indicators whether a firm belongs to a parent company, whether it has a defined R&D strategy, uses R&D tax credits, is exporting, holds or has applied for patents, holds or has applied for trademarks, and holds or has applied for design rights. We refer to Table A.2 in the Appendix for further explanations on the variables applied.[4] In addition, we examine whether there are differences between companies in the treatment vs. control group in terms of R&D grants received prior to the innovation voucher program. We use probit models to understand whether treatment and control group differ in some characteristics and, more importantly, whether the firm characteristics are jointly different between the two groups (McKenzie, 2015).

We apply randomization checks on three different levels: 1) a treatment vs. control group comparison of the entire population (Model (1), Table A.2 in the Appendix), 2) the comparison after the eligibility decision (i.e., after firms were excluded that did not pass the eligibility checks; Model (2), Table A.2 in the Appendix), and 3) the comparison of firms that responded to the survey and passed the eligibility checks (Model (3), Table A.2 in the Appendix).

We note differences on some dimensions of firm characteristics. That is, throughout all three levels of comparison, the treatment group is significantly less likely to hold a patent/patent application than the control group. Moreover, there seem to be differences between treatment and control group in the distribution of companies' main industry[5]. Lastly, in the eligible survey sample, the treatment group is significantly more likely to use R&D tax credits. Importantly, despite these differences on some dimensions of firm characteristics, the Chi^2-test for joint orthogonality (McKenzie, 2015) is not significant for any of the sample specifications.

As we will explain in detail in Section 4.3, we will also investigate heterogeneous effects based on the specific goal of the innovation project to be conducted with the innovation voucher. In particular, we will analyze treatment effects for companies that aimed to pursue a product-and service-related project. Moreover, we will examine treatment effects for those companies that aimed to improve the intellectual property protection with the help of the innovation voucher. Therefore, we categorized the survey sample according to the project objective (cf Section 4.3.). Here, we would like to explore, to what extent the randomization process also worked for these subsamples. In the subsample of companies that aimed to pursue a product- or service-related project, we do not observe any significant differences in the firm characteristics between treatment and control group (Model (4), Table A.2 in the Appendix). In the subsample of companies that aimed to pursue a project to improve their intellectual property protection, we observe that companies in the treatment group are more likely to have a defined R&D strategy and are significantly less likely to be exporting than companies in the control group (Model (5), Table A.2 in the Appendix). However, the Chi^2-test for joint orthogonality is not significant for any of the particular subgroups of interest, which favors the notion of an overall random assignment also within these subgroups.

Based on these analyses, we conclude on the one hand that overall the differences between treatment and control group seem to be small and that the randomization process was largely successful. On the other hand, to account for the differences observed, we will investigate treatment effects not only by fully relying on the validity of the randomization process, but by also controlling for firm characteristics (cf Section 4.3.).

4.2.2. Response bias

A potential threat to the external validity (or generalizability) of our findings could be due to the non-random responses of firms to our surveys. We test for this potential response bias between respondents, i.e., firms that participated in at least one of our two survey rounds, and non-respondents (see Table A.3 in the Appendix). We apply probit regressions with the decision whether to respond to any of the survey, whether to respond to survey one, and whether to respond to survey two as the dependent variable. We investigate these response biases using the same dependent variables on firm characteristics as for the randomization checks.

When looking at the individual coefficients, we see that there are some differences between respondents and non-respondents. For instance, irrespective of the survey round, respondents are significantly more likely to be a patent holder/applicant (Table A.3 in the Appendix; Models (1), (2), and (3)). However, besides these differences, it is important to note that the Chi^2- tests for joint orthogonality are insignificant when comparing all survey respondents with non-respondents (Model (1), Table A.3 in the Appendix), when comparing respondents to the first survey round with non-respondents (Model (2), Table A.3 in the Appendix) and when comparing respondents to the second survey round with non-respondents (Model (3), Table A.3 in the Appendix).

Next, we examine response biases separately by treatment and control group. As for the analyses on the overall population, the Chi2-tests for joint orthogonality are also insignificant when comparing the survey respondents from the treatment group with treatment-group non-respondents (Model (4), Table A.3 in the Appendix) and when comparing the survey respondents from the control group with the control-group non-respondents (Model (5), Table A.3).[6]

4.3. Variables

4.3.1. Outcome variables

All outcome measures rely on survey data and capture information on the 12 months before the respective survey round. Based on the objective of the innovation voucher program, we consider two groups of outcomes. First, we try to replicate the findings from previous studies that have found positive (short-term) effects of similar subsidies on external collaborations (e.g., Cornet et al. 2006). External collaborations are measured by the probability of having received any external support

[4] Note that in principle, our analyses in this Section 4.2 could suffer from multicollinearity between covariates, which would artificially eliminate statistical significance. Therefore, we also investigated the variance inflation factors of the model coefficients. Based on these analyses, we deem the basic model specification with the above-mentioned variables appropriate. We refer to the Online Appendix 1 for the details on the multicollinearity analyses.

[5] We infer this from Kolmogorov-Smirnov tests of equal industry distributions amongst treatment and control group (the lottery sample: p=0.199; the eligible sample: p=0.070; the survey sample: p=0.067).

[6] Since the categorization by innovation project (e.g., product- and service related projects, IP related projects) has been conducted for the survey sample only, we cannot assess response biases by project category.

for innovation activities (binary indicator based on the set of questions under "Q10" of the survey, see the survey in the Online Appendix 2), the proportion of innovation activities conducted with the help of external partners (survey question "Q11"), and the total number of external partners that the firm worked with within its innovation activities (set of questions under "Q10" of the survey).

Second, in line with the aim of the voucher program to support beneficiaries to conduct an innovation-related project, we measure several innovation outcomes reflecting possible project outcomes. In particular, we analyze the number of minimum viable products (MVPs), the number of new products and services, the number of award received due to new products and services, the number of newly established internal processes, as well as the number of new patent, design right, and trademark applications (all variables from set of questions under "Q12" of the survey). This is in line with other papers studying innovation performance in both manufacturing and service firms (Criscuolo et al., 2012; Leiponen & Helfat, 2010).

4.3.2. *Explanatory variables – the treatment variable*

The most important explanatory variable in this study is of course the indication whether or not a firm was awarded an innovation voucher. This is captured by a binary variable (treatment effect) that is equal to one if the firm was randomly assigned to receiving the subsidy and passed the eligibility check and zero if it passed the eligibility check but was not assigned the voucher. Note that the treatment group also includes 107 firms that were assigned to the voucher, passed the eligibility checks but then failed the due diligence test. We had to include these firms in the treatment group, because due to legal reasons, firms in the control group could not be subjected to a due diligence check.

As in many randomized controlled trials, participation is voluntary among those randomly assigned to the treatment group. In our case, another 335 firms that were randomly assigned to receiving an innovation voucher ultimately did not redeem it (33.5% of those offered the voucher). We elaborate on the reasons for this in Section 5.3. Since we do not know, which of the firms in the control group would have redeemed the voucher if they had been offered the subsidy, in our main analyses, we do not restrict the treatment group to those that eventually redeemed the voucher. Consequently, we base our evaluation on the initial treatment assignment and not on the treatment actually received, thus applying an intention-to-treat analysis. Hence, the treatment effect we estimate in the main body of this paper is the effect of being offered a voucher. Since governments can also only offer certain programs but will not be able to force people to actually take-up and use them, we feel that this effect is also the most interesting from a policy perspective. At the same time, there is also merit in understanding the effect on those companies that eventually redeemed the voucher, i.e., on the treatment compliers. We will also investigate this effect instrumenting the endogenous decision of treatment compliance with the exogenous treatment assignment.

4.3.3. *Explanatory variables – control variables*

In principle, the setup of a randomized controlled trial should have resulted in random assignment of firms with different (observed and unobserved) characteristics to the two groups, which would allow us to estimate the unbiased effect of the innovation voucher program on the above-mentioned outcome variables without controlling for firm characteristics. At the same time, the use of control variables may help increase precision in the estimation (i.e., reduce variance). Moreover, if estimated effect sizes are similar with and without the inclusion of control variables, this provides a strong case for truly unbiased estimates and a case against an omitted variable bias.

