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2026

Document Version:
Other version

Link to publication

Citation for published version (APA):
Fink, J., & Torregrosa-Hetland, S. (2026). *The effect of public funding on Swedish innovation, 1970-2001*. (Lund Papers in Economic History; No. 2026:270).

Total number of authors:
2

Lund Papers in Economic History

No. 270, 2026

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The effect of public funding on Swedish innovation, 1970-2001*

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August 10, 2026

Abstract

This paper analyses the effects of innovation policy on innovation output. We use a database of Swedish innovations (1970-2001), linked to both approved and non-approved public funding projects, and combine logistic regressions with matching approaches. We address: (1) the characteristics of firms applying for public funding, (2) the effects of public funding on the generation of significant innovations, and (3) whether granting more funding to a project impacts on the importance of the innovation. We find evidence of strong output additionality, as approved public funding projects were twice as likely than non-approved ones to translate into significant innovations. Moreover, our results indicate that firms were more likely to apply for public funding when they had already obtained it previously, were publicly owned, small, and located in major cities. Innovations that applied for greater amounts of public funding were of higher significance. Output additionality was strongest during the 1980s, pointing towards greater importance of public funding when private funding availability is limited, as venture capital became only widely available from the 1990s onwards. This aligns with the finding that output additionality was highest among small firms, whose access to alternative innovation finance is limited.

Keywords: innovation, LBIO, public funding, public policy.

JEL codes: O38, N44, N74

*This paper has been presented at the Public University of Navarre, the University of Barcelona (Economic History PhD series), the University of Deusto, and the EU-SPRI 2026 conference at the Universitat Politècnica de València. We are grateful for all the comments received therein, as well as those by Josef Taalbi, Martin Andersson, and Fredrik NG Andersson. Jakob Nyqvist provided important assistance in the collection of archival data. All errors remain our own. We acknowledge funding from VINNOVA, project *"SWINNO 3.0. Significant New Products and Processes in Sweden 1970 to the present"*, as well as from the Ramón y Cajal Fellowship RYC2022-037917-I, funded by MCIU/AEI/10.13039/501100011033 and by FSE+.

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1 Introduction

Innovation policy in most Western countries is to a large extent geared towards public support of innovation activities conducted by firms. The justification of such government intervention is rooted in neoclassical economic theory, positing that governments should intervene in economic activity in the presence of market failure. Since individual firms do not take into account externalities when making their investment decisions, governments should actively foster innovation to reach socially optimal levels of R&D activity (Nelson, 1959; Arrow, 1962). More recent work has underlined the importance of government initiatives in innovation, not only as a complement but as a central actor for important breakthroughs, for example in the United States during the postwar era (Mazzucato, 2013).

Public innovation funding, like all use of public money, should be scrutinized. The concept of additionality is crucial in such evaluation: good public policy should entail a positive change in some outcome that we are interested in. If this change is not found (i.e., if there is no additionality), we may conclude that the policy was not effective and that public resources might have been put to better use elsewhere.

In the innovation literature, additionality has been approached in different ways, by looking at inputs, outputs, or behaviors in the innovation process (Falk, 2007). For inputs, the usual question has been whether public funds crowd out, complement, or even foster private R&D spending. Behavioral additionality has dealt with how firms innovate. This paper is located in the second stream of this literature, focusing on the outputs or results of the innovation process. We ask whether we can detect additionality in the public funding of Swedish innovation projects between 1970 and 2001, in the sense of actual new products introduced in the market and how significant they were.[1]

Three questions are addressed in the paper: (1) What innovative firms apply for public funding? (2) Are approved public funding projects more likely to translate into significant innovations? (3) How is getting more funding translated into innovation significance? To approach these questions, we combine logistic regressions with three alternative matching approaches (propensity score matching, nearest neighbor matching and inverse probability weighting).

[1]Our definition of innovation follows the Oslo Manual (2005, p.46): "An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations". However, because of data availability, our focus is on products and not processes.

The main contribution of the paper is the combination of a robust control group with the use of innovations themselves as an output indicator. We construct our control group from a pool of rejected public funding applicants, thus addressing the self-selection of firms into applying for public funding. Although similar approaches have been used in some recent studies, they are still rather rare and recognized as an area of needed improvement in the literature.[2] We link the project applications with a database of Swedish innovations that gathers the most significant new products introduced in the Swedish economy since 1970 (Sjöö et al., 2014; Kander et al., 2019). Our data covers three decades and thus allows us to look at long-term effects and variation over time.

Sweden ranks among the most innovative countries today (Dutta et al., 2023; EU, 2023), and was among the first to establish a second generation innovation agency, aiming at promoting applied research (Weinberger, 1997; Arnold and Barker, 2022). Since the establishment of the first Swedish innovation agency in 1968, several important reconfigurations took place. This entails the creation of different innovation agencies, changes in decision-making processes, and granted funding. All these changes increase the complexity but also enrich our analysis.

The rest of the paper consists of a review of previous literature (section 2), a description of the Swedish system for public innovation funding (section 3), a presentation of our data (section 4) and methods (section 5), followed by the discussion of the results (section 6). We perform several robustness checks in section C and close in section 7.

2 Literature review

Studies on innovation policy have given great importance to the issue of additionality, but have not always been able to approach it with robust methods and sufficient data. Our paper is part of a recent strand of the literature that aims to econometrically identify additionality. We will here summarize the evolution of the literature in terms of methods and results.

The innovation outcome that we are interested in can be conceptualized in different ways. According to Falk (2007), we may consider three main areas: *input additionality* (e.g. how firms invest private funds), *output additionality* (firms' innovation performance), and *behavioral additionality* (on the process: how do the firms innovate). Out of the three, input additionality has been the object

[2] Take, for example, Czarnitzki and Hussinger (2018, p. 1337): "Finally, it would be great to also have information about rejected grant applications to further improve our analysis. We share with the vast majority of previous studies on R&D subsidies that this information is not available."

of the most well-developed literature, with origins in the 1980s, trying to measure the possible crowding-out effects of public funds on private R&D investments. In the words of Zúñiga-Vicente et al. (2014, p.37), "the major research question has been whether public R&D subsidies are either complementary and, thus, 'additional' to company-financed R&D or whether they substitute for and, thus, 'crowd out' private R&D" (see also David et al., 2000).

Several studies conducted in the last two decades have found no *crowding-out* effects, and actually *crowding-in* in some contexts. The latter refers to cases in which public funding triggered additional private funding; see, for example, Görg and Strobl (2007); González and Pazó (2008); Aerts and Schmidt (2008); Hussinger (2008) or Bloch and Graversen (2012). However, other studies show the opposite: no additionality or even substitution between both types of funding (for example, Marino et al., 2016 on the French system of tax credits). Lee (2011), in a study using firm-level data for six countries in Asia and North America, showed that public funding could be both complementary and substitute to private funding, depending on factors such as the technological level of the firm. The survey by Zúñiga-Vicente et al. (2014) reports that approximately 60% of the reviewed studies indicated additionality, but a substantial diversity of results is highlighted. This diversity cannot be traced back just to methodological issues, but might be better explained by the variation in aspects like the constraints faced by firms, the amount of public subsidies, etc.

Less work seems to have been done until recently on understanding behavioral additionality (OECD, 2006). Examples of firm behavior include, whether they conduct collaborative innovation, or with which priorities they innovate. According to Cameron et al. (2005), behavioral additionality might take place even if neither input nor output additionality can be found. Some examples of this literature are Clarysse et al. (2009), who point toward organizational learning in Flemish firms (2001-2004), Bergman et al. (2010), who look at scale and acceleration effects in small and medium-sized Swedish firms (2002-2008), or Berrutti and Bianchi (2020), who find some improvements in organization in Uruguayan firms (2001-2015).

Our paper deals with output additionality, which is why we concentrate on this strand of the literature for the remainder of the section. We also focus on quantitative studies and not on studies with qualitative approaches. Output additionality can be of many kinds, depending on the actual output considered (Falk, 2007). The literature has quite extensively analyzed effects on firms (for example, on sales or profits). Patents have also been used as an indicator of innovation output. We will review the studies based on the dependent variable they used.

Some of the first quantitative studies about the effects of innovation subsidies on firms were conducted to evaluate the SBIR (*Small Business Innovation Research*) program in the United States. Wallsten (2000) found no effects of the program on employment, while Lerner (1999) did. Both studies have significant methodological differences. Wallsten (2000) discusses that the absence of positive effects was the result of the program financing firms who would have been successful *also* in the absence of the public support they received, which he could capture by using an instrumental variable approach. On the other hand, Lerner (1999) argues that the positive effects he does find on both revenue and employment can be partly derived from the longer time horizon considered (ten years instead of at most three). Lerner (1999) compared the results of firms receiving public funds with those who did not (not accounting for whether they actually had applied). He attributed the positive results mostly to signaling effects: publicly funded firms attracted more private capital in the future. This argument, related to input additionality, has also been put forward in other contexts, e.g. Belgium (Meuleman and De Maeseneire, 2012), Sweden (Söderblom et al., 2015), and China (Wu, 2017).

A more recent study on the SBIR program shows positive effects on the publicly funded firms: they were more likely to get subsequent venture capital and to patent, and they generated higher revenue. The author in this case argues that the effect is not only about signaling (a kind of "seal of approval" from the public institutions), but also about the actual funding: "the grants are useful because they fund technology prototyping" (Howell, 2017, p. 1136).

Several studies of this kind have also been conducted in Sweden. Bager-Sjögren and Lööf (2005) analyzed data from the public agency NUTEK, considering applications made between 1994 and 1997. They compared the firm outcomes until 2003 of a group which received public support to those of a control group based on age and sector. Their results showed positive effects on firm assets, sales, employment, and labor productivity – but only on new and independent firms. Johnson et al. (2008) focused on new firms receiving public seed finance, following and further developing the previous study. They considered the 1994 applicants using data until 2006, and constructed the control group using also information on firm size, finding positive effects on revenue and employment.

One problem with these studies is that they did not take into account selection into applying for a public funding innovation program. Firms who apply can be thought as being different from firms who do not, as they at least have an innovation idea. Therefore, when not controlling for this and simply comparing their outcomes to those of other firms in the country, the results might be partially driven by selection bias (see the discussion in Cerulli, 2010).

Even if it is a more dated article, Klette et al. (2000) remains interesting because it pays particular attention to conceptual aspects. They review several econometric studies on both input and output additionality, discussing the challenges in obtaining a valid control group. As will be shown in this paper as well, neither firms applying for public funding nor those receiving it are random. This leads to thinking about the interpretation of the results of the studies, in the presence of potential selection bias. They also focus on the existence of spillovers, which may lead to underestimating the effects of public R&D support programs, but which are often an important justification for these.

In order to tackle this issue, Norrman and Bager-Sjögren (2010) used a different control group in their evaluation of the Swedish Innovation Center, which was active between 1994 and 2003. The control group was built by matching the supported firms with non-supported ones who had applied for public funding but were rejected, on the basis of a set of variables.[3] Their conclusion was that positive impacts of the SIC support on their outcome variables (sales, assets, employment) were “weak or non-existent" (Norrman and Bager-Sjögren, 2010, p. 615). The authors suggest, however, that a longer time frame might be needed to fully capture any effects.

A couple of recent papers have looked at other Swedish innovation programs from the early 21st century. Daunfeldt et al. (2016) study *Forska & Väx* and *Vinn Nu* in the period 2002-2010. They generate a control group by coarsened exact matching and estimate a diff-in-diff model to evaluate the effects of the program on the economic performance of firms. This study did not find any effects on the considered variables (number of employees, labor productivity, revenue growth, and researchers in staff). On the other hand, Söderblom et al. (2015) studied the *Vinn Nu* program, considering applications from 2002-08, and with data until 2011. Their method is an OLS regression with a control group built out of firms who were rejected *at the last stage* of the selection process. They find positive effects on firm performance in terms of sales and employment, which are not driven by the subsidy itself but by the fact that firms funded by the program also get access to more human and financial capital. This is closely connected to the signaling effect mentioned above.

As advanced earlier, other studies have considered patents as the output of interest. This literature has normally found positive effects, in the sense that firms with access to public funding

[3] A precedent to this approach can be found in Brown et al. (1995), who evaluated a US Department of Energy program based on such a control group of rejected applicants.

were more likely to file patents. This is the case, for example, of Czarnitzki and Licht (2006) in a study about Germany in the 1990s, Plank and Doblinger (2018) with respect to the German renewable energy sector (2006-2015), or Widmann (2024) on Austria in the early 2000s. Czarnitzki et al. (2007) compared Finland to Western Germany in the late 1990s, finding stronger effects in the first.[4]

Finally, what about looking at innovations themselves, the actual new products introduced? Our paper is part of a still scarce but developing literature that aims to explore output additionality with this angle. Hewitt-Dundas and Roper (2010) found positive effects of public support in the share of sales corresponding to new products, in a study on manufacturing firms in Ireland and Northern Ireland (1994-2004). A similar approach and results are found in Prencipe et al. (2024), who studied Spanish firms in 2009-14. Bérubé and Mohnen (2009) analyze the case of Canada in 2002-04, finding that firms that benefited from R&D grants introduced more new products, including more world-first innovations.[5] Foreman-Peck (2013) studied UK manufacturing and service firms in the same period, showing that publicly-supported firms were more likely to introduce new products or processes. In the United States, Smith (2020) found that firms granted funding by the "Advanced Technology Program" between 1998 and 2000 announced more new products in the following years (2001-14). Similarly, van der Have and Deschryvere (2026) study R&D grants in Finland between 1997 and 2018, showing that publicly supported firms were much more likely to introduce innovations in the following years. This last article is the closest to ours, since it also uses an LBIO database to identify innovations.

In the context of this literature, our paper aims to make a number of significant contributions. First, we argue that it is important to look further than into the effects on firms: precisely because innovation may have important externalities, some of the positive effects might not be captured by firms. We use innovations themselves, coming from a rather unique source which has not been previously used for this purpose. To the extent of our knowledge, this will be the first study to approach additionality with a LBIO-based database of significant innovations, other than the recent article by van der Have and Deschryvere (2026).[6] In difference to van der Have and Deschryvere (2026), we are able to directly link innovations (instead of firms) to public funding projects. Second,

[4]Both Czarnitzki and Licht (2006) and Czarnitzki et al. (2007) also look at input additionality in terms of firms' R&D expenditures.

[5]These firms are compared with other firms receiving no grants, but both groups get support in the form of R&D tax credits.

[6]LBIO means *Literature-Based Innovation Output*, and it is the method used to collect our innovation data. See further explanations in section 4.

we consider a longer time frame than that of many studies. A few years or even a decade might not be enough to capture the effects of public funding. We have three decades of data, which allows us to look at long projects and to explore changes through time in the Swedish innovation landscape.[7] Third, we use data on rejected applicants in order to construct a robust control group. This approach has been used by a number of studies but it is still not the most common, as the data is often difficult to obtain.

3 Public innovation funding in Sweden

The Swedish public funding system underwent frequent changes and restructuring during the observation period (Åström et al., 2011; Fink and Taalbi, 2024). Alone the main innovation agency changed three times between 1968 and 2001. An overview over the Swedish public funding landscape is presented in table 1.

The Board for Technical Development (*Styrelsen för teknisk utveckling* STU) was established in 1968 as Sweden's first central innovation agency (Sveriges Riksdag, 1968). It is generally considered an early example for a second-generation innovation agency (Arnold and Barker, 2022), where funds were no longer only directed towards basic research but rather towards applied research and product development. STU's purpose was described as follows:

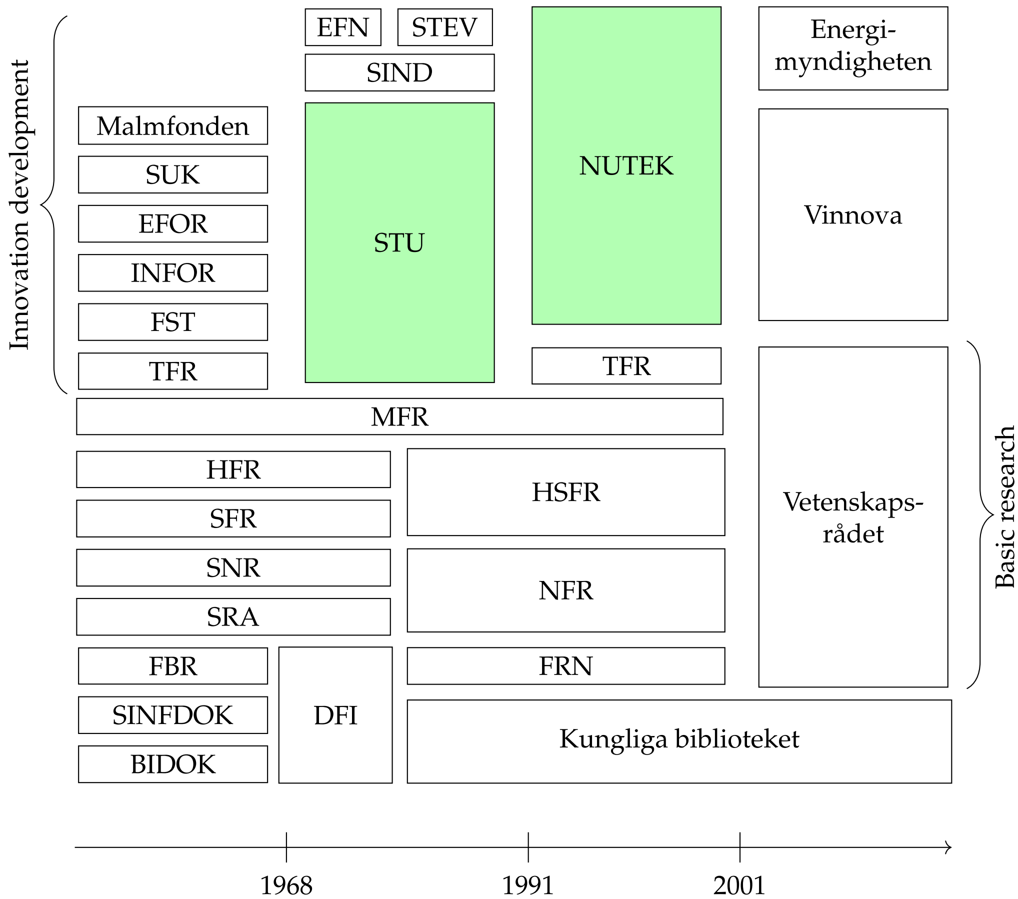
"It is proposed to establish the Board for Technical Development, a central agency for this kind of support, on the 1st of July 1968. The board is intended to take over tasks from the Technical research council [TFR], Malmfonden, INFOR, EFOR, and the Swedish inventor's office. [...]
Apart from funding, STU should conduct certain service activities, among others guidance for inventors, researchers, and dissemination of research results. STU shall have a planning and coordinating function regarding international technical collaboration, information, documentation, as well as certain research stations. A separate council shall coordinate all scientific information and documentation."[8]

During the early years of STU's existence, organizational issues constrained its efficiency. STU took over responsibilities from multiple agencies, including the TFR (*Statens Tekniska Forskningsrådet*), EFOR (*Stiftelsen för Exploatering av Forskningsresultat*), INFOR (*Institutet för Nyttiggörande av Forskn-*

[7] Indeed, the average difference between being funded and appearing in Swinno amounts to 3.3 years in our data, but there is are 92 innovations (17.7%) where this number is higher than 5, a longer time period than that covered in most studies.

[8] Own translation from Government Bill 1968:68.

Figure 1: The public funding landscape



Source: author's elaboration.
Note: Funding years were slightly adjusted. For example, Malmfonden was listed as a separate agency until 1971 and Energimyndigheten was established in 1998. Colored areas mark funding organizations included in our data set.

ingsresultat), *Malmfonden*, and the Swedish inventor's office SUK (*Svenska Uppfinnarkontoret*).[9] The integration of six separate agencies into a single one did not go smoothly. Some competencies, especially administrative capacities, were in over-supply while others were absent and needed to be built up (Weinberger, 1997, pp. 385-395).

The situation was even more charged between the 19 expert committees (*facknämnder*)[10] of

[9]TFR: founded in 1942 with the purpose to support long-term projects unfeasible for single companies in the area of technical basic research (Arnold and Barker, 2022; Weinberger, 1997, pp. 89-92). INFOR and EFOR: founded in 1963 and 1964 respectively, they fostered the commercialization of research findings (Sveriges Riksdag, 1964). *Malmfonden*: created in 1961 with the purpose to support large, long-term research projects with industry connection falling outside the scope of the research council (Sveriges Riksdag, 1961). SUK: established in 1947, it provided general support for inventors, as well as information on patenting (Riksarkivet, 2022).

[10]Separate expert committees existed for the areas of general technical development, biotechnology, medical technology, technical-industrial, inventors, applied mathematics (incl. information processing and computer technology), transportation, material science, geotechology, astronautics, flutists, electronic components, aeronautics, disability aids,

which STU consisted in its early days (Weinberger, 1997, pp. 385-395). Expert committees operated basically independently, as they held full authority to make decisions on projects as long as they stayed within their budget. As each committee struggled to maintain it's share in total STU funds, committees frequently threatened to push for independence if they perceived that other committees were favored over them. Weinberger (1997, p. 389) goes so far as describing the situation as an internal "civil war". To resolve these conflicts an internal reorganization of STU took place in 1972 (Weinberger, 1997, p. 390). These internal conflicts affected even book-keeping and documentation, as comprehensive data catalogs are only available from 1972 onwards.

In 1972 the expert committees were transformed into "areas of need" (*behovsområden*) and had merely an advisory function, with project decisions instead taken by case managers. The creation of the "areas of need" is in line with Sweden's tradition of sectoral research programs dating back to the 1960s. Public funding was especially during the 1960s and 70s directed towards materials, production and forestry (Åström et al., 2011; Arnold and Barker, 2022; Eklund, 2007, p. 92). From the 1980s onwards, information and biotechnology become of major importance (Soete and Freeman, 2012; Eklund, 2007, pp. 72-77).

A series of external evaluation investigated the efficiency of STU's work throughout its existence (SOU, 1977; Weinberger, 1997, pp. 454-456,460-463). Especially during the 1970s, these pointed out several weaknesses of STU, such as the lack of both coordination between projects and long-term finance, as well as insufficient follow-ups of approved projects (Arnold and Barker, 2022; SOU, 1977, pp. 224-225). In reaction to this, STU established framework programs (*ramprogram*) in 1977, with the aim to provide long-term funding for projects in target areas, and to foster long-term collaboration (Weinberger, 1997, pp. 427-432). Moreover, detailed peer reviews were introduced in 1979 with the purpose to ensure high scientific quality and ensure coordination across projects (Arnold and Barker, 2022).

STU was replaced by the the Agency for Technical and Industrial Development (*Närings- och teknikutvecklingsverket* NUTEK) in 1991. While STU existed in parallel with separate organizations for the energy sector (*Energiforskningsnämnd* EFN and *Statens energiverket* STEV) and for regional development (*Statens industriverket* SIND), NUTEK took over all three organizations' responsibilities, involving the creation of a combined innovation, energy, business support, and regional development agency (Arnold and Barker, 2022). A special aim of NUTEK was the fostering of

marine technology, remote-sensing, teaching, desalination, and nuclear research (SOU, 1977, p. 21).

innovation networks, particularly of connections between small and medium sized enterprises (SMEs) and universities (Rolfstam and Ågren, 2013; Eklund, 2007, p. 78).

It is no coincidence that the reorganization of the innovation agency took place in the same year as the power shift from the Social democratic party to the Center-conservative government in the midst of the Scandinavian Banking Crisis in 1991. According to Arnold and Barker (2022), the Center-conservative government believed it would only stay in office for a single term, rushing to restructure Swedish industrial and research policy. STU had been established under Social Democratic rule and had ever since its establishment been unpopular among conservatives. With the establishment of STU the Center-conservative coalition aimed to re-establish the power of universities and researchers over research funding. Further, they privatized 10 funding foundations to prevent future public micro-management of research grants.

Nonetheless, combing all different innovation-related agencies in a single one did not diminish the debate around an effective restructuring of the public funding system during the 1990s (Eklund, 2007, pp. 85-136). Proponents of the innovation systems literature criticized the lacking regard for the actual nature of technical change in neoclassical economic thinking. Edquist (1993) voiced the need to establish an innovation agency that took the complexity of innovation systems into account. This was realized with the public funding reform of 2001 during which responsibilities for the development of innovation were taken over by Vinnova (*Verket for Innovationssystem*), Sweden's incumbent innovation agency at the time of writing. Since data protection laws prevent Vinnova from publishing information on non-approved projects, the year 2001 marks the end of our analysis.

It should be noted that the responsibility to foster the development of energy innovation was outsourced to the Swedish energy agency (*Energimyndigheten*) in 1998 (Åström et al., 2011). Data from Energimyndigheten is available, but only includes approved projects. Thus, it can only be utilized for part of our analysis, and energy-related projects are most likely underrepresented during the final three years of our research period. This concern also applies to the earlier years where the EFN and STEV existed in parallel with STU.[11] However, findings from Fink (2026) detect a significant drop in energy innovation funding provided by main innovation agencies only around the time that Energimyndigheten was established.[12] Previous restructuring of public funding

[11]We searched the National Archives for similar project registries from STEV and EFN, as we found for main innovation agencies. However, project registries were far more fragmented as for main innovation agencies and contained far smaller number of projects. The project registry from EFN consists of a single volume (D1) for 1982-1990, while STU had 8 volumed between 1972-1978. For STEV, there exist two digital registries 1983-1987 and 1988-1991 (D9-D10). Therefore, we opted to not include them in the final public funding dataset.

[12]Funding for energy innovation provided by NUTEK/Vinnova dropped by approximately 50% between 1998 and

institutions for energy innovation had no similar effect.

4 Data

This article combines data from various sources. The first is SWINNO, a database of significant innovations in the Swedish economy. The second is a novel database of projects applying for public funding (both approved and rejected projects). These two are linked to identify which innovations in SWINNO applied for public funding for their development, and in such case whether they obtained it. Finally, for the regression analysis these data is combined with some additional variables, which are described last.

4.1 Significant Swedish Innovations: SWINNO

SWINNO is a database of significant innovations developed in Sweden between 1970 and 2021 (Sjöö et al., 2014; Kander et al., 2019), which has been constructed based on the Literature Based Innovation Output (LBIO) approach. This approach entails the screening on trade journals, which aim to report on technological developments in their respective fields, for information on recently commercialized innovations. Innovations identified in this way are considered as significant since the editors are knowledgeable in their field of expertise and therefore able to identify the product introductions and developments with high degrees of novelty and economic significance. One advantage of LBIO over other approaches often used, like surveys, is that it tends to provide a better representation of small firm activity.

The latest release of SWINNO contains 4,838 innovations, commercialized between 1970 and 2021 (the first covered until 2014). Because inclusion in SWINNO is based on the criteria of innovations being recognized by editors of trade journals, we expect SWINNO to include the most significant Swedish innovations of the period, and therefore to represent some "top of the iceberg" in the innovation landscape. Thus, it covers a non-random subset of total innovations in Sweden.

Patents could be an alternative to SWINNO as a source for innovation data. However, patent data would be less appropriate for our approach as patenting propensity is highly sector-specific and not all patented products and processes are commercialized (Pless et al., 2020; Taalbi, 2025). SWINNO has been recently compared with patent data, showing that only 43.9% of innovations

2002.

were patented, and that the patent system would capture only 15% of all information about innovations included in SWINNO (Taalbi, 2025). In this paper, we therefore do not use patents to identify innovations, but we do include the existence of an innovation being patented prior to commercialization as a control variable in parts of our analysis.

For each innovation, the database contains a description, information on the innovating firms, the year of commercialization, product codes, level of market novelty, etc. A total of 948 innovations in SWINNO, corresponding to 19.6%, have been reported as being developed in collaboration. For collaborators information on their names, location on the national level, type, and firm id is included. Collaboration data from SWINNO has been analyzed in previous network studies (Taalbi, 2017; Chaminade, 2022; Bucaioni et al., 2025; Kreutzer and Taalbi, 2026). Innovating firm names have been linked to Statistics Sweden firm data (these data is introduced in section 4.4). SWINNO also includes a variable indicating whether public funding is known to have been obtained, which applies to 6.3% of innovations in the database. However, we know that the LBIO method might significantly under-estimate the extent of public funding received. In the SWINNO database, Torregrosa-Hetland et al. (2019) estimated that public funding was underestimated by a factor of 4. This result was later supported by Fink and Taalbi (2024), who showed that the share of publicly funded innovations in SWINNO amounts to 24.1% instead of 6.3%.

Innovations in SWINNO have been classified in terms of radicalness or degree of significance by Fink and Taalbi (2024), combining information on market novelty, firm novelty, and the number of trade journal sources. In this paper, we use their definition of *highly significant innovations* to distinguish innovations that were reported at least three times, or were reported twice but were new to the world market or radical from the firm perspective. This definition of ex-ante high significance has been compared to alternative definitions of ex-post significance by Fink and Taalbi (2024), showing high coincidence.[13] In the present analysis, for subquestions 1 and 3 alternative regressions are presented where the components of significance are disaggregated.

[13] Fink and Taalbi (2024) present three alternative definitions of ex-post significance, based on innovations identified in the literature (Wallmark and McQueen, 1991; Sedig and Olson, 2002; Krutmeijer, 2013; Berggren and Krutmeijer, 2023), innovations with own Wikipedia pages, and winners of the Polhem price. The Polhem price is awarded since 1878, and today among the most prestigious technical awards. It is directed towards high level environmental innovation (Polhempriset, 2026).

4.2 Public Funding Database

Data on public funding projects has been obtained from two innovation agencies that operated during the study period: STU (1968-1991) and NUTEK (1991-2001). The data was gathered from two different sources, as shown in table 1. STINS is a digital database containing information on public funding projects of both agencies, but it only starts in 1979, so data from the first decade of STU's operation has been manually digitized from archival sources in the Swedish National Archives (*Riksarkivet*). Information for the period after 2001 is merely available for approved public funding projects due to data protection restrictions, so it cannot be included in the analysis. For the same reason, we could not incorporate data from *Energimyndigheten*, which might lead to some under-representation of the energy sector after Energimyndigheten was established in 1998.

Table 1: Public Funding Database sources

	Time	Observations	Source
STU	1972-1978	10,576	Riksarkivet - Manually digitized
STINS	1979-2001	51,538	Digital Source from Riksarkivet
Total	1972-2001	62,114	

The resulting Public Funding Database contains 62,114 public funding projects and information on a wide range of variables. Similar to SWINNO, each public funding project contains a detailed description, collaboration partners, ownership status of applicant firms, sector and location information, etc. It additionally includes dates of decision, start and end of the projects, as well as applied and granted amounts.[14] To ensure comparability over time all monetary values have been expressed in 2020 SEK based on inflation data from Statistics Sweden (2025).

The raw data included 5,587 additional observations. Nonetheless, public funding projects were excluded if targeted towards non-innovation or non-project specific activities, such as conference and travel costs, culture, social science, regional development, and general non-project specific research activities.

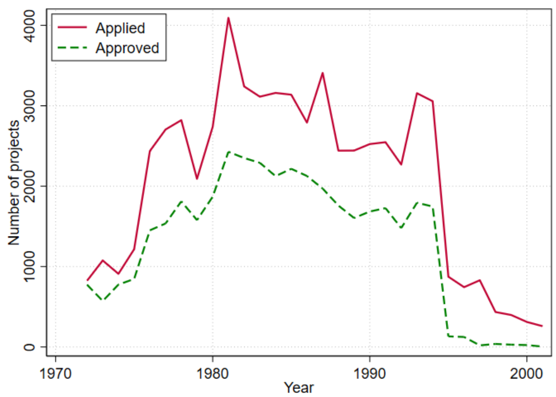
Figure 2 shows the number of applications and approved projects per year in the Public Funding Database. Both lines have an inverse-U shape. The innovation agencies received about 1,000 project applications per year in 1972-75, close to 3,000 per year in the 1980s and below 1,000 per year in the second half of the nineties. The maximum of 4,094 projects was attained in 1981. The number

[14] Granted amounts refer here to the amounts that the funding organizations approved (*beviljat*). They might exceed paid out amounts (*utbetalt*) in case that granted amounts were not fully used, or paid back to innovation agencies (*återfört*).