Hence, in our main specification, we include a set of control variables in our regression analyses, which mainly aim to cover *basic firm characteristics*. With this main specification, we aim to reduce the risk of an omitted variable bias without overfitting the regression models. The firm's age (elicited in our surveys) controls for the fact that older firms may already be better connected to the external knowledge base. In a similar vein, older firms might be less financially constrained compared to younger firms. Furthermore, we include a binary variable indicating whether a firm is active in the service industry to account for industry effects (elicited in our surveys based on the International Standard Industrial Classification – ISIC).[7] Service firms have been shown to be more likely to engage the services of external partners (especially consultants) compared to manufacturers (Tether & Tajar, 2008). Moreover, the number of employees at the time of application, as indicated by the firms on the application form, takes possible effects due to firm size into account (e.g., larger firms should have more relationships, all else equal). As a last set of control variables on basic firm characteristics, we control for firms' (main) location by including region fixed effects at the level of major socio-economic regions ("Nomenclature of Territorial Units for Statistics 1" – NUTS 1). We obtain this information based on the firms' postal code as obtained from the Companies House API. In our main specifications, we also include round fixed effects to control for the selection into one of the three subsidy rounds that are being analyzed in this study. We apply the main specification throughout all treatment effect analyses in the main body of the paper as well as for the estimated effects on the treatment compliers, i.e., the instrumental variable estimations.

To investigate the robustness of the results obtained with our main specification, we further analyze treatment effects on two extremes with respect to the inclusion of controls. These robustness checks are reported in the Appendix of the paper (see Tables A.4 to A.12). On the one hand, we analyze treatment effects *without any control variables* and thereby fully rely on the random assignment of firms into treatment and control group. On the other hand, we investigate robustness by including *extended firm characteristic* control variables in addition to above-mentioned control variables for the basic firm characteristics and round fixed effects. With the latter approach, we mitigate the risk of an omitted variable bias even further. For the extended firm characteristics, we mostly rely on information obtained from the application form that reflect the firm status at the date of application. Specifically, we cover firms' balance sheet total in GBP, turnover in GBP, as well as binary indicators whether a firm a) belongs to a parent company, b) has a defined R&D strategy, c) uses R&D tax credits, d) is exporting, e) holds or has applied for patents, f) holds or has applied for trademarks, and g) holds or has applied for design rights (for detailed variable definitions see Section 4.2 and the table notes for Table A.2). Moreover, we control for whether firms have received governmental R&D grants in the 5 years prior to the innovation voucher program (information obtained from the Innovate UK R&D grants database).

4.3.4. *Interaction variables*

As previously discussed, the innovation voucher program has a broad scope with respect to how the funding of the 5,000 GBP should be used. The regulations laid out that the program aimed to support SMEs to collaborate with knowledge-based institutions across the public or private sector. However, it can be assumed that the innovation outcomes we observe are strongly related to the specific objective of the innovation project (i.e., the project goal), as described at the time of application. In line with this argumentation, Belderbos et al. (2004a, 2004b) point out that the goals and thus the determinants of R&D collaborations differ depending on the type of innovation project. Therefore, we will analyze specific innovation outcomes conditional on the type of innovation project planned. To this end, an independent classifier manually classified all project descriptions from the application form in order to

[7] As described above, we also obtained the SIC codes from the Companies House API database. However, we feel that the self-reported industry better reflects their main industry classification at the time of the intervention. Moreover, unlike for the SIC codes, we have the information available for all companies in our survey sample.

Table 3
Descriptive statistics by treatment and control group

		Overall			Treatment (T)			Control (C)			T=C
	Type	Mean	St.D.	Obs.	Mean	St.D.	Obs.	Mean	St.D.	Obs.	T-C
Survey data year 1											
Basic firm characteristics (controls)											
Age	Cont.	6.40	11.38	459	6.35	10.89	364	6.56	13.14	95	-0.20
Service industry	0-1	0.72	0.45	459	0.73	0.44	364	0.67	0.47	95	0.06
Employees at application date	Count	7.27	24.66	459	7.30	24.36	364	7.15	25.87	95	0.15
Collaboration											
External innovation support	0-1	0.80	0.40	459	0.83	0.37	364	0.66	0.48	95	0.18***
Proportion inno. with partner (%)	Cont.	40.43	35.01	451	41.04	34.52	358	38.06	36.94	93	2.98
Partners	Count	56.60	941.41	451	68.27	1058	357	12.29	20.72	94	55.98
Innovation outcomes											
New MVPs	Count	2.02	4.41	442	2.04	4.63	349	1.97	3.51	93	0.07
New products and services	Count	2.01	4.60	442	2.12	5.07	349	1.61	2.09	93	0.50
Product and service awards	Count	0.60	3.10	442	0.68	3.46	349	0.30	0.69	93	0.38
New internal processes	Count	1.37	3.23	442	1.48	3.49	349	0.97	1.87	93	0.51
New patent applications	Count	0.51	1.82	442	0.49	1.80	349	0.59	1.91	93	-0.10
New design right applications	Count	0.21	1.50	442	0.23	1.68	349	0.14	0.41	93	0.09
New trademark applications	Count	0.46	1.74	442	0.46	1.87	349	0.45	1.16	93	0.01
Survey data year 2											
Basic firm characteristics (controls)											
Age	Cont.	7.44	10.84	298	7.34	10.63	237	7.82	11.70	61	-0.48
Service industry	0-1	0.68	0.47	297	0.68	0.47	236	0.69	0.47	61	-0.01
Employees at application date	Count	7.00	22.65	301	7.25	24.54	240	6.02	12.81	61	1.24
Collaboration											
External innovation support	0-1	0.92	0.27	205	0.92	9.27	162	0.93	0.26	43	0.05
Proportion inno. with partner (%)	Cont.	35.10	36.48	272	34.38	36.60	217	37.93	36.18	55	-3.55
Partners	Count	9.70	14.29	279	9.74	15.04	223	9.57	10.94	56	0.16
Innovation outcomes											
New MVPs	Count	2.40	7.36	272	2.63	8.11	215	1.56	3.08	57	1.07
New products and services	Count	1.91	3.58	272	1.93	3.62	215	1.81	3.45	57	0.13
Product and service awards	Count	0.51	1.65	272	0.52	1.77	215	0.47	1.07	57	0.05
New internal processes	Count	1.84	4.44	272	1.75	3.57	215	2.19	6.82	57	-0.44
New patent applications	Count	0.47	1.15	272	0.44	1.03	215	0.58	1.52	57	-0.14
New design right applications	Count	0.27	1.23	272	0.19	0.90	215	0.58	2.02	57	-0.39**
New trademark applications	Count	0.34	0.97	272	0.34	0.91	215	0.35	1.17	57	-0.01

*** $p<0.01$
** $p<0.05$
* $p<0.1$ (t-tests). “Employees at application date” based on information from the application forms

assign one of the following project categories: products and services (incl. MVPs, new and improved products or services), IP protection, sales- and marketing-related projects, conceptual projects (e.g., business planning, feasibility studies), as well as internal processes. This classification was done for all firms (both treatment and control groups), but the classifier was unaware of the treatment status of the firms. Part C of Table 2 provides an overview of the number of firms by project category.

Based on the project goal, diverse outcomes are to be expected from the innovation voucher program. We expect effects on new MVPs as well as new products and services to be strongest among those firms that aimed to conduct a product- or service-related project. Hence, we will analyze the voucher’s effect on these outcomes separately for these companies. Businesses that were planning to conduct IP-related projects are expected to apply for new patents, trademarks, or design rights. Thus, we will analyze IP-related outcomes for firms with these projects separately. Note that the IP-related subgroup analysis relies on a relatively small number of observations and should thus be interpreted with caution. Unfortunately, the number of observations is even more limited for the other project categories and the project-related goals tend to be very heterogeneous, for instance within the sales and marketing category, the internal processes category, and the conceptual category. Hence, we refrain from subgroup analyses on these project categories.

4.4. Empirical strategy

We analyze the effect of innovation vouchers on collaboration activities and innovation outcomes (both overall and by project goal subgroups). Of course, we are interested in the main effect of the innovation voucher program on the different outcome variables. Yet, in particular when it comes to innovation outcomes, we expect diverging outcomes depending on the project goal. We therefore expect some of the effects to be particularly strong for the subgroup of firms that pursued similar project goals. Accordingly, we will conduct two types of analyses: (1) studying the main effect on the full sample, (2) and unbundling the effect of the particular subgroup based on their project goal from the effect on other firms not belonging to that subgroup.

Most of our outcome variables are count variables and highly skewed. Hence, for these outcome variables we apply Poisson regressions. In case of continuous outcomes variables, we will investigate ordinary least squares (OLS) regressions; for binary outcome variables, we apply probit regressions.

Whenever we study the main effect on the full sample, we will estimate the following equation (example of a Poisson regression):

$$\mathrm{E}[Y_i] = \exp\left[\alpha + \beta_0 T_i + \boldsymbol{\gamma} \boldsymbol{X}_i + \epsilon_i\right] \tag{1}$$

T_i indicates whether an observation is from the treatment group. Accordingly, β_0 represents the treatment effect on the full sample. We further include control variables $\boldsymbol{X}$ as explained in Section 4.3. ϵ_i refers to the random error.

Whenever we are interested in subgroup specific effects, we will estimate the following equation.[8]

[8] For a similar estimation model, see Galasso & Schankerman’s (2018) instrumental variables regressions, which also consider differential effects.

Table 4
Treatment effects on collaboration outcomes

Model	Collaboration outcomes					
	Year 1			Year 2		
	External innovation support (dummy) (1)	Proportion of innovation activities with partner (2)	Total number of partners (3)	External innovation support (dummy) (4)	Proportion of innovation activities with partner (5)	Total number of partners (6)
Treatment effect	0.557***	2.031	-0.136	-0.052	-5.949	0.107
	(0.163)	(4.536)	(0.405)	(0.334)	(6.094)	(0.239)
Constant	0.876**	37.519***	0.934	1.704***	43.448***	2.116***
	(0.354)	(7.938)	(0.173)	(0.538)	(11.882)	(0.344)
Observations	457	451	451	190	268	274
Wald Chi²/F-statistic	27.20	1.55	130.80	10.81	0.53	20.51
p of model	0.039	0.074	0.000	0.626	0.931	0.198
(Pseudo) R^2	0.057	0.025	0.542	0.053	0.027	0.051

Models (1) and (4): probit regressions; Models (2) and (5): OLS regressions; Models (3) and (6): Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects. Exception: Model (4) without controls for innovation voucher round fixed effects because of perfect prediction.

*** $p<0.01$

** $p<0.05$

* $p<0.1$

$$E[Y_i] = \exp[\alpha + \beta_0 T_i\{1|S_i = \dot{S}_i\} + \beta_1 T_i\{1|S_i \neq \dot{S}_i\} + \beta_2 \dot{S}_i + \gamma \boldsymbol{X}_i + \epsilon_i] \quad (2)$$

Here, β_0 represents the treatment effect for companies that planned to conduct a project falling under the project goal of interest $\dot{S}$. For instance, for product- and service-related outcomes, we focus on the subsamples that have announced to conduct product- and service-related projects and β_0 captures the treatment effect for this subgroup. For IP protection outcomes, we examine firms that planned to conduct IP-related projects. The coefficient β_1 of the second interaction term reveals the treatment effect on all other project categories $S \neq \dot{S}$ whereas β_2 shows the coefficient for firms with the project goal of interest ($\dot{S}$) in the control group. Once more, we include control variables $\boldsymbol{X}$ as explained in Section 4.3.

In our main analyses, we investigate effects on the companies that were *offered* the voucher, i.e., the intent-to-treat effect. Yet, we will also estimate the effects on those companies that eventually *redeemed* it. Since the decision to redeem is endogenous, we will rely on instrumental variable approaches, in which being offered a voucher serves as an instrument for redeeming the innovation voucher. We will apply respective two-step instrumental variable Poisson regressions, Two-Stage Least Squares (2SLS) regressions and two-step instrumental variable probit regressions, in analogy to the intent-to-treat estimations explained above.

5. Results

5.1. Descriptive statistics and comparison of means

Table 3 presents descriptive results for the full survey sample, and by treatment and control group separately. Firms that responded to the first survey round were on average 6 years old, had on average 7 employees at the date of voucher application, and were mostly active in the service industry (72%). Our data indicates that 80% of the companies received external support for their last year's innovation activities and conducted 40% of their overall innovation activities with the help of external partners. They were further characterized by innovation outcomes that on average amounted to 2 new MVPs, 2 new products and services and 0.6 product and service awards within 12 months after the subsidy was awarded. The number of applications for new patents, design rights, and trademarks varied from 0.2 for design right applications to 0.5 for patent and trademark applications within the year following the voucher's award.

The firms that replied to the second survey round are comparable to the respondents of the first round in terms of age (mean: 7 years), industry classification (68% were active in the service industry), and measures such as collaboration, new products and services or IP. Overall, it is important to note that most of the variables are characterized by a high variance, which is an indication for the heterogeneity of the firms that applied for the innovation voucher program.

Treatment and control comparisons of the sample means show that there are some substantial positive average differences, for instance, for project-related outcomes in year one (new products and services, product and service awards, new internal processes) and for new MVPs in year two. Yet, in simple comparisons of means, these results are not significant. In the next section, we will analyze these effects more closely and additionally unbundle the effect of innovation vouchers for subgroups according to their project goals.

5.2. Main results

We first test if the innovation voucher indeed has the desired effect on external collaborations. Once we have established that, we will analyze the causal effect of the innovation voucher program on innovation outcomes in terms of the creation of MVPs, new products and services, awards received due to new products and services, newly established internal processes as well as its effect on firms' intellectual property protection.

5.2.1. Collaborations

Table 4 shows the treatment effect on collaboration outcomes. We observe that the innovation voucher significantly increases the probability of having received any external innovation support in year one after the innovation voucher award (Model (1): β_0=0.557, p=0.001). Hence, the voucher has a positive effect on establishing innovation collaborations in the year of the innovation voucher program. However, this is a one-time effect for the period of the innovation voucher award and does not translate to the second year after the innovation voucher award (Model (4), Table 4: β_0=-0.052, p=0.876). Beyond the effect on the probability of having received any external support, we do not observe any substantial differences on other collaboration indicators such as the overall proportion of innovation activities with external partners or the total number of partners. This applies to one year (Models (2) and (3), Table 4) as well as two years after the program (Models (5) and (6), Table 4).

We also estimate the causal effect of the innovation vouchers on collaborations for those companies that actually redeemed the voucher.

Table 5
Treatment effects on product and service outcomes as well as on process outcomes

	Product and service outcomes												Number of new processes	
	Overall effect						Treatment effect for companies with product and service projects						Overall effect	
	Year 1			Year 2			Year 1			Year 2			Year 1	Year 2
	Number of new MVPs	Number of new prod. &serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new proc.	Number of new proc.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment effect	0.044	0.264	0.738*	0.438	0.132	0.014							0.428*	-0.243
	(0.193)	(0.168)	(0.377)	(0.392)	(0.342)	(0.386)							(0.233)	(0.518)
Treatment effect for companies with product & service projects							0.001	0.563**	0.486	0.936**	0.107	0.056		
							(0.293)	(0.240)	(0.397)	(0.459)	(0.334)	(0.630)		
Treatment effect for all others							0.128	0.009	1.340**	-0.004	0.191	-0.025		
							(0.227)	(0.225)	(0.560)	(0.487)	(0.419)	(0.467)		
Companies with product & service projects (Dummy)							0.376	-0.457*	1.401***	-0.559	-0.667	-0.116		
							(0.323)	(0.257)	(0.506)	(0.503)	(0.445)	(0.672)		
Constant	0.118	0.225	-1.829**	0.447	-0.075	0.205	-0.180	0.468	-3.009***	0.540	0.530	0.291	0.184	0.608
	(0.357)	(0.298)	(0.794)	(0.634)	(0.522)	(0.621)	(0.361)	(0.348)	(0.867)	(0.704)	(0.608)	(0.745)	(0.400)	(0.770)
Observations	442	442	442	268	268	268	442	442	442	268	268	268	442	268
Wald Chi^2	25.09	35.58	22.40	41.71	26.23	20.20	26.99	44.65	28.79	40.77	32.27	22.22	129.40	12.32
p of model	0.093	0.005	0.170	0.000	0.051	0.212	0.105	0.001	0.069	0.002	0.020	0.222	0.000	0.721
Pseudo R^2	0.037	0.061	0.133	0.149	0.059	0.092	0.043	0.065	0.152	0.159	0.096	0.092	0.068	0.042

Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects.