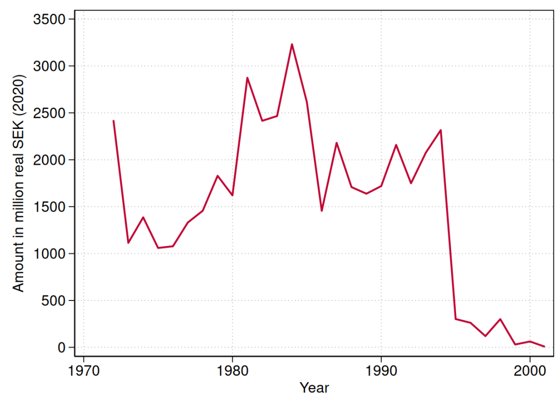
of approved projects oscillates less, with values around 2,000 in the central part of the period and below 200 since 1995.

Figure 2: Amount and number of public funding projects, 1972-2001

(a) Number



(b) Amount



Source: Public Funding Database.

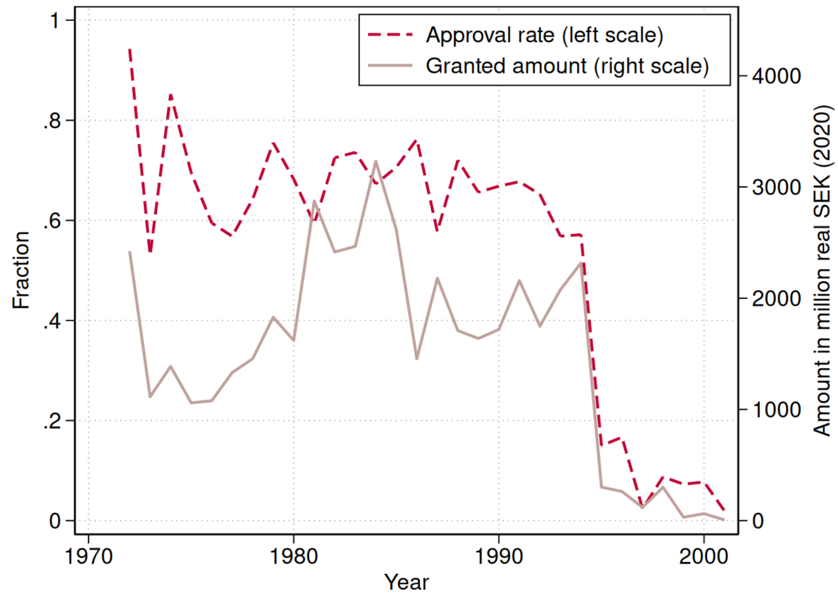
Of course, the combination of these two series yields an approval rate with significant changes over time (see figure 3). During STU's initial years, chances of approval were very high, and after some oscillation they remained at approximately 70% until the late 1980s. In the last part of the period, they rapidly declined to less than 20% from 1995 onwards. The initial gradual decline in approval rates (1990-94) corresponds to a temporary rise in the number of applications combined with a relatively constant number of approved projects per year, while the second, more abrupt drop is related to the significant cut in the number of approved projects due to reduced funding.[15] Recall the description in section 3 about the public funding bodies and their decision-making processes, which were very lax at the beginning of the period.

The figure also shows total granted amounts per year. These fluctuate at around 2 billion SEK annually, falling to bellow 200 million SEK in 1995 and onwards. Granted funding was significantly higher in the early 1980s, where it reaches a maximum of 3.25 billion in 1984. The sharp drop in both approval rates and granted amounts can be easily related to the economic crisis that the Swedish economy underwent during the 1990s. The Swedish government faced severe fiscal constraints and NUTEK's budget was cut by approximately 50% between 1995 and 1996 (Jonung et al., 2009; Eklund, 2007, p. 101).

The approval rates shown above can be compared with those from other studies on the Swedish

[15] Because of these important changes over time, we conduct some separate analyses by decade as robustness checks.

Figure 3: Public funding projects: rate of approval and total amounts granted, 1972-2001



Source: Public Funding Database.

innovation public funding bodies. For example, Norrman and Bager-Sjögren (2010) use data from the Swedish Innovation Center (1994-2003)[16] in which only 93 out of 603 firms were rejected from the program (approval rate of 84.6%). This is data cleaned after removing applications with not enough information, errors, applications out of the scope of the program, etc. The authors interpreted this result as strong self-section. Because of the way the application system worked, firms that firms with low success chances would realize this ex ante and not submit their applications. In contrast, the Swedish program *Forska & Väx*, which started in 2006, seems to have given funds to 20% of applicants (Svensson, 2011, cited in Daunfeldt et al., 2016). Similarly, the *Vinn Nu* program analyzed in Söderblom et al. (2015) received a total of 1,102 applications during 2002-08, out of which 130 were successful (a 11.8% approval rate). In this case, the process is described as around half the applications rejected at the onset, then sent to external review and retaining those with the highest scores, then internal decision based on those and fitting to 24 max yearly awarded. With respect to other contexts, Mina et al. (2021) work on the European Commission Horizon 2020 SME Instrument, which is shown to be very competitive, with 8.4% and 5.5% approval rates for its two first phases in 2014-17. In the United States, the SBIR program received between 1995 and 2013 a total of 9,659 applications from 4,545 firms for Phase 1. The result was of 1.7 awards per competition

[16]Stiftelsen Innovationscentrum is one of the foundations privatized under the center-conservative government. Since the government cannot direct its activities it is not considered in the present study (Sveriges Riksdag, 1993).

with 11 firms competing for each award on average, which implies a success rate of 15.5% in phase 1 (Howell, 2017).

4.3 The combined database

The linking of projects from the Public Funding Database to those in SWINNO was one of the major challenges in this study, due to the sheer size of the Public Funding Database. This process was first presented in Fink and Taalbi (2024), where it was used to link the approved projects to SWINNO. We follow the same approach to link the non-approved projects.

To reduce the number of potential links, the first step is to screen the Public Funding Database for name(s) of the innovating firm(s) and innovation names present in SWINNO. All projects returned by this search, with a start year differing by a maximum of 10 years from the commercialization year, are considered as potential matches.[17] In the second step, the descriptions of the innovation in SWINNO and the Public Funding Database are compared to determine whether they are likely to refer to the same innovation. This process is straightforward if the description in the Public Funding Database contains the innovation name, and/or keywords from the description in SWINNO. A detailed example is presented in Appendix B.

Next we provide information on the composition of our database, separately at the firm, innovation, and public funding project level. Table 2 shows the information compiled at the firm level. A total of 17,008 firms are considered in the final dataset. 1,520 of those are included in SWINNO. 15.7% of firms in SWINNO applied for public funding. The success rate for firms in SWINNO is 95.5%, compared to merely 51.7% among all firms included in the Public Funding Database.

Table 2: Observations classified: firms

	Applied for public funding?		Got public funding?		
In SWINNO?	Yes	No	Yes	No	Total
Yes	238	1,282	154	84	1,520
No	16,770	-	7,505	9,265	-
Total	17,008	-	8,787	9,349	-

Source: Public Funding Database.
Notes: The data includes research institutes along with actual firms. They are kept in the database because they also often act as innovators. We use the term 'firms' as a simplification.

[17] On average there exists a 3.3 year delay between a decision on a public funding project being made, and it turning into a significant innovation outcome.

Table 3 shows the innovations in SWINNO classified according to whether they are associated with applications for public funding, and whether these applications were successful. 441 out of a total of 2,865 innovations can be directly linked to public funding projects. Among these, 412 innovations (corresponding to 93.4%) were approved.

Table 3: Observations classified: innovations

Applied for public funding?		Got public funding?		
Yes	No	Yes	No	Total
441	2,424	412	29	2,865

Source: Public Funding Database.
Notes: For some innovations in Swinno we know that they got public funding according to LBIO, but we have not been able to find the links in the public funding database.

Table 4 displays approval and linkages to SWINNO among public funding projects. Direct links to SWINNO are presented in rows, while the columns show approval rates. According to this information, the approval rate of projects for public funding was quite high. Out of 62,037 applications, 38,875 were successful, which implies a success rate of 62.7% on average throughout the period. While the overall probability of being directly linked to SWINNO is merely 1.4%, approval rates for these projects amount to 80.9%, approximately 18 percentage points higher than for non-linked projects.

Table 4: Observations classified: public funding projects

	Got public funding?		
Linked to Swinno?	Yes	No	Total
Yes	707	167	874
No	38,168	22,995	61,163
Total	38,875	23,162	62,037

Source: Public Funding Database.
Notes: For some innovations in SWINNO we know that they got public funding according to LBIO, but we have not been able to find the links in the Public Funding Database.

4.4 Control variables

Individual firms and organizations, referred to simply as firms, are a central part of the analysis. To account for past innovation activity and facilitate the matching of the two data sets, firm names have been cleaned for differences in spelling, and compiled on the concern level.

Information on ownership status is given by the binary variable $Public$, indicating firms which are under full or partial public ownership. Information on this variable is obtained both from SWINNO and the Public Funding Database.

Location controls are included, since major public funding programs in Sweden were targeted towards urban areas (Asheim and Moodysson, 2017). Location data refers to companies' head offices in Sweden. These have been included in either of the two databases as a separate variable or extracted from the company name. *Major city* is assigned to firms located in Stockholm, Göteborg, or Malmö, which have been consistently the three most populous cities in the country since the 1870s. *Medium city* applies to firms located in the top 20 biggest cities in Sweden in terms of population size as of 1970, taken from Bäcklund (1991). The top three are excluded from this category. The omitted category are firms located in small cities, which refers to all other locations in this study.

The literature has identified firm size as an important determinant of innovation activity and reliance on public resources. Since most traditional forms of firm finance are geared towards large firms, SMEs are to a higher extent dependent on public funding (Asheim and Moodysson, 2017; Lerner and Tåg, 2013; Fink and Taalbi, 2024). This applies especially to the 1970s and 1980s, before venture capital became widely available in Sweden (Dahlstrand and Cetindamar, 2000). Moreover, established firms are less likely to generate radical of highly significant innovation, since they mostly focus on optimizing their existing production rather than developing entirely new products (Dahlstrand and Cetindamar, 2000; Asheim and Moodysson, 2017).

Information on firm size is obtained from Statistics Sweden. The variable is reported by employment classes. Firms with less than 50 employees are classified as small, while those with 200 or more are considered to be large. Universities and university colleges (*högskola*) are classified as large when employment data is missing. Firm size data was not perfectly matched to firms in the Public Funding Database and in some cases in SWINNO due to small variation in the spelling of firm names. While this affects merely 9% and 7% of firms and innovations in SWINNO, respectively, linking firm size data to the Public Funding database proved more challenging. Exact matches were found for 4,493 firms which were involved in 42,812 public funding projects, corresponding to two-thirds of the sample. We therefore present alternative results with this matched subsample in section 6.2.

Because sector information was only available for about half of the public funding projects, we have classified the projects looking for keyword lists in the project descriptions, to match the SNI 2007 official classification at the letter level. The keyword lists were generated using Gemini, through an iterative process, resorting to the descriptions of unclassified projects to improve. For example, projects were declared to correspond to SNI D "Electricity, gas, steam and air conditioning" if they included keywords such as *energi*, *elkraft*, *elektricitet*, or *solpanel* (and further related concepts).[18] Currently, 14.6% of the innovation projects remain unclassified. While the SNI classification at the letter level includes a total of 21 categories, not all these are relevant for innovation projects. We work with 10 sectors, of which the most frequent in the data are "Manufacturing" (C), "Professional, scientific and technical activities" (M), and "Information and communication" (J).[19] A complete overview of the sectors, including a subset of keywords on which we classify them, is presented in table 11. For consistency the same definition of sectors has been applied to classify innovations in SWINNO.

This study does not address the debate surrounding the potential crowding out of private R&D funding, since there is no data available on private funds at the innovation level.

5 Methodology

5.1 Q1: What innovative firms apply for public funding?

The first question addressed in this paper is which innovative firms apply for public funding. With innovative firms, we refer to any firm or organization engaged in the development of an innovation included in the SWINNO database. It should be clear that we do not exactly deal with "selection" into applying for public funding, since we depart from an ex-post situation. Our sample are the firms which have had at least one innovation project included in SWINNO: they succeeded in generating a new product that attracted attention in a trade journal. We do not have information about other firms, which might also have considered applying for funding, either got it of not, and did not generate such a significant innovation. What we can do here, therefore, is characterize those firms within SWINNO who had applied for public support for these innovations.[20]

To address this question, a logit model is used, measuring the probability of the developing

[18] We combined keywords in Swedish and English, since project descriptions often mix both languages.

[19] The rest of the sectors we contemplate, with the abbreviated names we use in the paper, are: Energy (D), Construction (F), Health (Q), Transportation and storage (H), Water and waste (E), Agriculture, forestry and fishing (A), and Other. We use "Professional services" hereafter to refer to category M.

[20] Of course, since we will later look at the effects of public funding for the generation of successful innovations, actual inclusion in SWINNO is influenced by the application decision (and the funding decision).

firm(s) to apply for public funding ($Apply_{ijt}$) based on a number of covariates X_{ijt}.[21] Since one firm might have several innovations listed in SWINNO, all covariates are binary variables defined at the level of the particular innovation project.

$$
\begin{aligned}
\operatorname{logit}(E[Apply_{ijt} \mid X_{ijt}]) = \alpha + \beta_1 Public_{jt} + \beta_2[\textstyle\sum_{t_z<t}^{t-1} Approval_{j,t_z} \neq 0] + \\
\beta_3[\textstyle\sum_{t_z<t}^{t-1} Innovation_{j,t_z} \neq 0] + \beta_4 Small_{jt} + \beta_5 Large_{jt} + \beta_6 Medium_{jt} + \beta_7 Major_{jt} + \\
+\beta_8 Collaboration_{it} + \beta_9 Patented_{it} + \beta_{10} High\ Significance_{it} + \beta_{11} \Delta GDP_t + \gamma_i + \delta_t + \varepsilon_{ijt},
\end{aligned} \tag{1}
$$

The logistic regression model is presented in equation 1. The model consists of firm and innovation characteristics. i denotes the innovation, j the developing firm, and t the commercialization year. As firm characteristics we include information on ownership, previous access to public funding and innovation activity, as well as on location and firm size. $Public_{jt}$ specifies whether the firm is partially or totally publicly-owned at the time of commercialization. The development of innovations and access to public funding in the past is measured by $[\sum_{t_z<t}^{t-1} Approval_{j,t_z} \neq 0]$ and $[\sum_{t_z<t}^{t-1} Innovation_{j,t_z} \neq 0]$, respectively [22]. In addition, controls are included for firm size ($Small_{jt}$, $Large_{jt}$) and location ($Medium_{jt}, Major_{jt}$).

The second set of controls are defined on the innovation level. These indicate whether an innovation has been developed in collaboration ($Collaboration_{it}$), whether it has been patented before commercialization ($Patented_it$), and whether it has been classified as being of high significance ($High\ Significance_{it}$).

Finally, the equation contains controls for macroeconomic conditions ΔGDP_t+, sector controls (γ_i) and time (δ_t) fixed effects. ε_{ijt} is the error term.

5.2 Q2: Are approved public funding projects more likely to translate into significant innovations?

Here, we deal with additionality: does public funding have the effect of generating more innovations? To operationalize it, we ask whether projects that were approved were more likely than similar non-approved projects to translate into significant innovations. That is, whether being

[21] The same variables are used in OLS and Probit regressions run as a robustness exercise.

[22] [·] is an Iverson bracket tacking the value 1 if the condition is fulfilled.

funded makes a particular project more likely to be linked to an innovation in SWINNO. Both the treatment variable ($Approval$) and the outcome variable ($Swinno$) are binary.

For this question, we only use data on the funding agencies STU and NUTEK, because it is for them that we were able to obtain both the approved and the non-approved projects (remember section 4).

When we look at the observable characteristics of approved and non-approved projects, significant differences are found in almost all the variables: decision year, public ownership, past public funding, location in major towns, as well as several sector controls (see table 5). This confirms the need to construct a relevant comparison group. The whole sample of non-funded projects cannot be used as such.

Table 5: Differences between approved and non-approved projects

Variable	**Non-approved** (N=23,162)	**Approved** (N=38,875)	**Diff**	**p-value**
Applied amount (million 2020 SEK)	1.0246	1.1101	0.0855	0.1858
Decision year	1986.40	1984.15	-2.2457***	<0.001
Public ownership	0.2929	0.4052	0.1123***	<0.001
Past public funding	0.5955	0.7718	0.1763***	<0.001
Medium town	0.1328	0.1361	0.0032	0.2546
Major town	0.1398	0.1833	0.0434***	<0.001
Sectors				
Manufacturing	0.1530	0.1539	0.0008	0.7782
Professional services	0.1168	0.1013	-0.0155***	<0.001
Information and communications	0.2701	0.3621	0.0919***	<0.001
Energy	0.0752	0.0737	-0.0014	0.5150
Construction	0.0384	0.0398	0.0014	0.3810
Health	0.0274	0.0371	0.0097***	<0.001
Transport	0.0133	0.0156	0.0023**	0.0232
Water and waste	0.0158	0.0137	-0.0021**	0.0315
Agriculture, forestry and fishing	0.0109	0.0093	-0.0016**	0.0484
Other	0.2790	0.1935	-0.0855***	<0.001

Source: Public Funding Database. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To construct the control group, we proceed by matching, following the approach taken by other studies in the field (for example, Czarnitzki and Licht, 2006, or Czarnitzki and Hussinger, 2018). We use several alternative matching estimators, given that the literature shows no consensus about which one would be superior to others (Orlic et al., 2019).[23] We have run regressions with propensity-score matching (i.e., based on the probability of approval), nearest-neighbor matching (i.e., identifying the most similar observations in terms of a set of variables), and inverse probability

[23]See Cerulli (2010) for a discussion of matching together with other methods.

weighting (weighting by the inverse of the propensity score).[24]

Equation 2 presents the logit model used to calculate the propensity score (approval probability):

$$\begin{aligned} \operatorname{logit}(E[Approval_{jkd} \mid X_{jkd}]) = \alpha + \beta_1 Amount_{kd} + \beta_2 Public_{jkd} + \beta_3[\textstyle\sum_{d_z<d}^{d-1} Approval_{j,d_z} \neq 0] \\ +\beta_4 Small_{jd} + \beta_5 Large_{jd} + \beta_6 Medium_{jd} + \beta_7 Major_{jd} + \gamma_k + \delta_d + \varepsilon_{jkd}. \end{aligned} \tag{2}$$

Equation 2 estimates the approval probability ($Approval_{jkd}$) of a project k, developed by firm j during decision year d. The variables included in the model are the applied amount ($Amount_{kd}$) (in million real SEK of 2020, logged), public ownership ($Public_{jd}$), past public funding ($[\sum_{d_z<d}^{d-1} Approval_{j,d_z} \neq 0]$), firm size ($Small_{jd}, Large_{jd}$), location in a medium or major city ($Medium_{jd}, Major_{jd}$). Sector (γ_k) and time (δ_d) fixed effects are also included. ε_{jkd} is the error term. The same variables are used for matching in the nearest-neighbor approach. All variable values are collapsed at the project level.

One important caveat is that we do not have information about private funding directed to the innovation project (this is not available in our database, and would be extremely cumbersome to obtain). Because the available private amounts might be related to the approval of an application, the absence of such variable could bias the results. However, we cannot establish the direction of such bias on theoretical grounds: innovation agencies could be both *more* and *less* likely to fund projects which already received substantial private amounts. Our approach to this problem is to control for as many variables as possible that could influence, also, how much private funding the project gets.

Once the control group is constructed, we calculate the Average Treatment Effect on the Treated, as the difference in the outcomes of the treated and the control group (see equation 3).

$$ATET = E(Swinno_1 - Swinno_0 | Approval = 1) \tag{3}$$

The treated projects are those in which $Approval = 1$. ATET is defined as the difference between their actual outcomes $Swinno_1$ and the counterfactual $Swinno_0$, which is obtained by estimating the

[24] Given that we have a large sample, for the propensity-score matching we apply a caliper of 0.10, more stringent than the default of 0.25. For the nearest-neighbor matching, we use exact matching on the time-period variable.

outcome for the matched projects.[25]

5.3 Q3: How is getting more funding translated into innovation significance?

The third question assesses whether getting more funding translates into innovations of higher significance. For this, we use the high significance variable constructed by Fink and Taalbi (2024), which captures innovations that received higher attention in the trade journals. This is, therefore, in some sense the *expected* importance of the innovation in the sector, but not economic significance in their actual use after some years.

In this part of the paper, we use only innovations in SWINNO which received public funding (i.e., which have been linked to one or multiple approved projects). We use a logistic regression model where $High\ Significance$ is the binary outcome variable. Our independent variables of interest are log applied amount ($Amount_{ikt}$) and the ratio of the amount granted over the amount applied ($Coverage_{ikt}$). All information is collapsed at the innovation level (see equation 4).

$$\begin{aligned} \text{logit}(E[High\ Significance_{ijkt} \mid X_{ijkt}]) = \alpha + \beta_1 Amount_{ikt} + \beta_2 Coverage_{ikt} \\ + \beta_3[\textstyle\sum_{t_z<t}^{t-1} Approval_{j,t_z} \neq 0] + \beta_4[\textstyle\sum_{t_z<t}^{t-1} Innovation_{j,t_z} \neq 0] + \beta_5 Collaboration_{it} + \beta_6 Public_{jt} \\ + \beta_7 Large_{jt} + \beta_8 Small_{jt} + \beta_9 Medium_{jt} + \beta_{10} Major_{jt} + \beta_{11} \Delta GDP_t + \gamma_i + \delta_t + \varepsilon_{ijkt}. \end{aligned} \tag{4}$$

The control variables included are the same ones introduced in the previous equations, and refer to characteristics of both the project and the firm. Sector dummies are as in the first model (see equation 1) based on the innovation (γ_i), and time dummies are constructed for 5-year intervals based on the commercialization year (δ_t). ε_{ijkt} is the error term.

As mentioned earlier, we do not have data on the amount of private R&D funding dedicated to each innovation by the involved firms. This would affect the interpretation of a variable representing the amount of public funding received in our equation. Thus, we cannot establish causality in this part of the analysis. Instead, we introduce the amount applied for, together with the coverage ratio. The idea is that applications with higher amounts are signaling important projects, which are

[25] The estimate of ATET would not be equal to ATE because there is selection into approval, i.e., approved projects differ from non-approved ones. We estimate ATET because we want to assess additionality on the funded firms, whether public funding contributed to their innovation outputs. ATE would give us the expected effect of public funding also on projects that did not get funded and that are thus different in a whole set of characteristics.

characterized by higher costs and risks in exchange for higher potential rewards (Mazzucato, 2013).

Because data on applied amounts is only available before 2001, we restrict our analysis to the period 1970-2001.

6 Results and discussion

6.1 Q1: What innovative firms apply for public funding?

The results of the logit regression on the characteristics of innovative firms that have applied for public funding are presented in table 6. The same table contains even a simple OLS regression for comparison. In columns (1) - (4), firm, innovation, sector, and time controls are stepwise added to the regression. Column (4) presents the full regression results.

Among the firm characteristics, applying for public funding is positively correlated with public ownership, past access to public funding, being a small firm, and having the headquarters in one of Sweden's major cities (Stockholm, Malmö, Göteborg). The determinant with the greatest magnitude is having previously obtained public funding, which increases the likelihood to apply by a factor of 5.78. On the other hand, large firms and those that had already developed innovations in the past are less likely to apply for public funding. These findings are in line with innovation literature discussing public funding access and the availability of alternative sources. Higher application rates for public funding among small firms and novel inventors is most likely related to the Swedish venture capital system being targeted towards large established firms until the 1990s (Dahlstrand and Cetindamar, 2000; Lerner and Tåg, 2013). Thus, SMEs only gained access to alternative forms of funding towards the end of the observation period.[26]

With respect to the innovation-level characteristics, highly significant innovations and those that had been patented before commercialization are twice and 1.63 times as likely to be linked to public funding applications. Innovations developed by multiple firms are instead less frequently linked to public funding applications. This would indicate that more ambitious projects would have a greater need for public support (Mazzucato, 2013). Literature on innovation networks suggests that one of the main purposes of collaborative innovation activity is the possibility to pool financial resources (Burt, 1992; Roberts, 2000). Thus, it might serve as an alternative source of funding.

[26] This would be consistent with the only period showing significant results being the post-1995 period, with lower application propensities (but of course it was also a period with lower budgets in the innovation agency).

Table 6: Characteristics of innovative firms applying for public funding, 1970–2001

	Logistic regression (odds-ratios)				OLS regression			
	(1) Firm	(2) Innovation	(3) Sector	(4) Time	(5) Firm	(6) Innovation	(7) Sector	(8) Time
Firm-level characteristics								
Public	1.084	1.182	1.133	1.173	1.018	1.037	1.032	1.036
	(0.838)	(0.675)	(0.765)	(0.724)	(0.724)	(0.475)	(0.533)	(0.482)
Past innovation	0.498***	0.524***	0.524***	0.523***	0.868***	0.877***	0.877***	0.878***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past funding	3.324***	3.504***	3.545***	3.602***	1.251***	1.260***	1.259***	1.264***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	2.972***	2.841***	2.814***	2.750***	1.273***	1.257***	1.254***	1.244***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Large (>200)	0.719	0.718	0.714	0.676*	0.946**	0.947**	0.948**	0.941**
	(0.127)	(0.131)	(0.129)	(0.085)	(0.032)	(0.035)	(0.039)	(0.018)
Medium city	0.809	0.776	0.787	0.762	0.959**	0.952**	0.955**	0.945***
	(0.269)	(0.195)	(0.228)	(0.167)	(0.049)	(0.020)	(0.029)	(0.008)
Major city	1.140	1.168	1.235	1.133	1.028	1.032	1.038	1.018
	(0.748)	(0.711)	(0.636)	(0.792)	(0.589)	(0.543)	(0.462)	(0.721)
Innovation-level characteristics								
Collaboration		0.758*	0.746*	0.736*		0.948***	0.947***	0.948***
		(0.082)	(0.069)	(0.057)		(0.007)	(0.005)	(0.006)
Patented		1.454**	1.474**	1.716***		1.080***	1.081***	1.114***
		(0.043)	(0.036)	(0.004)		(0.004)	(0.003)	(0.000)
High significance		1.814***	1.817***	2.076***		1.129***	1.129***	1.151***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Sectors								
Construction			2.210	2.260			1.117	1.110
			(0.107)	(0.116)			(0.154)	(0.174)
Health care			1.585	1.558			1.056	1.055
			(0.515)	(0.518)			(0.557)	(0.562)
Information			2.847***	2.695**			1.167***	1.145***
			(0.007)	(0.016)			(0.003)	(0.008)
Transport and storage			1.875	1.641			1.100	1.079
			(0.377)	(0.495)			(0.397)	(0.493)
Waste and water			2.322	1.946			1.116	1.071
			(0.191)	(0.310)			(0.284)	(0.501)
Professional services			2.457	3.365*			1.129	1.179
			(0.216)	(0.099)			(0.236)	(0.105)
Energy			3.985***	3.921**			1.239***	1.216**
			(0.008)	(0.017)			(0.006)	(0.012)
Primary sector			3.239	3.143			1.240	1.213
			(0.424)	(0.352)			(0.404)	(0.450)
Manufacturing			2.015	2.021			1.105	1.097
			(0.150)	(0.172)			(0.116)	(0.142)
Time								
1975–1979				1.229				1.025
				(0.398)				(0.444)
1980–1984				1.256				1.031
				(0.342)				(0.331)
1985–1989				1.337				1.048
				(0.298)				(0.172)
1990–1994				0.835				0.954
				(0.504)				(0.209)
1995–2001				0.456***				0.859***
				(0.001)				(0.000)
GDP growth				0.992				0.998
				(0.778)				(0.632)
Constant	0.242***	0.218***	0.080***	0.085***	1.235***	1.213***	1.049	1.084
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.412)	(0.198)
Observations	2660	2660	2660	2660	2660	2660	2660	2660
Pseudo R-sq	0.124	0.136	0.141	0.160				
R-sq					0.153	0.167	0.171	0.191

Note: Baseline categories – Medium sized firm, medium and low significance, other sector, 1970–1974. Clustered standard errors on the firm level.

We furthermore detect significant differences in application propensity across sectors. Compared to the reference category ("other sectors"), innovations in the energy, construction, manufacturing, professional services, and information and communication sectors are significantly more likely to apply for public funding. For innovations from the construction and energy sector this effect amounts to more than a factor of 10. This result is in line with the general set up of public innovation funding in Sweden, where funds are directed towards "areas of need" (Åström et al., 2011; Soete and Freeman, 2012; Arnold and Barker, 2022; Eklund, 2007, p. 92).[27] Moreover, the particularly high propensity to apply for public funding in the energy sector can be accounted to the extended development times and higher risks associated with developing new energy technologies (Mazzucato, 2015; Gallagher et al., 2012; Fouquet and Pearson, 2012; Pless et al., 2020).

The goodness of fit of the logit regression (0.160) is slightly below but close to the threshold for being considered good in social science literature.[28]

6.2 Q2: Are approved public funding projects more likely to translate into significant innovations?

We first run linear regressions and simple probit and logit regressions. Their results can be seen in Appendix E. The results of these are consistent with our preferred matching approaches in that they all show significant and positive effects of $Approval$ on $Swinno$, controlling for all the other relevant variables.

Propensity scores are calculated based on equation 2. These are then used to generate matches for our treated observations and produce an estimate of ATET with propensity-score matching. Secondly, we make a second matching estimate of ATET using nearest-neighbor matching (where observations are matched on the control variables instead of the propensity score). Finally, we go back to using the propensity scores to estimate the ATET with inverse probability weighting.

Results for the three approaches are given below. Before showing the ATET, we present the covariate balance in table 7. The table shows standardized differences and variance ratios between the raw and matched sample for the three models. After matching and weighting, the standardized differences are largely reduced, with the mean absolute difference going from 0.0899 to less than 0.0139 in all models.[29] The variance ratios also result close to 1, and within the 0.9-1.1 range in

[27] *Behovsområden*.

[28] Hemmert et al. (2018) give the reference of 0.2-0.4 being good, over 0.4 excellent.

[29] Rubin (2001) recommends using a threshold of 0.1 for adequate balance; below 0.05 would be considered excellent,

almost all variables. This indicates good matching quality. Both the standardized mean differences and the variance ratios show that the nearest-neighbor model works best, in terms of providing a balanced control group. Therefore, in what follows, we report results for the three models but consider nearest neighbor matching to give our preferred result.

The Average Treatment Effect on the Treated (ATET) estimated by the three models is shown in table 8. Treatment effects are strongly significant and remarkably robust across the three specifications. Our preferred result from nearest neighbor matching yields an ATET of 0.0098. This indicates that approved projects were 0.98 percentage points more likely to be linked to innovations in SWINNO. To put this number into perspective, we calculate relative effects: that is, we express the ATET in relation to *what would have been the probability of being in SWINNO for approved projects in absence of the public support*. This denominator is the counterfactual mean of the treated group, which we can obtain as the observed mean for the treated (percentage of approved observations in SWINNO from table 4: 1.82%) minus the estimated ATET. We calculate: 0.0182 - 0.0098 = 0.0084. Thus, 0.0084 would be the probability of making it into SWINNO for the approved projects, in the absence of treatment. We use this number as our denominator to calculate the relative treatment effect as: 0.0098/0.0084 = 1.17; a relative treatment effect of 117%. We may conclude that, for treated firms, public funding *more than doubled* their chances of delivering a significant innovation.