*** $p<0.01$

** $p<0.05$

* $p<0.1$.

Table 6
Treatment effects on IP protection outcomes

Model	Treatment effect for companies with IP projects Year 1 Number of new patent applications (1)	Number of new design right applications (2)	Number of new trademark applications (3)	Year 2 Number of new patent applications (4)	Number of new design right applications (5)	Number of new trademark applications (6)
Treatment effect for companies with IP projects	1.659**	0.356	0.253	-0.272	-0.716	1.135*
	(0.734)	(1.132)	(0.603)	(0.860)	(1.225)	(0.624)
Treatment effect for all others	-0.388	0.339	-0.112	-0.214	-1.387**	-0.069
	(0.335)	(0.450)	(0.280)	(0.400)	(0.662)	(0.470)
Companies with IP projects (0-1)	-1.531*	-0.900	-0.550	0.320	0.443	-0.452
	(0.795)	(1.101)	(0.597)	(0.863)	(0.921)	(0.650)
Constant	0.386	-1.828**	-1.843***	0.260	-1.501	-2.140***
	(0.621)	(0.781)	(0.653)	(0.625)	(1.215)	(0.690)
Observations	442	442	442	268	268	268
Wald Chi^2	51.36	29.40	23.23	23.68	7417.75	60.45
p of model	0.000	0.060	0.227	0.166	0.000	0.000
Pseudo R^2	0.107	0.157	0.082	0.094	0.356	0.125

Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects.
*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Respective two-step regression analyses, in which the decision to redeem is instrumented by the voucher assignment, show that the results obtained for the intent-to-treat group can be confirmed for the firms actually treated (for the year one effect on any external innovation support – Model (1), Table A.6 in the Appendix: β_0=0.925, p=0.000).

5.2.2. *Product- and service-related effects*

Table 5 summarizes the effects of the subsidy on newly created or significantly improved MVPs and products and services, as well as awards on products and services – on the full survey sample (Models (1) to (6)) and with a particular emphasis on those firms that had planned projects on product and service development (Models (7) to (12)). Each outcome variable is shown for the first and second survey round (i.e., one year and two years after the voucher's award, respectively).

The analysis of the full sample shows on average positive innovation voucher effects for newly created or significantly improved products and services: the positive coefficient of 0.264 corresponds to estimated 30.2%[9] more created or improved products and services for those that were offered a voucher compared to the control group. However, the estimated effect falls short of being significant (Model (2): β_0=0.264, p=0.117). Notably, for the overall sample, the innovation voucher significantly increases the firms' number of awards received for innovations or new products or services (Model (3): β_0=0.738; p=0.051).

In the second year after the innovation voucher award, the voucher is also estimated to increase the number of new or improved MVPs on average by 55%. Yet for the full sample, this difference is not statistically significant (Model (3): β_0=0.438, p=0.264). In the analysis of the subsample of companies that particularly aimed to conduct product- and service-related projects we observe more robust results. Here, the above discussed effects on new or improved products as well as on new or improved MVPs are stronger and significant (products and services – Model (8): β_0=0.563, p=0.019; MVPs – Model (10): β_0=0.936, p=0.041). This implies that firms that applied for the voucher with the aim to develop or improve their products or services and were offered the voucher are significantly more likely to be able to reach this innovation outcome compared to firms that had the same intention at application but were part of the control group. Furthermore, we observe no negative effects throughout both survey rounds, neither for the full survey sample nor for the subgroup. This indicates that the reported effect is net positive and not due to a speeding up effect of projects that is negated later on.

Lastly, we estimate the causal effect of the innovation vouchers on those companies that actually redeemed the voucher. Respective two-stage regression analyses, in which the decision to redeem is instrumented by the voucher assignment, show that the results obtained for the intent-to-treat group can be confirmed for the firms actually treated. The effect sizes are even larger (awards – Model (3), Table A.9 in the Appendix: β_0=0.952, p=0.042; products and services – Model (8): β_0=0.703, p=0.013; MVPs – Model (10): β_0=1.169, p=0.033).

5.2.3. *Internal processes-related effects*

Next, we look at new or significantly improved internal processes. The number of firms specifically targeting at internal processes is too low for causal inferences (survey 1: N=28; survey 2: N=18), therefore we rely on the full sample analyses, only. Model (13) in Table 5 shows that in year one the innovation voucher is estimated to increase the number of newly created or significantly improved internal processes significantly and by about 53% (β_0=0.428, p=0.066). The negative effect estimated for year two is smaller than the positive year-one effect and insignificant (Model (14), Table 5: β_0=-0.243, p=0.639).

We also examine the innovation voucher effect on internal process development for the group of firms that eventually redeemed the voucher. As for the intent-to-treat group, the firms that redeemed the voucher benefit from the innovation voucher and significantly increase the number of new or significantly improved internal processes (Model (13), Table A.9 in the Appendix: β_0=0.586, p=0.053); the negative treatment estimate for year two is once more insignificant (Model (14), Table A.9 in the Appendix: β_0=-0.345, p=0.656).

5.2.4. *Intellectual property-related effects*

We now turn our analyses to the effects of the innovation voucher on IP protection. Due to the specificity of this outcome measure, the analysis of the full sample yields no interesting findings. We refer the interested reader to the Online Appendix 3, Table O.1. In the main body of this paper, we focus on firms that applied for the innovation voucher in order to conduct an IP-related project Table 6. shows a significant treatment effect of the innovation voucher on the number of new patent applications in the first year after the voucher was awarded. The effects

[9] Taking the exponential of a Poisson regression coefficient and subtracting one yields the estimated percentage change of the dependent variable for a unit change of the independent variable (*here*: for changing from control group (0) to treatment group (1)).

Table 7
Predictors of innovation voucher acceptance and redemption

Model	Innovation voucher acceptance (0-1) (1)	Innovation voucher redemption (0-1) (2)
Supplier known at date of	0.278**	0.000
application (0-1)	(0.121)	(0.103)
Defined R&D strategy	0.178	0.083
(0-1)	(0.132)	(0.112)
Governm. R&D grants in the	0.378	-0.371*
year of the innov. voucher program (0-1)	(0.309)	(0.215)
R&D tax credits	-0.305*	0.021
(0-1)	(0.178)	(0.147)
Prior governmental R&D	-0.307	0.629**
grants (0-1)	(0.262)	(0.279)
Parent company	-0.823***	-0.245
(0-1)	(0.285)	(0.259)
Number of employees	-0.016***	-0.000
	(0.005)	(0.005)
Balance sheet total	-0.000***	-0.000*
in GBP	(0.000)	(0.000)
Turnover in GBP	0.000**	0.000
	(0.000)	(0.000)
Exporting (0-1)	0.040	0.059
	(0.161)	(0.129)
Patent holder/ applicant	-0.079	-0.048
(0-1)	(0.157)	(0.136)
Trademark holder/ applicant	0.301**	-0.134
(0-1)	(0.135)	(0.115)
Design right holder/	-0.113	-0.130
applicant (0-1)	(0.174)	(0.147)
SIC level 1 fixed effects	Yes	Yes
NUTS level 1 fixed effects	Yes	Yes
Round fixed effects	Yes	Yes
Constant	0.925*	0.954**
	(0.475)	(0.459)
Observations	909	818
Wald Chi^2	67.07	43.02
p of model	0.000	0.114
Pseudo R^2	0.099	0.048

Probit regressions. Robust standard errors in parentheses.
*** $p<0.01$
** $p<0.05$
* $p<0.1$

are sizeable – firms that applied with an IP-related project goal and were offered an innovation voucher, are estimated to have about 4 times more patent applications in the first year than firms that applied to conduct an IP-related project but were not offered a voucher (Model (1): β_0=1.659, p=0.024). We do not find a significant treatment effect for the number of design right or trademark applications in the first year after the voucher's award (design rights – Model (2): β_0=0.356, p=0.753; trademarks – Model (3): β_0=0.253, p=0.675). Two years after the award of the voucher, we observe another positive treatment effect – the innovation voucher significantly increases the number of trademark applications (Model (6): β_0=1.135, p=0.069). There are no significant treatment effects on the number of patent applications (Model (4): β_0=-0.272, p=0.752) or design right applications (Model (5): β_0=-0.716, p=0.559). Accordingly, the positive effect of the voucher on patent application in the first year does not continue in the second year, yet it does not revert either.

The analyses of intellectual property-related effects on those firms that eventually redeemed the voucher reveal even stronger results than those obtained for our intent-to-treat analyses. The estimated effect on year-one patent applications is substantially higher for the firms actually treated (Model (1), Table A.12 in the Appendix: β_0=1.967, p=0.012) than for the intent-to-treat group; the estimated effect on year-two trademark applications is moderately higher (Model (6), Table A.12 in the Appendix: β_0=1.298, p=0.058). Overall, our findings indicate that the relatively small treatment of the innovation voucher successfully supports SMEs in carrying out their plan to improve on their IP protection.

5.2.5. *Robustness tests*

As explained in Section 4.3, to test the robustness of our results obtained, we also conducted all intent-to-treat analyses without any control variable and with extended controls in addition to our main specification Tables A.4. and A.5 show robustness of our collaboration analyses, Tables A.7 and A.8 relate to robustness of product- and service-related results as well as results on internal processes Tables A.10. and A.11 show robustness of the IP-related findings. Except for the year-two result on new trademark applications, all results described above are robust across these model specifications and yield similar effect sizes.

5.3. *Additional results – predictors and behavior of non-complying and non-awarded firms*

Now that we have established these main effects, another thing that would be interesting is to gain more insights into the characteristics and behavior of the non-complying firms. Examining these firms that applied and were offered a voucher, and either did not accept it or did accept it but did not redeem the voucher, seems particularly important from a policy perspective. Understanding their problems within the innovation voucher program may be useful to reduce the rate of non-compliers and ultimately to improve the effectiveness of future innovation voucher programs.

To this end, we first conduct some descriptive analyses to understand more about the characteristics of these firms and the circumstances under which they decide to accept and redeem the voucher. Specifically, we run probit regressions to investigate whether the decision to accept the voucher (Model (1), Table 7) and whether to redeem the voucher (Model (2), Table 7) is correlated with the following factors: a) firms' readiness for innovation project execution (measured by a binary variable indicating whether a firm has already chosen a supplier at the date of application), b) firms' other governmental funding prior to and during the innovation voucher program, and c) firms' characteristics (cf Section 4.2. for variable definitions). We make use of information from the application form as well as information on other funding activities (cf Section 4.1. for detailed information on the data sources).

Next, we also use our survey data to provide descriptive evidence to what extent, and how non-redeeming firms and firms from the control group conduct the project with which they applied for the innovation voucher. For the non-redeeming group, we also investigate the stated reasons for not redeeming the innovation voucher. In order not to contaminate the main analyses of program effects with questions that make the connection to the innovation voucher program particularly salient, we decided to ask the respective questions only at the very end of the second survey.[10]

5.3.1. Predictors of non-compliance

When looking at non-compliance, we find that several factors seem to play a role. First, an important predictor of voucher acceptance seems to be readiness, as indicated by having already chosen an external partner at the time of application (Model (1): β=-0.278, p=0.022). Another reason for non-acceptance seems to be firm size, as measured by the number of employees (Model (1): β=-0.016, p=0.001), as well as having a parent company (Model (1): β=-0.823, p=0.004). That is, larger firms and those that have a parent company are less likely to accept the voucher. Finally, there seems to be some interaction with other R&D related funding. In terms of redemption, we find that conditional on having accepted the voucher, if firms also received other types of funding in 2015 (the year of the innovation voucher project), they are less likely to redeem (Model (2): β=-0.371, p=0.084). If they were successful in securing other types of funding before the year 2015, they are more likely to redeem the voucher (Model (2): β=0.692, p=0.024). That is, receiving other R&D funding prior to the voucher program seems to crowd in or complement the innovation voucher program, whereas other funding in the same year seems to crowd out innovation voucher redemption.

We now turn our attention to the behavior of the non-redeeming firms and stated reasons for non-redemption as well as to the behavior of firms in the control group (i.e., non-awarded firms), as elicited at the end of survey two.

5.3.2. Behavior of non-redeeming firms and reasons for non-redemption

Amongst those companies that were offered a voucher but ultimately did not redeem it, 62% still conducted the project they applied for. Those firms that conducted the project mostly financed the project themselves (80%). In this group, 26% firms conducted the project on their own. For the companies that opted for external support, prominent collaboration partners were universities, research and technology organizations, and users.

When being asked about the reasons for not redeeming the voucher, firms could choose from a diversity of different aspects, e.g., complicated voucher processes, other funding opportunities, lack of a suitable collaboration partner and lack of project completion time. Multiple answers were possible as well as the indication of other reasons not particularly listed in the survey items. Strikingly, about half of the respondents indicated that the project completion time of six months was too short in order to redeem. Moreover, 27% of them stated that the process was too complicated.

5.3.3. Behavior of non-awarded firms

Of the firms that replied to the second survey, about half the firms in the control group, i.e., that were not offered an innovation voucher, still managed to conduct the project for which they applied (51%). In 70% of these cases, the project was financed by own funds. Importantly, for many of these conducted projects, firms decided to move on without any collaboration partner (in 38% of these cases). Those who collaborated did so with a large variety of partners, the most popular being university partners, IP advisors, suppliers and design collaborators. This finding is in line with the above-mentioned treatment difference in the probability of having had external support in the year of the innovation voucher program (cf Section 5.2.). Behavior of the control group suggests that this collaboration effect may not only be driven by those firms that did not conduct the project they aimed for, but also by those conducting the project on their own.

[10] We base this analysis on those companies that correctly self-indicated at the end of the second survey whether they were offered an innovation voucher (N=231) and do not consider those firms that failed to do so (N=37).

6. Discussion and conclusion

Policymakers around the globe use public funding and government policies to support SMEs in their innovation activities. The rationale behind these policy measures is that these ventures have been shown to contribute substantially to economic growth (e.g., Haltiwanger et al., 2013; Scherer & others, 1986) and are more likely to introduce radical innovations (Criscuolo et al., 2012; Hottenrott & Lopes-Bento, 2015). However, due to their size, SMEs are also more likely to face financial constraints and have limited access to innovation-relevant knowledge (Lerner, 2000; van de Vrande et al., 2009). To ease knowledge constraints, firms of all sizes increasingly rely on external collaborations for their innovation activities. Yet, here again, SMEs seem to be at a disadvantage to implement these collaborations successfully, for example, due to a lack of available resources to search for the right partner. In this paper, we examine a policy instrument, called innovation voucher that promotes R&D collaboration between SMEs and external partners in order to improve innovation outcomes.

To test the effectiveness of this policy tool for SMEs' innovation outcomes, we make use of a large-scale RCT on the innovation voucher program in the UK. Our findings provide evidence that the innovation voucher program successfully fosters the execution of innovation projects with positive effects on innovation outcomes. For example, we find that it fosters the creation of products and service in the first year after the innovation voucher award and the development of MVPs in the second year among those firms that applied for the voucher with product- and service-related project goals. Second, our results show an increase in the number of new or improved internal processes for all firms in the treatment group. Finally, it seems that firms with IP-related project goals benefited from collaboration with IP advisors, leading to more patent applications as well as trademark applications in the treatment group among those firms.

However, we do not find measurable impacts of the voucher on several other objectives that the subsidy was targeted at. While we find evidence for the innovation voucher to increase the likelihood of interaction with external partners in the year of the program, we do not observe a significant impact on ongoing collaborations one year later. This is in line with previous studies that find no evidence for medium-term network externalities (Bakhshi et al., 2015). Thus, it seems that while the voucher provides an effective stimulus to reduce knowledge constraints for SMEs for a specific project, it does not seem to help SMEs resolve knowledge constraints in the long run. This means that the idea that this one-time positive experience would help SMEs in finding their way to external knowledge providers for future projects, does not materialize in our setting. Furthermore, our results show that the innovation voucher does not lead to a general improvement in all innovation activities, but only to positive effects on the specific outcome that they had in mind at the time of application. To determine if the successful innovation project, implemented with the support of the voucher, are the result of crowding out other activities or projects or if it actually leads to better business performance in the long run, one would need to follow these firms for a longer period of time, which is beyond the scope of this paper. (In our data, i.e., one and two years after the program, we do not find any differences in business performance between the firms in the treatment and the control group.)