Since SWINNO includes the most important innovations in the Swedish economy, we interpret this coefficient as strong evidence of output additionality, in the sense that public funding contributed to the generation of significant innovations between 1972 and 2001. Importantly, innovations could have positive effects on the firms which introduce them, potentially leading to employment and growth effects. Spillover effects and externalities could even spread outside of the firm. We do not enter the discussion on the economic effects of these innovations; this might be a topic for further research. In any case, within the Swedish context, our study lies closer to the (positive) results of Söderblom et al. (2015) than to the (no) results of Daunfeldt et al. (2016), both reviewed in the literature section. These, however, refer to more recent innovation funding programs from the early 2000s.

Our positive additionality result is also in line with some studies from other geographic contexts (Bérubé and Mohnen, 2009; Hewitt-Dundas and Roper, 2010; Foreman-Peck, 2013; Smith, 2020; Prencipe et al., 2024). All these refer to a later period, always after the mid-1990s and mostly the

which is also the case in most of our variables.

Table 7: Comprehensive Covariate Balance: Standardized Differences and Variance Ratios

Variable	Standardized Mean Difference				Variance Ratio			
	Raw	Model 1 (PSM)	Model 2 (NNM)	Model 3 (IPW)	Raw	Model 1 (PSM)	Model 2 (NNM)	Model 3 (IPW)
Applied (log)	0.0838	-0.1415	-0.0488	-0.0666	0.2711	0.5825	1.2629	0.3897
Public	0.2373	-0.0095	0.0297	0.0125	1.1638	0.9964	1.0125	1.0050
Past public funding	0.3860	0.0117	0.0072	0.0069	0.7312	0.9851	0.9908	0.9911
Medium city	0.0095	0.0062	0.0084	-0.0084	1.0205	1.0133	1.0181	0.9826
Major city	0.1182	-0.0018	0.0142	0.0201	1.2443	0.9971	1.0240	1.0342
1973	-0.0525	0.0004	0.0000	-0.0056	0.6814	1.0035	1.0000	0.9566
1974	0.1250	0.0002	0.0000	-0.0073	3.3633	1.0013	1.0000	0.9514
1975	0.0425	-0.0109	0.0000	-0.0042	1.3547	0.9321	1.0000	0.9730
1976	-0.0271	-0.0168	0.0000	-0.0025	0.8804	0.9231	1.0000	0.9880
1977	-0.0530	-0.0032	0.0000	-0.0082	0.7914	0.9852	1.0000	0.9622
1978	0.0148	0.0069	0.0000	-0.0036	1.0670	1.0304	1.0000	0.9849
1979	0.1064	0.0480	0.0000	0.0182	1.8026	1.2708	1.0000	1.0909
1980	0.0520	0.0338	0.0000	0.0278	1.2660	1.1611	1.0000	1.1296
1981	-0.0378	0.0090	0.0000	0.0239	0.8772	1.0335	1.0000	1.0929
1982	0.1015	-0.0019	0.0000	0.0150	1.5355	0.9929	1.0000	1.0580
1983	0.1104	-0.0008	0.0000	0.0131	1.6176	0.9971	1.0000	1.0510
1984	0.0463	-0.0214	0.0000	-0.0065	1.2121	0.9216	1.0000	0.9750
1985	0.0802	0.0074	0.0000	-0.0177	1.4063	1.0288	1.0000	0.9360
1986	0.1302	-0.0274	0.0000	-0.0222	1.8538	0.9013	1.0000	0.9189
1987	-0.0500	-0.0168	0.0000	-0.0117	0.8247	0.9347	1.0000	0.9539
1988	0.0832	-0.0001	0.0000	-0.0032	1.5095	0.9995	1.0000	0.9862
1989	0.0261	0.0012	0.0000	0.0009	1.1331	1.0054	1.0000	1.0044
1990	0.0368	-0.0134	0.0000	-0.0016	1.1898	0.9425	1.0000	0.9931
1991	0.0457	-0.0186	0.0000	-0.0053	1.2409	0.9228	1.0000	0.9770
1992	0.0211	-0.0061	0.0000	0.0004	1.1109	0.9710	1.0000	1.0018
1993	-0.0568	0.0094	0.0000	-0.0070	0.7953	1.0421	1.0000	0.9705
1994	-0.0536	0.0322	0.0000	0.0002	0.8023	1.1594	1.0000	1.0008
1995	-0.2189	0.0022	0.0000	0.0008	0.1082	1.0395	1.0000	1.0141
1996	-0.1940	-0.0027	0.0000	0.0006	0.1244	0.9547	1.0000	1.0100
1997	-0.2633	-0.0083	0.0000	-0.0002	0.0152	0.7144	1.0000	0.9928
1998	-0.1712	-0.0024	0.0000	-0.0007	0.0580	0.9269	1.0000	0.9793
1999	-0.1676	0.0010	0.0000	-0.0005	0.0475	1.0357	1.0000	0.9812
2000	-0.1469	0.0091	0.0000	-0.0002	0.0504	1.4997	1.0000	0.9918
2001	-0.1463	0.0051	0.0000	0.0001	0.0119	1.6666	1.0000	1.0128
Manufacturing	0.0023	-0.0113	0.0000	-0.0123	1.0045	0.9787	1.0000	0.9769
Prof. services	-0.0498	-0.0187	0.0036	-0.0019	0.8825	0.9527	1.0096	0.9951
Inf. and comm.	0.1987	0.0312	-0.0034	0.0225	1.1715	1.0192	0.9981	1.0135
Energy	-0.0054	0.0187	0.0000	0.0025	0.9826	1.0642	1.0000	1.0083
Construction	0.0073	-0.0005	0.0000	-0.0007	1.0353	0.9975	1.0000	0.9967
Health	0.0551	0.0127	0.0000	0.0035	1.3416	1.0655	1.0000	1.0176
Transport	0.0190	0.0080	0.0027	0.0126	1.1677	1.0657	1.0215	1.1062
Water and waste	-0.0177	0.0054	0.0000	0.0011	0.8672	1.0465	1.0000	1.0091
Agri., forestry, fishery	-0.0162	0.0063	0.0030	0.0019	0.8525	1.0676	1.0312	1.0202
Mean Absolute Diff.	**0.0899**	**0.0139**	**0.0028**	**0.0089**				
Max Absolute Diff.	**0.3860**	**0.1415**	**0.0488**	**0.0666**				

Table 8: Treatment effect of approval (ATET)

Estimator	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
Propensity score matching	.0095721	.0014732	6.50	0.000	.0066848	.0124595
Nearest neighbor matching	.0097999	.0017618	5.56	0.000	.0063469	.0132529
Inverse probability weighting	.0105241	.0010472	10.05	0.000	.0084717	.0125765

Notes: Number of obs = 62,037; out of which 38,875 treated and 23,162 controls.
Source: author's calculations.

early 21st century, and they use dependent variables taken from surveys, so there are important differences with respect to data. However, they all report positive output additionality. Bérubé and Mohnen (2009) shows that firms benefiting from both R&D grants and tax credits were more likely to introduce a "World first" innovation than those in the control group (matched firms only receiving tax credits): 25% versus 17%; thus the treatment effect can be identified as 8 percentage points, corresponding to 47%. Our result might seem quite large in comparison, but the different nature of the data should be considered here, since SWINNO is a very restricted set of innovations. Prencipe et al. (2024) estimate treatment effects of between 1 and 4 percentage points on the sales from new products, depending on the size of the firm; given the averages reported in the paper, these correspond to a percentage effect between 11 and 50% (results being higher for the large firms, with 250 to 500 thousand employees). Finally, van der Have and Deschryvere (2026) report an effect close to 10 percentage points in the probability of introducing an innovation (Finland, 1997-2018), with innovations also measured by LBIO. Their results, however, are difficult to compare to ours because the baseline probability of 0.09% refers to the whole population of registered Finnish firms, and thus not only those conducting innovation activity and applying for public funding.

The reader might wonder if the fact that an innovation received public funding would make it more likely to be mentioned in the trade journals (independently of its importance). If this were true, the "effect" that we see would not be an effect on actually developing a significant innovation, but only on it being written about. However, from what we know about how trade journals work, this does not seem to be the case. In fact, the articles rarely mention the fact that public funding was obtained for a project, and as a result (as discussed in section 4) public funding is very under-represented in SWINNO (Torregrosa-Hetland et al., 2019; Fink and Taalbi, 2024).

What characterizes the projects for which public funding had positive effects? These were projects applying for lower quantities, and less likely publicly-owned (4.9 versus 37%) or previous receivers of public funding for their projects (51 versus 71%). They were less likely to be located in major cities. Benefited firms were more likely in Information and Communication, Water & Waste, and Transport; less in Health. The average year for benefiting firms is 1982.0, while that for non-benefiting is 1985.1, so earlier applications were more likely to experience positive effects.

Table 9 presents regression results for the subsample of projects where we have firm size data (42,797 projects, 69% of the original sample). Here, the precision of our PSM estimates is lower, but all the models provide significant and positive ATET. The estimated treatment effects are slightly lower in PSM and IPW, but not statistically different from our main results, and the NNM estimate is very close, at 0.99 percentage points. Since the baseline probability of being in SWINNO (approved projects) is higher in this subsample (2.19%), the relative treatment effect is lower, at 82.5% [0.99 / (2.19 - 0.99)].

Additionality was higher for small firms than for medium and large ones, as can be seen in table 9, where we have run the models separately by size. This result is consistent with the expectations from the literature, given the stronger funding constraints faced by small firms.

Table 9: Treatment effect of approval (ATET), subsample with size data

Estimator	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
		All firms				
Propensity score matching	.0074063	.0026535	2.79	0.005	.0022056	.0126071
Nearest neighbor matching	.0099485	.0021864	4.55	0.000	.0056632	.0142338
Inverse probability weighting	.0095975	.0017398	5.52	0.000	.0061875	.0130075
		Small firms				
Propensity score matching	.0113728	.0047691	2.38	0.017	.0020255	.0207201
Nearest neighbor matching	.0143723	.005026	2.86	0.004	.0045216	.024223
Inverse probability weighting	.0149256	.003487	4.28	0.000	.0080913	.0217599
		Non-small firms				
Propensity score matching	.0049064	.0020404	2.40	0.016	.0009072	.0089055
Nearest neighbor matching	.0048313	.0032065	1.51	0.132	-.0014533	.0111159
Inverse probability weighting	.0063497	.0022890	2.77	0.006	.0018633	.010836

Notes: Number of obs = 42,797 (14,294 small; 28,503 non-small); out of which 30,433 treated and 12,379 controls.
Source: author's calculations.

6.3 Q3: How is getting more funding translated into innovation significance?

The results regarding our third question are presented in table 10. Like in section 6.1, the logit estimates are compared to an OLS regression in the same table, and controls are added stepwise.

The estimated effect of the logarithm of the applied amount is positive and statistically significant at the 5% level. The estimate of 0.338 in column 4 indicates that a 1% increase in the applied

Table 10: Correlation between granted amount and innovation significance

	Logistic regression				OLS regression			
	(1) Innovation	(2) Firm	(3) Sector	(4) Time	(5) Innovation	(6) Firm	(7) Sector	(8) Time
Log applied amount	1.293*	1.453**	1.483**	1.435**	1.043*	1.063**	1.066**	1.062**
	(0.067)	(0.020)	(0.024)	(0.042)	(0.056)	(0.015)	(0.016)	(0.025)
Coverage	0.421	0.814	0.852	0.476	0.853	0.971	0.982	0.934
	(0.307)	(0.862)	(0.898)	(0.646)	(0.285)	(0.871)	(0.921)	(0.752)
Innovation controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Sector controls	No	No	Yes	Yes	No	No	Yes	Yes
Time controls	No	No	No	Yes	No	No	No	Yes
Observations	215	186	173	173	215	186	186	186
Pseudo R-sq	0.057	0.080	0.092	0.137				
R-sq					0.060	0.083	0.117	0.156

amount increases the log-odds of producing a highly significant innovation by 0.34%. Evaluated at the sample mean probability (21%), doubling the amount of public funding applied for would be associated with an approximately 5.6 percentage points increase in the probability of producing a highly significant innovation, which can be considered modest.[30] This variable would signal more ambitious projects and not necessarily the effect of public funding itself, since we do not know the amounts of private funding directed to the innovations, as mentioned earlier.

The $Coverage$ variable, which we were interested in as an indication of to what extent the public funding agency granted the amounts requested, does not attain statistical significance. This might be explained by small variation in this variable, as 86% of projects receive at least 90% of the funds that they applied for.

It must be acknowledged that the fit of these regressions is below the threshold normally considered good (our pseudo R^2 in the full regression is of 0.117, below the reference of 0.2 given in Hemmert et al., 2018). One explanation for this is the drop in sample size by over 95%, as only innovations that actually received public funding are considered here.

[30]Marginal effect: 0.01 x log-coefficient x baseline probability of high significance $= 0.01 * \beta * p(1-p) = 0.01 * 0.338 * 0.21(1-0.21) = 0.00056$

7 Concluding remarks

This study analyses the public innovation funding in Sweden between 1970 and 2001, and particularly its additionality effects. Data on public funding projects is obtained from the Swedish National Archives which has been linked to significant innovations in Sweden. Three questions have been addressed: (1) What innovative firms apply for public funding? (2) Are approved public funding projects more likely to translate into significant innovations? and (3) How is getting more funding translated into innovation significance?

First, we show that firms are more likely to apply for public funding if they are publicly owned, small, and located in major cities. Most importantly, they are very likely to keep applying for public funding if their applications have been approved in the past. This analysis is restricted to firms which have introduced significant innovations; therefore, we cannot fully assess selection into applying for public funding with the available data.

Second, we find strong evidence of public funding additionality. Approved projects were *more than twice* as likely than non-approved ones to translate into significant innovations.[31] This result is very robust to diverse matching approaches, and to controlling for size with a subsample. The additionality effect was larger for small firms than for medium-sized and large ones, which would confirm the intuition in the literature that it is the first which are more constrained in terms of funding for their projects. In terms of change through time, the impact was greater during the 1980s, when the decision process was significantly revised and before drastic cuts in innovation agencies' budget during the following decade. This result points towards the importance of public funding when private funding availability is limited, since alternative funding in form of venture capital become only widely available from the 1990s onwards.

Third, we find that projects applying for higher amounts were more likely to generate highly significant or major innovations, defined as those with more mentions in the trade journals or a higher perceived novelty. This cannot be interpreted as a direct effect of the funding itself, since we lack data on private funding applied, but as an indication of the project's magnitude.

The paper provides a number of robustness tests, which confirm our main results. We provide simple OLS, probit and logit estimates. We exploit the variation in approval rates as an alternative for the matching approach, explore the amount to which the granted funds were used, and decompose

[31] our estimate of the average treatment effect on the treated, in relative terms, is 117%

significance into its three components.

Our results refer to Sweden, a country consistently ranked among the most innovative in Europe (Eurostat, 2022; Gasser et al., 2022). There is some literature pointing at positive additionality effects in other countries (for example, Bérubé and Mohnen, 2009; Prencipe et al., 2024; van der Have and Deschryvere, 2026), but the magnitude of the effects cannot be directly compared because of methodological differences. The impact we have found is very large, and we can only hope that future research would make such comparison possible. We would then have more elements with which to judge under what conditions public funding has positive effects on innovation output.

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Appendices

Appendix A Sector keywords

The table below presents examples of keywords using for classifying the sectors (not the full list).

Table 11: Sector definition

	Sector	Keywords
A	Agriculture, forestry and fishing	jordbruk, skog, lantbruk odling, växt, fiske, gödsel, djurhållning
C	Manufacturing	tillverkning, produktion, industri, fabrik, verkstad, teknik
D	Energy	energi, energy, elhandel, kraft, värme, kyla, bränsle, förbränning
E	Water and Waste	vatten, avlopp, renhållning, avfall | återvinning, sanering, recycling
F	Construction	bygg, entreprenad, anläggning, snickeri, måleri, fasad, fönster, renovering, ventilation
H	Transportation and storage	transport, logistik, lager, frakt, gods, leverans, distribution
J	Information and communication	mjukvara, software, it-konsult, programmering, kod, systemutveckling, app, webb, artificiell, nätvärk, maskininlärning
M	Professional services	forskning, utveckling, innovation, analys, laboratorium, verifiering, rådgivning, redovisning
Q	Health	vård, omsorg, hälsa, terpi, sjuk, klinik, virus, operation

Appendix B Example of the linking process

In this section an example of the linking process between SWINNO and the Public Funding Database is presented.