Our results contribute to the innovation policy literature by supporting and extending previous findings on the positive impact of the innovation voucher on the innovativeness of SMEs (e.g., Bakhshi et al., 2015; Sala et al., 2016). While other studies mainly focused on collaboration outcomes or a more narrow scope of the subsidy in terms of type of collaboration partner or location (Bakhshi et al., 2015; Cornet et al., 2006), we present evidence for treatment effects on innovation outcomes of a nationwide, all-industry program with a broad scope of potential partners. The use of an RCT with two follow-up surveys enables us to estimate the causal impact of external collaborations on innovation outcomes. From a policy perspective, our results provide causal evidence on the effectiveness of the voucher scheme and thus strengthen the rationale for this type of governmental funding. Hence, our study adds to the policy debate on how to support innovation activities of SMEs. Our results on the factors of non-compliance also provide guidance on how to increase the effectiveness of innovation voucher programs. For example, by targeting small firms and requiring a certain demonstrated readiness at the application stage. To some extent, firms also state complicated processes to be another reason for not redeeming the voucher. In this light, an innovation voucher program that allows for longer project execution phases and further reduces administrative barriers could be advisable. Furthermore, our results indicate that there are limits to the behavioral change in terms of long-term external collaborations: the collaborations and the positive innovation outcomes only show up immediately after the treatment period. This suggests that, even though the innovation voucher provides a promising first step, more is needed to increase the innovation outcomes of SMEs in the long-term.

We also acknowledge several limitations of our study. For example, our analyses rely on self-reported data. Data collected via survey responses provides a great source of primary data but is not without downsides. For example, while the treatment assignment was done via lottery and is thus random, this does not necessarily hold true for the survey responses. One thing that can be noted from our randomization and response bias checks is that there seems to be a certain pattern with regards to firms that are patent holders at the time of application. These results suggest that survey respondents in both the treatment and the control group were more likely to be patent holders than non-respondents, and thus could be more innovative ex-ante. This pattern could limit the external validity (or generalizability) of our findings because we cannot be certain that our findings would also hold for less innovative firms. Furthermore, we observe that, prior to the innovation voucher program, the firms in the treatment group were less likely to be patent holders or applicants than firms in the control group, which potentially threatens the internal validity of our results. However, when we control for this difference in our regression analyses, the results remain unchanged with similar effect sizes and significance levels.

Another limitation is that we only observe short -term effects by examining innovation outcomes one and two years after the award of the voucher. Even though our analysis extends the timeframe of existing studies, we might still miss potential medium- and long-term effects of the voucher scheme. Since R&D projects can take several years until measurable results can be identified, our analysis might miss some of those effects. Furthermore, except for our results on awards received for innovations or newly introduced products and services, we only assess the quantity of innovation outcomes without examining the quality of the developed products or patent applications (e.g., commercial success of products or number of patent citations if being granted). Inferences about these measures would take several years to materialize. Following this line of reasoning, a promising endeavor may be to evaluate subsidies over longer time periods with additional data from governmental databases on patents or business outcomes.

Finally, there are many different types of support programs available for SMEs in the UK. These range from support to gain access to expertise or equipment to more direct financial support in terms of loans or grants. Because of the difference in scope, amount of funding provided and the collaboration element in this particular program, it is difficult to compare or make claims about the efficacy or value for money of the innovation voucher program vis-à-vis other R&D support programs. And even though our analysis broadens the scope from existing literature from a regional to a national level (Bakhshi et al. 2015), the question remains whether our findings will be transferable to similar programs in other countries. By and large, we are confident that our findings can be translated to other developed countries. Given the small financial intervention, innovation vouchers might also represent an efficient instrument for emerging economies. We must leave it to future research to investigate if this is indeed the case.

CRediT authorship contribution statement

Marco Kleine: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Jonas Heite:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Laura Rosendahl Huber:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2022.104515.

Appendix

Supplementary Tables

Table A.1
Innovation voucher's logic chain (as developed by Innovate UK).

Inputs Public investment	Activities Collaboration	Outputs Knowledge	Outcomes Innovation	Impacts Growth
Voucher	R&D	Technology/ business questions answered	Investment in R&D and innovation	GVA
	Technology advice	Increased innovation capabilities	Product/ process/service development	Employment
	Design	New relationships developed	Increased engagement with knowledge providers	Productivity
	IP advice		Increased awareness of innovation support programs	

Table A.2
Randomization checks with test for joint orthogonality

Sample	Total sample	Eligibility sample	Survey sample (after lottery and eligibility check)	Product- and service-related survey subgroup (after lottery and eligibility check)	IP-related survey subgroup (after lottery and eligibility check)
Dep. Var.: IV lottery assigned (0-1)					
Model	(1)	(2)	(3)	(4)	(5)
Number of employees	0.000	0.001	0.000	0.023	-0.099
	(0.002)	(0.003)	(0.004)	(0.021)	(0.115)
Balance sheet total in GBP	-0.000	-0.000	0.000	0.000	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
Turnover in GBP	-0.000	-0.000	-0.000	-0.000	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
Parent company (0-1)	0.081	0.144	0.213	0.879	
	(0.167)	(0.219)	(0.409)	(0.685)	
Defined R&D strategy (0-1)	0.096	0.118	-0.060	-0.211	0.631*
	(0.073)	(0.088)	(0.145)	(0.199)	(0.355)
R&D tax credits (0-1)	0.044	0.055	0.406**	0.447	0.528
	(0.100)	(0.117)	(0.206)	(0.335)	(0.608)
Exporting (0-1)	-0.030	-0.022	-0.027	0.074	-1.130**
	(0.084)	(0.103)	(0.173)	(0.288)	(0.482)
Patent holder/applicant (0-1)	-0.160*	-0.296***	-0.326**	-0.001	-0.312
	(0.092)	(0.104)	(0.164)	(0.244)	(0.366)
Trademark holder/ applicant (0-1)	0.063	0.088	-0.044	0.205	-0.029
	(0.078)	(0.094)	(0.151)	(0.227)	(0.511)
Design right holder/ applicant (0-1)	0.120	0.081	0.174	0.204	0.329
	(0.105)	(0.121)	-0.060	(0.293)	(0.836)
Prior govern. R&D grants (0-1)	0.215	0.209	0.091	-0.110	-0.122
	(0.171)	(0.190)	(0.295)	(0.418)	(0.756)
SIC level 1 fixed effects	Yes	Yes	Yes	Yes	No
NUTS level 1 fixed effects	Yes	Yes	Yes	Yes	No
Constant	0.617**	0.916**	0.601*	0.555	0.953***
	(0.314)	(0.386)	(0.358)	(0.493)	(0.312)
Observations	1910	1317	516	256	100
Log likelihood	-1072.358	-710.969	-258.316	-128.970	-39.814
Wald Chi^2 test for joint orthogonality	30.44	38.58	33.35	23.19	14.65
p of model	0.444	0.135	0.223	0.675	0.145

Probit regressions. Standard errors in parentheses. Explanation and definition of variables: Unless mentioned otherwise, data obtained from application form questionnaire (questionnaire wording in parantheses) – number of employees ("number of employees"), balance sheet total in GBP ("balance sheet total"), turnover in GBP ("turnover"), parent company ("Does your business have a parent company or are you part of a group of linked enterprises?"), defined R&D strategy ("Does your firm have a defined R&D strategy?"), R&D tax credits ("Does your firm use R&D tax credits"?), exporting ("Does your firm currently export?"), patent holder/applicant ("Does your firm hold or has it applied for patents?"), trademark holder /applicant ("Does your firm hold or has it applied for trademarks?"), design right holder ("Does your firm hold or has it applied for design rights?"), prior governmental R&D grants (data from InnovateUK), SIC level 1 fixed effects (from Company House API database; we are unable to assign a SIC code classification to 160 companies due to missing information in the Company House API database), NUTS level 1 fixed effects (from Company House API data base). The Parent company coefficient in Model (5) is omitted because of perfect prediction, no SIC or NUTS level 1 fixed effects because of overfitting.

*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Table A.3
Check for response bias with test for joint orthogonality

Dependent variable: Survey respondent (0-1) Model	Any survey to population (1)	Survey 1 to population (2)	Survey 2 to population (3)	Any survey treatment respondent to treatment population (4)	Any survey control group respondent to control group population (5)
Number of employees	-0.002	-0.000	-0.003	-0.002	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
Balance sheet total in GBP	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover in GBP	0.000	-0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parent company (0-1)	-0.084	0.073	-0.431*	-0.041	-0.409
	(0.193)	(0.196)	(0.243)	(0.213)	(0.535)
Defined R&D strategy (0-1)	0.008	-0.001	-0.019	-0.038	0.180
	(0.081)	(0.083)	(0.090)	(0.092)	(0.177)
R&D tax credits (0-1)	-0.183*	-0.306***	-0.091	-0.082	-0.610**
	(0.107)	(0.112)	(0.120)	(0.122)	(0.252)
Exporting (0-1)	0.039	0.128	0.037	0.076	-0.082
	(0.094)	(0.097)	(0.105)	(0.108)	(0.215)
Patent holder/applicant (0-1)	0.224**	0.233**	0.242**	0.241**	0.333
	(0.095)	(0.098)	(0.105)	(0.111)	(0.208)
Trademark holder/applicant (0-1)	-0.008	-0.090	0.040	-0.089	0.296
	(0.085)	(0.088)	(0.095)	(0.098)	(0.194)
Design right holder/applicant (0-1)	-0.130	-0.178	-0.231*	-0.107	-0.289
	(0.110)	(0.115)	(0.127)	(0.126)	(0.251)
Prior governmental R&D grants (0-1)	0.162	0.197	0.059	0.123	0.270
	(0.165)	(0.170)	(0.181)	(0.186)	(0.386)
SIC level 1 fixed effects	Yes	Yes	Yes	Yes	Yes
NUTS 1 fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	-0.132	-0.543	-0.538	0.050	-0.050
	(0.326)	(0.346)	(0.353)	(0.357)	(0.434)
Observations	1,317	1,317	1,312	997	315
Log likelihood	-872.090	-809.782	-664.999	-662.329	-194.937
Wald Chi^2 test for joint orthogonality	27.06	36.93	27.79	25.17	23.58
p of model	0.62	0.18	0.53	0.72	0.65

Probit regressions. Comparison of eligible firms. Standard errors in parentheses. Explanation and definition of variables – see Table A.1.

*** $p<0.01$

** $p<0.05$

* $p<0.1$.

Table A.4
Treatment effects on collaboration outcomes (no controls)

Model	Collaboration outcomes Year 1 External innovation support (dummy) (1)	Proportion of innovation activities with partner (2)	Total number of partners (3)	Year 2 External innovation support (dummy) (4)	Proportion of innovation activities with partner (5)	Total number of partners (6)
Treatment effect	0.543***	2.980	1.715**	-0.074	-3.549	0.017
	(0.154)	(4.232)	(0.838)	(0.324)	(5.453)	(0.184)
Constant	1.261***	38.065***	2.509***	1.478***	37.927***	2.259***
	(0.419)	(3.818)	(0.173)	(0.291)	(4.852)	(0.152)
Observations	459	451	451	205	272	279
Wald Chi²/F-statistic	12.38	0.50	4.19	0.05	0.42	0.01
p of model	0.000	0.482	0.041	0.819	0.516	0.926
(Pseudo) R^2	0.026	0.001	0.025	0.001	0.002	0.000

Models (1) and (4): probit regressions; Models (2) and (5): OLS regressions; Models (3) and (6): Poisson regressions. Robust standard errors in parentheses. All models without controls.
*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Table A.5
Treatment effects on collaboration outcomes (extended controls)

Model	Collaboration outcomes Year 1 External innovation support (dummy) (1)	Proportion of innovation activities with partner (2)	Total number of partners (3)	Year 2 External innovation support (dummy) (4)	Proportion of innovation activities with partner (5)	Total number of partners (6)
Treatment effect	0.591***	2.146	0.334	0.133	-6.304	-0.041
	(0.168)	(4.754)	(0.442)	(0.402)	(6.491)	(0.258)
Constant	0.505	37.790***	-3.014***	1.728***	41.726***	2.298***
	(0.371)	(8.852)	(0.919)	(0.604)	(12.507)	(0.319)
Observations	443	438	438	180	256	262
Wald Chi²/F-statistic	47.24	1.16	379.69	62.98	2.03	33.89
p of model	0.007	0.270	0.000	0.000	0.003	0.138
(Pseudo) R^2	0.098	0.045	0.834	0.295	0.118	0.088

Models (1) and (4): probit regressions; Models (2) and (5): OLS regressions; Models (3) and (6): Poisson regressions. Robust standard errors in parentheses. All models controlling for basic and extended firm characteristics as well as innovation voucher round fixed effects. Exception: Model (4) without controls for parent company and innovation voucher round fixed effects because of perfect prediction.
*** $p<0.01$
** $p<0.05$
* $p<0.1$

Table A.6
Treatment effects on collaboration outcomes for treatment compliers

Model	Collaboration outcomes Year 1 External innovation support (dummy) (1)	Proportion of innovation activities with partner (2)	Total number of partners (3)	Year 2 External innovation support (dummy) (4)	Proportion of innovation activities with partner (5)	Total number of partners (6)
Treatment effect	0.925***	2.926	-0.190	-0.074	-8.071	0.142
	(0.249)	(6.399)	(0.580)	(0.486)	(8.009)	(0.310)
Constant	0.661	36.826***	0.913	1.723**	45.533***	2.080***
	(0.409)	(8.423)	(0.950)	(0.709)	(12.416)	(0.393)
Observations	457	451	451	190	268	274

Instrumental variable regressions. Models (1) and (4): Two-step instrumental variable probit regressions; Models (2) and (5): 2SLS regressions; Models (3) and (6): Two-step instrumental variable Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects. Exception: Model (4) without controls for innovation voucher round fixed effects because of perfect prediction.
*** $p<0.01$
** $p<0.05$
* $p<0.1$

Table A.7
Treatment effects on product and service outcomes as well as on process outcomes (no controls)

	Product and service outcomes												Number of new processes	
	Overall effect						Treatment effect for companies with product and service projects						Overall effect	
	Year 1			Year 2			Year 1			Year 2			Year 1	Year 2
	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new proc.	Number of new proc.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment effect	0.035	0.272	0.822**	0.521	0.068	0.095							0.422*	-0.226
	(0.221)	(0.185)	(0.359)	(0.334)	(0.281)	(0.377)							(0.236)	(0.432)
Treatment effect for companies with product & service projects							0.019	0.576**	0.668	1.102***	0.135	0.156		
							(0.351)	(0.287)	(0.489)	(0.416)	(0.337)	(0.630)		
Treatment effect for all others							0.072	-0.003	1.293***	-0.023	0.031	0.035		
							(0.194)	(0.212)	(0.448)	(0.445)	(0.381)	(0.420)		
Companies with product & service projects (Dummy)							0.236	-0.529**	1.148**	-0.591	-0.673	-0.039		
							(0.327)	(0.254)	(0.468)	(0.464)	(0.451)	(0.602)		
Constant	0.677***	0.478***	-1.200***	0.446*	0.592**	-0.747**	0.543***	0.727***	-1.969***	0.693*	0.867**	-0.728**	-0.033	0.785*
	(0.184)	(0.133)	(0.236)	(0.260)	(0.251)	(0.297)	(0.147)	(0.186)	(0.379)	(0.362)	(0.338)	(0.345)	(0.199)	(0.409)
Observations	442	442	442	272	272	272	442	442	442	272	272	272	442	272
Wald Chi^2	0.02	2.17	5.24	2.43	0.06	0.06	1.36	7.78	12.23	7.03	8.24	0.08	3.19	0.27
p of model	0.875	0.141	0.022	0.119	0.808	0.801	0.715	0.051	0.007	0.071	0.041	0.995	0.074	0.601
Pseudo R^2	0.000	0.004	0.015	0.010	0.000	0.000	0.004	0.008	0.032	0.030	0.029	0.001	0.007	0.003

Poisson regressions. Robust standard errors in parentheses. All models without controls

*** $p<0.01$

** $p<0.05$

* $p<0.1$.