Carbogel is described in SWINNO as an "environmentally friendly, coal-based fuel system [...] with properties similar to oil" [32]. The project was developed in collaboration between AB Scaniainventor and Boliden, and was commercialized in 1980. To identify potential matches for this innovation, the Public Funding Database was scanned for projects linked to the two developing firms or including the innovation name.

- Developing firms: 27 and 53 potential matches were identified for AB Scaniainventor and Boliden, respectively. Out of these, 14 were excluded because the projects started a decade after the innovation was commercialized.
- Innovation name: one match was returned linked to AB Scaniainventor and two for project from Jernkontoret. Interestingly, Carbogel is also the name of a firm in the Public Funding Database. The 9 projects developed by this firm were also considered as potential matches.

In total, scanning for firm and innovation names produced 76 potential matches. From these I selected the most likely matches, by scanning the projects descriptions for keywords such as "coal (*kol*)", "coal paste (*kolpasta*)", or the innovation name Carbogel. Thereafter, 12 potential matches remain which are presented in table 12.

These 12 potential matches were closer inspected. Projects 8, 10, and 11 were declared matches, as they include the innovation name *Carbogel*, as well as terms such as heating, gasification (*förgasning*), and coal water (*kolvatten*), which all seem to be related to different applications of the innovation. Project 9 contains the term *Carbogel* but was not declared a match, as the description indicates a collaboration with the firm of the same name, rather than a relation to the innovation.

Among the remaining seven projects, projects 3, 4, 5, 6, and 7 all include the term coal paste (*kolpasta*). Thus, they refer with high certainty to the innovation in question. Projects 1 and 2 refer to "coal as an energy source"[33], nonetheless the descriptions do not indicate a clear link to the description of Carbogel in SWINNO, as the terms do not specifically refer to a coal-water mixture

[32] Own translation from original in Swedish.
[33] Own translation from original in Swedish.

Table 12: Potential matches for Carbogel

	Firm	Description	Start	End	Amount	Approval	Source
1	Scaniainventor	Kol som energikälla. Undersökning angående ny metod för integration av hantering, distribution, konsumentlagring, förbränning och avgasrening	1974	1974	455,569	1	STU
2	Carbogel	Kol som energikälla	1974	1975	455,569	1	STINS
3	Carbogel	Utveckling av komplett system för användning av kol i form av kolpasta vid termisk energiomvandling	1975	1975	1,560	1	STINS
4	Carbogel	Utveckling av komplett system för användning av kol i form av kolpasta vid termisk energiomvandling	1976	1977	3,007,967	1	STINS
5	Carbogel	Utveckling av komplett system för användning av kol i form av kolpasta vid termisk energiomvandling	1976	1976	751,992	1	STINS
6	Carbogel	Kolpasta – utveckling av komplett system för användning av kol i form av kolpasta vid termisk energiomvandling	1978		0	0	STU
7	Carbogel	Utveckling av komplett system för användning av kol i form av kolpasta vid termisk energiomvandling	1978	1978	2,351,750	1	STINS
8	Scaniainventor	Carbogel Heating	1980	1983	1,196,756	1	STINS
9	Jernkontoret	Ämnesvärmning med Carbogel lab förs	1983		0	0	STINS
10	Jernkontoret	Förgasning av Carbogel	1983		0	0	STINS
11	Carbogel	Kolvatten Carbogel	1983	1984	0	0	STINS
12	Carbogel	Utveckling av teknik för produktion och karaktärisering av högrenade kolvattenbränslen (CAM)	1984	1986	9,853,537	1	STINS

or coal paste. Thus, a total of 9 public funding projects were directly linked to Carbogel.

Appendix C Robustness

In this section we conduct some additional analyses. We first estimate our main models separately for periods when the assessment procedures or the main innovation agency changed (STU 1: 1970-78, STU 2: 1979-90, NUTEK: 1991-2001). Second, we check for any differences in the effects of the components of the significance variable (Q1 and Q3). Thirdly, we exploit the information about the use of the granted funds by the firms, trying to see if the firms that did not use the money had lower effects (Q2). Finally, we exploit the variation in the approval rates (Q2), with the main aim to use the sharp drop in approval rates in the 1990s.[34]

C.1 Separating different periods

As discussed previously, the public funding system in Sweden underwent significant changes over time: in the selection mechanisms of approved projects, in the targeted firms and sectors, as well as fiscal restrictions following the Scandinavian banking crisis of the early nineties (Åström et al., 2011; Arnold and Barker, 2022; Jonung et al., 2009). The application and approval process underwent major changes. As discussed in Åström et al. (2011, pp. 30-34), public funding applications were only critically screened regarding their scientific quality from 1979 onwards. Previously, public funding was granted to the best applications as long as funds were sufficient. Connections between them were not considered. Furthermore, STU established in the late 1970s a system to systematically evaluate the results of previous projects, which affected decisions on project renewals and follow-up projects. Because of these differences, we break up our 31-year-long observation period by decade to get a deeper insight into changes across time. The final decade is extended by two years to include observations from 2000 and 2001.

Table 13 illustrates the regression results of innovative firms applying for public funding by decade. Overall, findings are very similar, with past funding having the stronger effects throughout, and positive associations of the application behavior with small firm size and high significance of the innovation. Some variation over the decades is that we do not find a significant effect of the $Public$ nor $Major$ variables in the 1980s, nor of the $Patented$ variable in the 1990s. However, this could be related to the lower number of observations in the regressions by decade, which reduces

[34]We have tried to use text notes available for 6,306 projects which had more information about the granting decision. One possible approach was to run a sentiment analysis on these texts, and use the sentiment score as a predictor of the approval of a project. However, this strategy was not possible because there was not enough variation in the sentiment scores of the projects.

Table 13: Characteristics of innovative firms applying for public funding, by sub-period

	Logistic regression (odds-ratios)			
	(1) STU 1	(2) STU 2	(3) NUTEK	(4) All
Public	1.321	0.569	3.443**	1.173
	(0.622)	(0.169)	(0.025)	(0.562)
Past innovation	0.525***	0.622***	0.424***	0.523***
	(0.003)	(0.005)	(0.000)	(0.000)
Past funding	3.195***	3.651***	4.280***	3.602***
	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	2.752***	2.941***	2.737***	2.750***
	(0.001)	(0.000)	(0.000)	(0.000)
Large (>200)	0.963	0.562***	0.605*	0.676***
	(0.899)	(0.007)	(0.096)	(0.007)
Medium city	0.980	0.587***	0.943	0.762**
	(0.930)	(0.002)	(0.809)	(0.020)
Major city	1.626	1.480	0.631	1.133
	(0.331)	(0.338)	(0.441)	(0.648)
Collaboration	0.691*	0.755*	0.802	0.736***
	(0.095)	(0.070)	(0.346)	(0.005)
Patented	2.465***	1.784***	1.440	1.716***
	(0.003)	(0.009)	(0.129)	(0.000)
High significance	2.882***	1.825***	1.720**	2.076***
	(0.000)	(0.003)	(0.013)	(0.000)
Construction	3.708	4.185*	0.948	2.260*
	(0.271)	(0.057)	(0.950)	(0.084)
Health care	0.971	4.295	0.886	1.558
	(0.985)	(0.105)	(0.906)	(0.445)
Information	4.378	3.698**	1.338	2.695***
	(0.163)	(0.011)	(0.601)	(0.004)
Transport and storage	14.324*	1.008	1.000	1.641
	(0.070)	(0.994)	(.)	(0.475)
Waste and water	3.447	2.799	1.000	1.946
	(0.330)	(0.216)	(.)	(0.242)
Professional services	4.603	6.401*	1.789	3.365**
	(0.274)	(0.098)	(0.489)	(0.034)
Energy	8.744*	2.794	5.828**	3.921***
	(0.075)	(0.132)	(0.032)	(0.003)
Primary sector	1.000	1.000	1.000	3.143
	(.)	(.)	(.)	(0.383)
Manufacturing	2.600	2.224	2.184	2.021*
	(0.405)	(0.198)	(0.258)	(0.089)
1975-1979	1.558**	1.000		1.229
	(0.044)	(.)		(0.273)
1980-1984		1.248		1.256
		(0.419)		(0.201)
1985-1989		1.273		1.337
		(0.412)		(0.126)
1990-1994		0.615	1.000	0.835
		(0.330)	(.)	(0.394)
1995-2001			0.514***	0.456***
			(0.001)	(0.000)
GDP growth	1.016	1.026	0.915**	0.992
	(0.629)	(0.609)	(0.035)	(0.698)
Constant	0.035***	0.060***	0.168***	0.085***
	(0.002)	(0.000)	(0.007)	(0.000)
Observations	782	1152	714	2660
Pseudo R-sq	0.153	0.157	0.186	0.160

Note: Baseline categories - Medium sized firm, medium and low significance, other sectors, first half of decade.

estimation precision. The stronger likelihood of applications from the $Energy$ sector is driven by the 1970s and 1990s, while that of $Construction$ arises from the 1980s.

The effect of approval on generating significant innovation split by sub-periods is presented in table 14. Evidence of output additionality, indicated by a positive and significant ATET, can be clearly detected in the 1970s and 1980s, while with the data from the 1990s it does not attain significance in the propensity score and nearest neighbor matching approaches. Of course, part of the explanation can again lie in the lower number of observations when we break the data by sub-periods. The estimated treatment effects are biggest in magnitude during the 1970s, with 1.7 percentage points in the NNM, while in the 1980s they decrease to 0.9 and in the 1990s they lie close to 0.5 when significant (IPW).

Table 14: Treatment effect of approval by sub-periods

Estimator	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
		1970–1978				
Propensity score matching	.0189359	.0036695	5.16	0.000	.0117438	.026128
Nearest neighbor matching	.0174723	.0063929	2.73	0.006	.0049425	.0300022
Inverse probability weighting	.0203828	.0029452	6.92	0.000	.0146103	.0261553
		1979–1990				
Propensity score matching	.0095666	.0013511	7.08	0.000	.0069184	.0122147
Nearest neighbor matching	.0093180	.0016354	5.70	0.000	.0061127	.0125232
Inverse probability weighting	.0090712	.0011849	7.66	0.000	.0067488	.0113936
		1991-2001				
Propensity score matching	-.0012696	.0043570	-0.29	0.771	-.0098091	.00727
Nearest neighbor matching	.0040474	.0031396	1.29	0.197	-.002106	.0102008
Inverse probability weighting	.0053273	.0021911	2.43	0.015	.0010329	.0096217

Source: author's calculations.

Notes: Number of obs = 11,972 in 1970–1978 (out of which 7,756 approved); 35,185 in 1979–1990 (out of which 24,002 approved); 14,880 in 1991 onwards (out of which 7,117 approved).

In relative terms, the estimated ATET is highest during the 1980s (155%), followed by the 1970s (134%). Additionality, thus, was strongest before venture capital markets developed, pointing towards the important effects of public intervention in this context. The smaller estimated effect during the 1990s (58%) could be related to the large drop in the budgets of innovation agencies, project applications, as well as the emergence of alternative private funding sources. While public funding collapsed in the mid-1990s, the amount of venture capital more than doubled between 1991 and 1995. The total volume in 1995 corresponded to 0.95% of GDP (Karaomerlioglu and Jacobsson, 2000).

Correlations between innovation significance, applied amount, and ratios by decade are presented in table 15. When results are divided into the three time periods, no significant correlation with wither applied amount nor coverage can be detected. This can most likely be accounted to the low number of observations in each period, dropping from 201 to 39-107. Nevertheless, the model

Table 15: Correlation between granted amount and innovation significance, by sub-periods

	Logistic regression (odds-ratios)			
	(1) STU 1	(2) STU 2	(3) NUTEK	(4) All
Log applied amount	-0.215	0.356	0.086	0.295*
	(0.729)	(0.199)	(0.815)	(0.066)
Coverage	-1.096	4.056	-5.113	-1.920*
	(0.646)	(0.487)	(0.159)	(0.082)
Collaboration	-15.495	1.688**	0.939	1.068**
	(0.994)	(0.026)	(0.529)	(0.047)
Past innovation	1.052	1.118	-2.222	0.062
	(0.449)	(0.145)	(0.152)	(0.898)
Past public funding	0.489	-0.601	0.914	-0.366
	(0.755)	(0.458)	(0.476)	(0.451)
Public	16.748	-0.890	1.686	-0.231
	(0.993)	(0.391)	(0.439)	(0.750)
Large (>200)	-1.553	0.041	15.135	-0.592
	(0.384)	(0.969)	(0.995)	(0.391)
Small (<50)	0.896	0.905	15.451	0.489
	(0.506)	(0.284)	(0.995)	(0.371)
Medium city	-0.518	0.023	2.105*	0.479
	(0.775)	(0.978)	(0.068)	(0.369)
Major city	0.000	0.599	-0.759	0.270
	(.)	(0.420)	(0.588)	(0.613)
Construction	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Health care	0.000	2.721	0.000	1.385
	(.)	(0.209)	(.)	(0.334)
Information	-1.640	0.156	-0.748	-0.485
	(0.314)	(0.905)	(0.721)	(0.522)
Transport and storage	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Waste and water	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Professional services	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Energy	0.000	1.281	0.000	-0.771
	(.)	(0.575)	(.)	(0.604)
Primary sector	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Other sectors	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
1975-1979	-1.284	0.000		-0.670
	(0.362)	(.)		(0.432)
1980-1984		-0.400		0.247
		(0.766)		(0.758)
1985-1989		-1.481		-0.859
		(0.330)		(0.359)
1990-1994		0.671	0.000	0.480
		(0.718)	(.)	(0.594)
1995-2001			-1.347	0.062
			(0.188)	(0.942)
Constant	0.685	-6.372	-10.642	0.646
	(0.828)	(0.279)	(0.997)	(0.637)
Observations	39	107	48	201
Pseudo R-sq	0.252	0.218	0.251	0.111

fit is improved when considering time periods separately, exceeding the threshold of 0.2 which indicates a good fit (Hemmert et al., 2018).

C.2 Significance components

Apart from investigating changes across time, we have split the definition of high significance into three different components, market novelty, firm novelty, and the number of journal articles. Regarding the latter we distinguish whether innovations are mentioned in three or more articles. This is relevant for Q1 and Q3 only since Q2 does not consider variation in the level of significance. The results are presented in Tables 16 and 17 for Q1 and Q3, respectively.

For Q1 correlations are positive for all components of high significance. The amplitude is greatest for innovations declared to be a world novelty, amounting to a 54%. It should be noted that this is only half as strong a correlation as that of high significance.

When conducting a separate analysis of significance components for Q3, neither of the three components is positively correlated with a higher amount of public funding. However, similar to the main regression results, the number of journal articles is negatively correlated with public funding coverage.