Table A.8
Treatment effects on product and service outcomes as well as on process outcomes (extended controls)

	Product and service outcomes												Number of new processes	
	Overall effect						Treatment effect for companies with product and service projects						Overall effect	
	Year 1			Year 2			Year 1			Year 2			Year 1	Year 2
	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new proc.	Number of new proc.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment effect	0.026	0.185	0.742**	0.379	-0.001	-0.023							0.427*	-0.385
	(0.177)	(0.165)	(0.372)	(0.436)	(0.359)	(0.419)							(0.251)	(0.523)
Treatment effect for companies with product & service projects							0.016	0.545**	0.653	0.754*	0.068	-0.278		
							(0.301)	(0.276)	(0.459)	(0.424)	(0.351)	(0.581)		
Treatment effect for all others							0.081	-0.141	1.206**	0.097	-0.004	0.183		
							(0.249)	(0.255)	(0.583)	(0.563)	(0.443)	(0.472)		
Companies with product & service projects (Dummy)							0.333	-0.490*	1.147**	-0.677	-0.806	-0.061		
							(0.348)	(0.283)	(0.502)	(0.607)	(0.500)	(0.683)		
Constant	0.098	0.050	-2.021**	-0.272	-0.124	-0.504	-0.160	0.295	-3.056***	0.086	0.492	-0.286	0.107	0.808
	(0.366)	(0.283)	(0.895)	(0.784)	(0.561)	(0.778)	(0.397)	(0.353)	(0.942)	(0.946)	(0.667)	(0.795)	(0.421)	(0.751)
Observations	429	429	429	256	256	256	429	429	429	256	256	256	429	256
Wald Chi^2	437.14	169.49	35.62	68.96	73.08	37.87	255.38	194.99	38.10	66.49	81.37	37.94	305.31	28.64
p of model	0.000	0.000	0.124	0.000	0.000	0.062	0.0000	0.000	0.120	0.000	0.000	0.100	0.000	0.328
Pseudo R^2	0.080	0.122	0.156	0.235	0.135	0.088	0.087	0.128	0.174	0.239	0.172	0.097	0.087	0.086

Poisson regressions. Robust standard errors in parentheses. All models controlling for basic and extended firm characteristics as well as innovation voucher round fixed effects.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

Table A.9
Treatment effects on product and service outcomes for treatment compliers

	Product and service outcomes												Number of new processes	
	Overall effect						Treatment effect for companies with product and service projects						Overall effect	
	Year 1			Year 2			Year 1			Year 2			Year 1	Year 2
	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new MVPs	Number of new prod. & serv.	Number of awards	Number of new proc.	Number of new proc.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treatment effect	0.062	0.360	0.952**	0.582	0.178	0.019							0.586*	-0.345
	(0.271)	(0.222)	(0.469)	(0.493)	(0.449)	(0.519)							(0.302)	(0.775)
Treatment effect for companies with product & service projects							-0.001	0.703**	0.593	1.169**	0.120	0.075		
							(0.401)	(0.284)	(0.494)	(0.547)	(0.438)	(0.824)		
Treatment effect for all others							0.186	0.011	1.678***	0.023	0.257	-0.036		
							(0.324)	(0.340)	(0.646)	(0.705)	(0.543)	(0.668)		
Companies with product & service projects (Dummy)							0.377	-0.443*	1.408***	-0.533	-0.661	-0.115		
							(0.320)	(0.256)	(0.520)	(0.501)	(0.441)	(0.661)		
Constant	0.103	0.142	-2.049**	0.268	-0.128	0.200	-0.189	0.346	-3.182***	0.320	0.477	0.284	0.038	0.702
	(0.391)	(0.326)	(0.868)	(0.726)	(0.615)	(0.646)	(0.368)	(0.374)	(0.921)	(0.792)	(0.663)	(0.743)	(0.446)	(0.930)
Observations	442	442	442	268	268	268	442	442	442	268	268	268	442	268

Two-step instrumental variable Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects.

*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Table A.10
Treatment effects on IP protection outcomes (no controls)

	Treatment effect for companies with IP projects					
	Year 1			Year 2		
Model	Number of new patent applications (1)	Number of new design right applications (2)	Number of new trademark applications (3)	Number of new patent applications (4)	Number of new design right applications (5)	Number of new trademark applications (6)
Treatment effect for companies with IP projects	1.424**	0.390	0.220	-0.310	-1.427	0.788
	(0.672)	(1.014)	(0.477)	(0.712)	(1.010)	(0.690)
Treatment effect for all others	-0.397	0.537	0.013	-0.292	-1.076	-0.232
	(0.431)	(0.536)	(0.385)	(0.441)	(0.673)	(0.532)
Companies with IP projects (0-1)	-1.368*	-0.575	-0.342	0.308	0.979	-0.385
	(0.732)	(1.009)	(0.500)	(0.768)	(0.995)	(0.781)
Constant	-0.424	-1.910***	-0.757***	-0.596	-0.756	-1.001**
	(0.343)	(0.315)	(0.289)	(0.396)	(0.541)	(0.483)
Observations	442	442	442	272	272	272
Wald Chi^2	5.90	2.19	0.65	1.47	6.06	3.05
p of model	0.117	0.533	0.885	0.690	0.109	0.385
Pseudo R^2	0.012	0.012	0.001	0.006	0.064	0.012

Poisson regressions. Robust standard errors in parentheses. All models without controls.
*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Table A.11
Treatment effects on IP protection outcomes (extended controls)

	Treatment effect for companies with IP projects					
	Year 1			Year 2		
Model	Number of new patent applications (1)	Number of new design right applications (3)	Number of new trademark applications (4)	Number of new patent applications (5)	Number of new design right applications (6)	Number of new trademark applications (7)
Treatment effect for companies with IP projects	1.321	0.103	-0.225	-0.318	-0.398	1.749**
	(0.846)	(1.297)	(0.648)	(0.974)	(1.222)	(0.737)
Treatment effect for all others	-0.107	0.416	-0.128	-0.184	-1.486**	-0.056
	(0.282)	(0.614)	(0.315)	(0.431)	(0.632)	(0.539)
Companies with IP projects (0-1)	-1.097	-0.627	-0.182	0.341	0.391	-0.912
	(0.767)	(1.123)	(0.583)	(0.909)	(1.150)	(0.760)
Constant	-0.344	-2.109**	-2.417***	-0.547	-2.310*	-2.249***
	(0.630)	(0.822)	(0.696)	(0.681)	(1.215)	(0.828)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	429	429	429	256	256	256
Wald Chi^2	148.58	99.35	131.80	115.50	8012.11	389.79
p of model	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.239	0.215	0.160	0.224	0.420	0.164

Poisson regressions. Robust standard errors in parentheses. All models controlling for basic and extended firm characteristics as well as innovation voucher round fixed effects.
*** $p<0.01$
** $p<0.05$
* $p<0.1$.

Table A.12
Treatment effects on IP protection outcomes for treatment compliers

	Treatment effect for companies with IP projects					
	Year 1			Year 2		
	Number of new patent applications	Number of new design right applications	Number of new trademark applications	Number of new patent applications	Number of new design right applications	Number of new trademark applications
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect for companies with IP projects	1.967**	0.536	0.351	-0.382	-1.235	1.298*
	(0.784)	(1.477)	(0.815)	(1.324)	(3.018)	(0.685)
Treatment effect for all others	-0.641	0.474	-0.171	-0.288	-1.777	-0.161
	(0.586)	(0.605)	(0.428)	(0.599)	(1.324)	(0.710)
Companies with IP projects (0-1)	-1.532*	-0.915	-0.548	0.314	0.673	-0.448
	(0.787)	(1.108)	(0.599)	(0.887)	(0.977)	(0.674)
Constant	0.494	-1.966**	-1.808**	0.338	-3.597	-2.157***
	(0.703)	(0.894)	(0.712)	(0.682)	(1.486)	(0.784)
Observations	442	442	442	268	269	268

Two-step instrumental variable Poisson regressions. Robust standard errors in parentheses. All models controlling for basic firm characteristics as well as innovation voucher round fixed effects. Model (5) does not control for age, since the regression model estimation with age did not converge.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

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