Table 16: Characteristics of innovative firms applying for public funding, 1970-2001 – Significance components

	Logistic regression (odds-ratios)			
	(1) Articles	(2) World nov.	(3) Firm nov.	(4) High sign.
Public	1.160	1.156	1.064	1.099
	(0.587)	(0.594)	(0.821)	(0.732)
Past innovation	0.525***	0.511***	0.553***	0.516***
	(0.000)	(0.000)	(0.000)	(0.000)
Past funding	3.580***	3.548***	3.533***	3.576***
	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	2.846***	2.705***	2.701***	2.559***
	(0.000)	(0.000)	(0.000)	(0.000)
Large (>200)	0.683***	0.679***	0.684***	0.667***
	(0.008)	(0.008)	(0.008)	(0.005)
Medium city	0.769**	0.772**	0.766**	0.757**
	(0.024)	(0.027)	(0.022)	(0.018)
Major city	1.160	1.103	1.180	1.113
	(0.585)	(0.719)	(0.544)	(0.697)
Collaboration	0.754***	0.760**	0.743***	0.736***
	(0.009)	(0.012)	(0.006)	(0.005)
Patented	1.759***	1.694***	1.761***	1.625***
	(0.000)	(0.000)	(0.000)	(0.001)
Articles	1.766***			1.667***
	(0.000)			(0.001)
World novelty		1.847***		1.693***
		(0.000)		(0.000)
Firm novelty			1.443***	1.177
			(0.000)	(0.119)
Construction	2.275*	2.127	2.149	2.036
	(0.082)	(0.116)	(0.110)	(0.139)
Health care	1.705	1.884	1.871	1.627
	(0.358)	(0.269)	(0.275)	(0.401)
Information	2.828***	2.669***	2.799***	2.591***
	(0.003)	(0.005)	(0.003)	(0.006)
Transport and storage	2.015	1.611	1.900	1.616
	(0.298)	(0.491)	(0.347)	(0.488)
Waste and water	2.282	1.788	2.032	1.820
	(0.148)	(0.305)	(0.217)	(0.292)
Professional services	3.361**	3.267**	3.491**	3.241**
	(0.035)	(0.040)	(0.030)	(0.041)
Energy	3.969***	3.828***	3.776***	3.647***
	(0.003)	(0.004)	(0.004)	(0.006)
Primary sector	2.986	3.445	2.891	3.600
	(0.403)	(0.344)	(0.411)	(0.324)
Manufacturing	2.156*	1.997*	2.088*	1.923
	(0.063)	(0.095)	(0.075)	(0.115)
1975-1979	1.198	1.175	1.111	1.201
	(0.334)	(0.391)	(0.573)	(0.331)
1980-1984	1.213	1.122	1.122	1.126
	(0.277)	(0.516)	(0.518)	(0.505)
1985-1989	1.291	1.099	1.183	1.114
	(0.176)	(0.619)	(0.374)	(0.573)
1990-1994	0.837	0.831	0.824	0.800
	(0.395)	(0.377)	(0.355)	(0.292)
1995-2001	0.471***	0.463***	0.451***	0.453***
	(0.000)	(0.000)	(0.000)	(0.000)
GDP growth	0.991	0.993	0.992	0.993
	(0.670)	(0.762)	(0.695)	(0.755)
Constant	0.086***	0.088***	0.083***	0.086***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2660	2660	2660	2660
Pseudo R-sq	0.153	0.160	0.154	0.164

Note: Baseline categories - Medium sized firm, medium and low significance, other sectors, first half of decade.

Table 17: Correlation between granted amount and innovation significance - Significance components

	Logistic regression (odds-ratios)			
	Articles	World nov.	Firm nov.	High sign.
Log applied amount	1.061	1.018	1.010	1.044*
	(0.366)	(0.557)	(0.730)	(0.065)
Coverage	0.344**	0.799	0.938	0.745*
	(0.033)	(0.322)	(0.766)	(0.096)
Collaboration	1.346	1.000	1.053	1.186**
	(0.218)	(1.000)	(0.621)	(0.047)
Past innovation	1.161	1.030	0.824**	1.016
	(0.422)	(0.725)	(0.017)	(0.807)
Past public funding	0.895	0.941	0.993	0.945
	(0.577)	(0.496)	(0.937)	(0.423)
Public	1.056	1.299*	1.267	0.961
	(0.872)	(0.086)	(0.104)	(0.736)
Large (>200)	0.974	0.954	0.979	0.931
	(0.921)	(0.687)	(0.852)	(0.438)
Small (<50)	0.977	1.097	1.240**	1.071
	(0.912)	(0.340)	(0.021)	(0.369)
Medium city	1.110	0.999	1.067	1.079
	(0.633)	(0.989)	(0.493)	(0.327)
Major city	0.956	0.982	1.026	1.045
	(0.839)	(0.857)	(0.785)	(0.573)
Construction	1.118	0.925	0.903	0.837
	(0.831)	(0.741)	(0.649)	(0.334)
Health care	3.174*	0.872	1.044	1.266
	(0.085)	(0.652)	(0.882)	(0.321)
Information	1.187	0.807	0.752*	0.932
	(0.616)	(0.167)	(0.054)	(0.560)
Transport and storage	2.570	1.302	1.264	2.399**
	(0.425)	(0.623)	(0.647)	(0.038)
Waste and water	1.000	1.000	1.000	1.000
	(.)	(.)	(.)	(.)
Professional services	0.918	1.045	0.467**	0.828
	(0.923)	(0.913)	(0.046)	(0.546)
Energy	1.079	0.882	0.845	0.907
	(0.907)	(0.674)	(0.551)	(0.675)
Primary sector	0.708	0.539	0.464	0.812
	(0.769)	(0.249)	(0.133)	(0.619)
Other sectors	0.592	0.753	0.609	0.719
	(0.477)	(0.397)	(0.121)	(0.209)
1975-1979	1.082	0.934	1.097	0.914
	(0.826)	(0.673)	(0.549)	(0.477)
1980-1984	1.665	1.090	1.208	1.028
	(0.153)	(0.596)	(0.220)	(0.829)
1985-1989	1.152	1.198	1.191	0.894
	(0.711)	(0.297)	(0.290)	(0.407)
1990-1994	1.956*	1.143	1.355*	1.062
	(0.096)	(0.464)	(0.081)	(0.674)
1995-2001	1.470	1.029	1.207	0.996
	(0.318)	(0.869)	(0.259)	(0.977)
Constant	7.453***	2.077**	1.909**	1.709**
	(0.001)	(0.010)	(0.017)	(0.016)
Observations	216	216	216	216
Pseudo R-sq				
R-sq	0.110	0.084	0.178	0.141

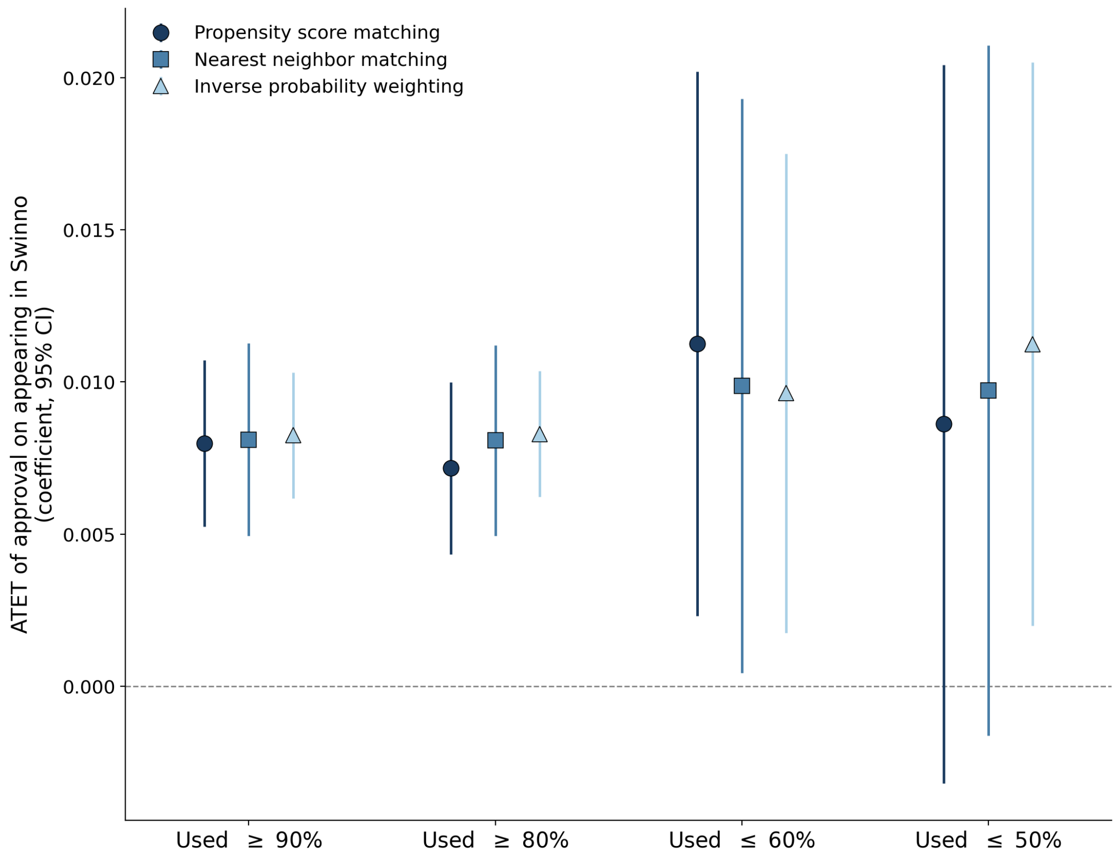
C.3 Use of the funds

For the STINS sample (1979-2001), we have information on the funds returned from the firms to the agency, i.e., the part not used. As mentioned above, most of the approved projects used their granted funds completely (the average is 96%). However, there is some variation that we can use to investigate whether the use of funds had an impact on the success of the projects in terms of developing a significant innovation (variation of Q2). If the actual use of the funds makes no difference, we may conclude that the approval of a project simply has an important "seal of approval" effect, which is similar for both groups. However, if the treatment effect is larger for projects where the funds were used, this would point towards the actual funding being important in addition to the prestige.

We have run separate regressions using sub-samples of projects according to the extent to which they used the granted amounts. The results (figure 4) show that the significance of the treatment effects is weaker in the sub-samples of projects using less of the funds, with the confidence intervals sometimes crossing 0. This could point towards the actual use of the money being important, which would be consistent with the conclusions of Howell (2017); however, it should be noted that we have few observations in the low-use sub-samples, which affects the precision of the estimates. Therefore, we have to be cautious when interpreting this result. Projects that used less of the granted amounts might be projects which failed, for example cases of discontinued work after the development of a prototype that was not viable. Unfortunately, this is something we have no information on.[35]

[35]The full results can be found in table 4 in the Appendix. We have also run linear probability (OLS), probit, and logit regressions separately for these sub-samples. In all three, the coefficient on approval is positive and statistically significant at the 1% level in every sub-sample. The estimated effect of approval does not differ significantly across sub-samples: in the OLS specifications, the $\leq$60% and $\leq$50% sub-samples yield slightly larger coefficients, while in the probit and logit specifications they are slightly lower. These results are available upon request.

Figure 4: Treatment effect of approval by extent of funds usage



Source: authors' elaboration using Claude.

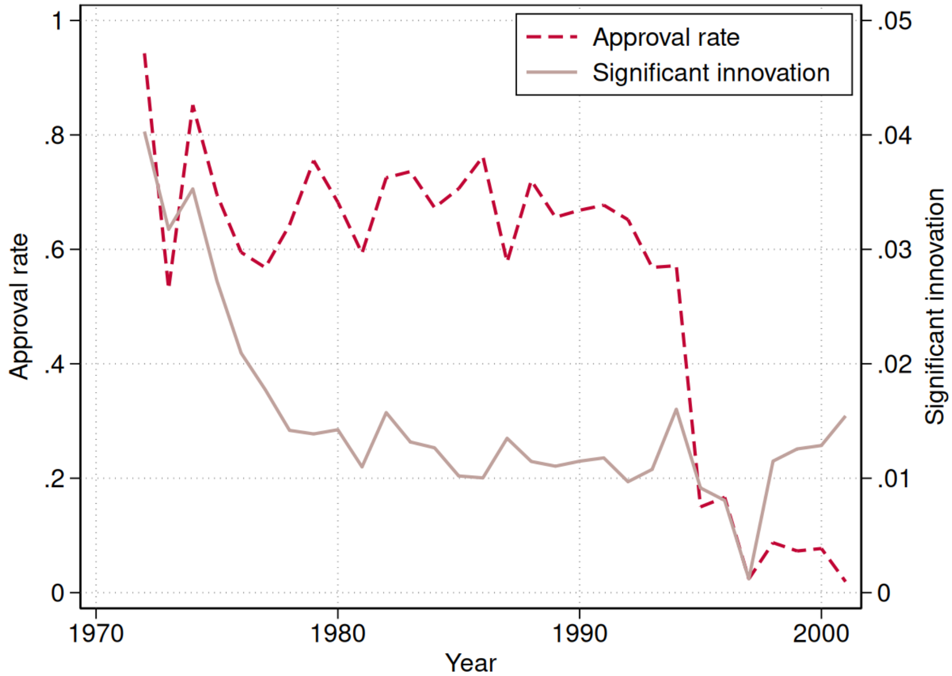
C.4 Exploiting approval rates

As was discussed in the data section, approval rates experienced significant variation through time (see Figure 5). It is shown that the percentage of projects connected to an innovation in Swinno was quite stable during the 1980s and early 1990s, before experiencing a drop in 1995 (57 to 15%) and a second drop in 1997 (17 to 2%) (blue line). These drops are related with an even more intense fall in the share of approved projects (red line). We exploit this variation in two ways: a) with an Instrumental Variable approach, where the yearly approval rate instruments approval; and b) with a Regression Discontinuity (RD) design, where we specifically look at the drop in approval rates in 1997.[36]

Table 18 shows the estimated treatment effects with both approaches. The IV estimation yields

[36]The drop in approval rate is larger in 1995 than in 1997, but unfortunately we cannot use that year for the RD because the number of applied projects dropped as well, and many control variables present significant differences when comparing before and after (which is not the case in 1997).

Figure 5: Rates of significant innovation and project approval per year, 1972-2001



Source: combined Public Funding and Swinno Databases.
Note: the projects are classified here according to the decision year, but this does not mean that project approval and appearance in Swinno happened at the same time. Normally, there is a delay between both, as discussed in the text, which is not seen in this figure.

positive results, consistent with our main analysis. The amplitude of the estimated effect is higher especially in comparison with the subsample with confirmed size data. The RD analysis does not produce significant results. The effect is imprecisely estimated because the variable has generally low values and large variation, as the creation of a significant innovation is a rare outcome. Further, the sample containing only projects with a decision year after 1997 is relatively small having less than 3,300 observations. Finally, the economic downturn during the 1990s also affected innovation development negatively. The annual number of innovations in SWINNO during the 1990s is only around 70 compared to over 100 during previous decades.

Table 18: Treatment effect of approval: IV and Regression Discontinuity approaches

Specification	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
Instrumental Variables (approval rate as instrument)						
Full sample (N=62,037)	.0149902	.0028566	5.25	0.000	.0093914	.020589
With size controls (N=42,797)	.0211254	.0034786	6.07	0.000	.0143075	.0279433
Regression Discontinuity (1997 policy change, Wald estimate)						
Wald estimate (N=3,281)	.0388302	.0499758	0.78	0.437	-.0591224	.1367829

Notes: The IV approach instruments approval with the mean approval rate by decision year; the second specification restricts the sample to observations with firm-size information and includes small/large firm controls. The RD approach exploits the 1997 policy change: the Wald estimate is calculated as the reduced-form effect of the post-1997 period on Swinno inclusion (coefficient = -.0062347, SE = .0079411) divided by the first-stage effect of the post-1997 period on approval (coefficient = -.1605640, SE = .0296906), with the standard error obtained via the delta method.

C.5 Projects not granted because of budgetary reasons

In this section, we identify a sample of projects that were not granted because of budgetary reasons. That is, they were judged of sufficient quality, but the funds available to the innovation agency were not enough. This information is taken from a variable in the STINS database which contains more detailed information on the reasoning behind 6,306 rejected public funding projects. In this way, we can use a subsample of rejected projects that resembles even more closely the granted ones, in terms of quality. The analysis only covers years 1987-2001, since the subsample did not include any projects from earlier years.

As can be seen in table 19, the coefficients tend to be positive but they are barely significant at the 10 percent level. This is because the number of observations, particularly for rejected projects, is very low compared to the original sample. We might take this as a weak confirmation of the additionality effects.

Table 19: Treatment effect of approval (ATET), with projects rejected because of budget

Estimator	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
Propensity score matching	.0063676	.0042418	1.50	0.133	-.0019461	.0146813
Nearest neighbor matching	.0071459	.0042574	1.68	0.093	-.0011985	.0154903
Inverse probability weighting	.0055028	.0033023	1.67	0.096	-.0009697	.0119753

Notes: Number of obs = 15,377; out of which 14,134 treated and 1,243 controls.
We run the models using lustrum instead of decision year to reduce the number of variables.
Source: author's calculations.

Appendix D Additional regressions for Q1

Table 20: Characteristics of innovative firms applying for public funding, 1970–2001 – Logistic regression (conventional standard errors)

	Logistic regression (odds-ratios)			
	(1) Firm	(2) Innovation	(3) Sector	(4) Time
Firm-level characteristics				
Public	1.084	1.182	1.133	1.173
	(0.754)	(0.534)	(0.645)	(0.562)
Past innovation	0.498***	0.524***	0.524***	0.523***
	(0.000)	(0.000)	(0.000)	(0.000)
Past funding	3.324***	3.504***	3.545***	3.602***
	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	2.972***	2.841***	2.814***	2.750***
	(0.000)	(0.000)	(0.000)	(0.000)
Large (>200)	0.719**	0.718**	0.714**	0.676***
	(0.017)	(0.019)	(0.017)	(0.007)
Medium city	0.809*	0.776**	0.787**	0.762**
	(0.059)	(0.026)	(0.037)	(0.020)
Major city	1.140	1.168	1.235	1.133
	(0.620)	(0.564)	(0.436)	(0.648)
Innovation-level characteristics				
Collaboration		0.758***	0.746***	0.736***
		(0.009)	(0.006)	(0.005)
Patented		1.454***	1.474***	1.716***
		(0.005)	(0.004)	(0.000)
High significance		1.814***	1.817***	2.076***
		(0.000)	(0.000)	(0.000)
Sectors				
Construction			2.210*	2.260*
			(0.087)	(0.084)
Health care			1.585	1.558
			(0.419)	(0.445)
Information			2.847***	2.695***
			(0.002)	(0.004)
Transport and storage			1.875	1.641
			(0.345)	(0.475)
Waste and water			2.322	1.946
			(0.130)	(0.242)
Professional services			2.457	3.365**
			(0.114)	(0.034)
Energy			3.985***	3.921***
			(0.002)	(0.003)
Primary sector			3.239	3.143
			(0.358)	(0.383)
Manufacturing			2.015*	2.021*
			(0.083)	(0.089)
Time				
1975–1979				1.229
				(0.273)
1980–1984				1.256
				(0.201)
1985–1989				1.337
				(0.126)
1990–1994				0.835
				(0.394)
1995–2001				0.456***
				(0.000)
GDP growth				0.992
				(0.698)
Constant	0.242***	0.218***	0.080***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2660	2660	2660	2660
Pseudo R-sq	0.124	0.136	0.141	0.160

Note: Baseline categories – Medium sized firm, medium and low significance, other sector, 1970–1974.

Table 21: Characteristics of innovative firms applying for public funding, 1970-2001 - Probit regression

	Probit regression			
	(1) Firm	(2) Innovation	(3) Sector	(4) Time
Public	1.031	1.079	1.058	1.097
	(0.843)	(0.628)	(0.722)	(0.555)
Past innovation	0.663***	0.684***	0.683***	0.681***
	(0.000)	(0.000)	(0.000)	(0.000)
Past funding	1.985***	2.055***	2.065***	2.094***
	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	1.953***	1.889***	1.878***	1.845***
	(0.000)	(0.000)	(0.000)	(0.000)
Large (>200)	0.836**	0.832**	0.831**	0.803***
	(0.029)	(0.027)	(0.026)	(0.010)
Medium city	0.886*	0.863**	0.871**	0.851**
	(0.069)	(0.029)	(0.041)	(0.019)
Major city	1.114	1.134	1.167	1.089
	(0.485)	(0.419)	(0.323)	(0.586)
Collaboration		0.844***	0.836***	0.835***
		(0.007)	(0.005)	(0.005)
Patented		1.258***	1.266***	1.389***
		(0.004)	(0.004)	(0.000)
High significance		1.429***	1.430***	1.532***
		(0.000)	(0.000)	(0.000)
Construction			1.567*	1.571*
			(0.094)	(0.095)
Health care			1.266	1.249
			(0.477)	(0.508)
Information			1.842***	1.758***
			(0.001)	(0.003)
Transport and storage			1.422	1.303
			(0.368)	(0.512)
Waste and water			1.601	1.416
			(0.152)	(0.297)
Professional services			1.691	1.975**
			(0.111)	(0.041)
Energy			2.219***	2.164***
			(0.003)	(0.004)
Primary sector			2.026	1.999
			(0.363)	(0.399)
Manufacturing			1.531*	1.516*
			(0.061)	(0.070)
GDP growth				0.996
				(0.748)
1975-1979				1.100
				(0.383)
1980-1984				1.122
				(0.267)
1985-1989				1.162
				(0.176)
1990-1994				0.879
				(0.298)
1995-2001				0.620***
				(0.000)
Constant	0.430***	0.404***	0.226***	0.243***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2660	2660	2660	2660
Pseudo R-sq	0.122	0.134	0.139	0.158

Note: Baseline categories - Medium sized firm, medium and low significance, other sectors, 1970-1974.

Table 22: Characteristics of innovative firms applying for public funding, 1970-2001 - clustered standard errors on firm level

	Logistic regression (odds-ratios)			
	(1) Firm	(2) Innovation	(3) Sector	(4) Time
Public	1.084	1.182	1.133	1.173
	(0.838)	(0.675)	(0.765)	(0.724)
Past innovation	0.498***	0.524***	0.524***	0.523***
	(0.000)	(0.000)	(0.000)	(0.000)
Past funding	3.324***	3.504***	3.545***	3.602***
	(0.000)	(0.000)	(0.000)	(0.000)
Small (<50)	2.972***	2.841***	2.814***	2.750***
	(0.000)	(0.000)	(0.000)	(0.000)
Large (>200)	0.719	0.718	0.714	0.676*
	(0.127)	(0.131)	(0.129)	(0.085)
Medium city	0.809	0.776	0.787	0.762
	(0.269)	(0.195)	(0.228)	(0.167)
Major city	1.140	1.168	1.235	1.133
	(0.748)	(0.711)	(0.636)	(0.792)
Collaboration		0.758*	0.746*	0.736*
		(0.082)	(0.069)	(0.057)
Patented		1.454**	1.474**	1.716***
		(0.043)	(0.036)	(0.004)
High significance		1.814***	1.817***	2.076***
		(0.000)	(0.000)	(0.000)
Construction			2.210	2.260
			(0.107)	(0.116)
Health care			1.585	1.558
			(0.515)	(0.518)
Information			2.847***	2.695**
			(0.007)	(0.016)
Transport and storage			1.875	1.641
			(0.377)	(0.495)
Waste and water			2.322	1.946
			(0.191)	(0.310)
Professional services			2.457	3.365*
			(0.216)	(0.099)
Energy			3.985***	3.921**
			(0.008)	(0.017)
Primary sector			3.239	3.143
			(0.424)	(0.352)
Manufacturing			2.015	2.021
			(0.150)	(0.172)
GDP growth				0.992
				(0.778)
1975-1979				1.229
				(0.398)
1980-1984				1.256
				(0.342)
1985-1989				1.337
				(0.298)
1990-1994				0.835
				(0.504)
1995-2001				0.456***
				(0.001)
Constant	0.242***	0.218***	0.080***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2660	2660	2660	2660
Pseudo R-sq	0.124	0.136	0.141	0.160

Note: Baseline categories - Medium sized firm, medium and low significance, other sectors, 1970-1974.

Appendix E Additional regressions for Q2

In this appendix we show the results of OLS, probit, and logit regressions of $Swinno$ on $Approval$ and our control variables. They seek to illustrate simpler approaches to the question in our Q2 section, namely whether getting public funding leads to a higher probability of developing a top innovation. In all these regressions the $Approval$ variable is statistically significant and with a positive sign, which reinforces the robustness of our results. The regressions shown here, however, do not control for selection (for the fact that approval is not random).

Secondly, we add the full results of the robustness analysis regarding the use of the funds (table 24).

Table 23: Summary of Regression Results (Q2): OLS, Probit, and Logit

Variable	**OLS**	**Probit**	**Logit (Odds Ratio)**
Approval	0.0118***	0.4349***	2.9465***
	(0.0011)	(0.0366)	(0.2774)
Applied amount (log)	0.0029***	0.1456***	1.4271***
	(0.0002)	(0.0101)	(0.0338)
Past public funding	0.0073***	0.1530***	1.3969***
	(0.0012)	(0.0329)	(0.1109)
Public ownership	-0.0258***	-1.0125***	0.0684***
	(0.0012)	(0.0511)	(0.0103)
Major town	-0.0044***	-0.1390***	0.7054***
	(0.0013)	(0.0397)	(0.0687)
Medium town	0.0043***	0.0963**	1.2744**
	(0.0014)	(0.0397)	(0.1192)
Sectors			
Manufacturing	0.0045***	0.1168**	1.3192**
	(0.0016)	(0.0463)	(0.1479)
Professional services	-0.0001	-0.0335	0.9254
	(0.0018)	(0.0567)	(0.1300)
Information & Communication	0.0011	0.0177	1.0719
	(0.0013)	(0.0407)	(0.1068)
Energy	0.0017	0.0226	1.0517
	(0.0020)	(0.0588)	(0.1496)
Construction	0.0008	0.0031	0.9797
	(0.0026)	(0.0747)	(0.1781)
Health	-0.0016	-0.1105	0.7911
	(0.0028)	(0.0997)	(0.1949)
Transport	0.0061	0.1031	1.3948
	(0.0040)	(0.1068)	(0.3384)
Water & Waste	0.0118***	0.2328**	1.8197***
	(0.0040)	(0.1008)	(0.4110)
Agriculture, Forestry, & Fishing	-0.0016	-0.1020	0.7750
	(0.0048)	(0.1688)	(0.3270)
Constant	0.0358***	-2.0079***	0.0208***
	(0.0043)	(0.0964)	(0.0045)
Observations	62,037	62,037	62,037
R-squared / Pseudo R-squared	0.0148	0.1163	0.1171
Year FE	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Treatment effect of approval by extent of funds usage

Estimator	Coefficient	Robust std. err.	z	P>∣z∣	[95% conf. interval]	
		Used ≥90% of granted funds				
Propensity score matching	.0079828	.0013964	5.72	0.000	.0052458	.0107197
Nearest neighbor matching	.0081057	.0016121	5.03	0.000	.0049459	.0112654
Inverse probability weighting	.0082494	.0010541	7.83	0.000	.0061835	.0103153
		Used ≥80% of granted funds				
Propensity score matching	.0071634	.0014433	4.96	0.000	.0043347	.0099922
Nearest neighbor matching	.0080789	.0015963	5.06	0.000	.0049502	.0112075
Inverse probability weighting	.0082911	.0010542	7.87	0.000	.0062249	.0103572
		Used ≤60% of granted funds				
Propensity score matching	.0112594	.0045633	2.47	0.014	.0023155	.0202032
Nearest neighbor matching	.0098693	.0048134	2.05	0.040	.0004352	.0193035
Inverse probability weighting	.0096272	.0040177	2.40	0.017	.0017527	.0175017
		Used ≤50% of granted funds				
Propensity score matching	.0086175	.006021	1.43	0.152	-.0031833	.0204184
Nearest neighbor matching	.0097176	.005787	1.68	0.093	-.0016248	.02106
Inverse probability weighting	.0112418	.0047221	2.38	0.017	.0019866	.0204971

Source: author's calculations.

Notes: Number of obs = 47,082 for projects using ≥90% of granted funds (out of which 28,256 with positive approval); 47,774 for projects using ≥80% of granted funds (out of which 28,948 with positive approval); 19,771 for projects using ≤60% of granted funds (out of which 1,199 with positive approval); 19,481 for projects using ≤50% of granted funds (out of which out of which 909 with positive approval). In the last two sub-samples, decision year 2001 was excluded, since it was a perfect predictor.

Appendix F Alternative estimation for Q3

Since significance has three different outcomes, an ordered logistic regression model is used as an alternative to the simple logit model presented in equation 4 .[37] This model presented in equation 5 predicts the probability that an innovation i is equal to or below a certain threshold m of innovation quality, based on a set of covariates $X_i t$.

$$
\begin{aligned}
\text{logit}(P(Q_i \leq m \mid X_{it})) = \log\left(\frac{P(Q_i \leq m \mid X_{it})}{P(Q_i > m \mid X_{it})}\right), \qquad (1 \leq m < M) \\
= \alpha_m - \beta_1 Amount_i - \beta_2 Ratio_i - \beta_3 C_i - \beta_4 [\textstyle\sum_{t_z<t}^{t-1} Approval_{j,t_z} \neq 0] \\
-\beta_5 [\textstyle\sum_{t_z<t}^{t-1} Innovation_{j,t_z} \neq 0] - \beta_6 Public_j - \beta_7 Large_j - \beta_8 Small_j \\
-\beta_9 Medium_j - \beta_{10} Major_j - \delta_i - \theta_t - \varepsilon.
\end{aligned} \tag{5}
$$

The results are presented in table 25. The results are very close to those of the main text. Under this model specification the correlation between higher applied amount and innovation significance disappears. Nonetheless, collaborative innovation continues to be positively associated with innovation quality, while past access to public funding indicates lower innovation quality. The latter might be concerning for policy makers aiming to develop primarily highly significant rather than incremental innovations, since firms repeatedly applying for public funding are associated with generating innovations with a low degree of novelty.

Nonetheless, it should be considered that firms with past access to public funding are primarily large conglomerates like ABB, Saab, and Volvo, which are traditionally most likely to optimize their production processes rather than developing new products (Dahlstrand and Cetindamar, 2000; Asheim and Moodysson, 2017). Moreover, this might simply be related to structural cycles in economic development. Based on the model of structural cycles by Schön (2010), economic activity undergoes regularly shifts between (1) phases where new technologies are introduced and (2) existing ones are optimized. Schön classifies both the early 1970s and 1990s, and thus half the research period, as the latter type where existing technologies are improved.

[37] For further details on ordered logistic regression models, see Fullerton (2009).

Table 25: Correlation between granted amount and innovation quality - Alternative regression model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log applied amount	1.121								1.135
	(0.116)								(0.135)
Coverage		0.724							0.789
		(0.105)							(0.274)
Collaboration			1.437						1.831*
			(0.146)						(0.075)
Past innovation				1.055					1.005
				(0.807)					(0.986)
Past public funding					0.659*				0.594*
					(0.089)				(0.060)
Public						1.100			0.900
						(0.789)			(0.825)
Large (>200)							1.267		1.275
							(0.540)		(0.572)
Small (<50)							1.995**		2.050**
							(0.044)		(0.048)
Medium city								0.912	0.809
								(0.790)	(0.570)
Major city								1.376	1.419
								(0.289)	(0.289)
1975									0.971
									(0.947)
1980									1.132
									(0.787)
1985									1.594
									(0.335)
1990									1.640
									(0.316)
1995									1.051
									(0.966)
Chemistry									0.608
									(0.372)
Energy									1.729
									(0.252)
Environment									2.079
									(0.149)
Equipment									1.217
									(0.696)
Food									1.572
									(0.504)
Information									1.586
									(0.257)
Material									0.847
									(0.734)
Medicine									1.066
									(0.888)
Natural resource									2.779
									(0.416)
Product dev.									0.819
									(0.518)
Production									1.195
									(0.742)
Transport									0.806
									(0.639)
Cut 1	0.052***	0.037***	0.055***	0.052***	0.037***	0.051***	0.080***	0.052***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cut 2	3.954***	2.794***	4.078***	3.825***	2.742***	3.754***	6.150***	3.866***	5.807***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)
Observations	412	412	434	434	434	434	434	434	412
Pseudo R-sq	0.004	0.004	0.003	0.000	0.005	0.000	0.010	0.002	0.045

Source: authors' calculations.

Lund Papers in Economic History
ISRN LUSADG-SAEH-P--64/270--SE

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