UNIVERSITÀ CATTOLICA del Sacro Cuore

DIPARTIMENTO DI POLITICA ECONOMICA

Assessing changes in EU innovation policy programs: from SME instrument to EIC accelerator for start-up funding

Maria del Sorbo

Carina Faber

Marco Grazzi

Francesco Matteucci

Miriam Ruß

Quaderno n. 37/luglio 2024

VP VITA E PENSIERO

Università Cattolica del Sacro Cuore

DIPARTIMENTO DI POLITICA ECONOMICA

Assessing changes in EU innovation policy programs: from SME instrument to EIC accelerator for start-up funding

Maria del Sorbo

Carina Faber

Marco Grazzi

Francesco Matteucci

Miriam Ruß

Quaderno n. 37/luglio 2024

VP VITA E PENSIERO

Maria del Sorbo, European Innovation Council, Bruxelles, Belgium

✉ Maria.DEL-SORBO@ec.europa.eu

Carina Faber, European Innovation Council, Bruxelles, Belgium

✉ Carina.FABER@ec.europa.eu

Marco Grazzi, Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy

✉ marco.grazzi@unicatt.it

Francesco Matteucci, European Innovation Council, Bruxelles, Belgium

✉ Francesco.MATTEUCCI@ec.europa.eu

Miriam Ruß, Wuppertal Institut für Klima, Umwelt, Energie gGmbH, Wuppertal, Germany

✉ Miriam.russ@wupperinst.org

Dipartimento di Politica Economica
Università Cattolica del Sacro Cuore – Largo A. Gemelli 1 – 20123 Milano
Tel. 02-7234.2921

✉ dip.politicaeconomica@unicatt.it

https://dipartimenti.unicatt.it/politica_economica

© 2024 Maria del Sorbo, Carina Faber, Marco Grazzi, Francesco Matteucci, Miriam Ruß

ISBN digital edition (PDF): 978-88-343-5860-3

www.vitaepensiero.it

This E-book is protected by copyright and may not be copied, reproduced, transferred, distributed, rented, licensed or transmitted in public, or used in any other way except as it has been authorized by the Authors, the terms and conditions to which it was purchased, or as expressly required by applicable law. Any unauthorized use or distribution of this text as well as the alteration of electronic rights management information is a violation of the rights of the publisher and of the author and will be sanctioned according to the provisions of Law 633/1941 and subsequent amendments.

Abstract

A novel analysis of the European Innovation Council (EIC) Accelerator pilot is presented, marking the first extensive examination of its selection process and the impact of its funding on deep tech ventures, in comparison to its predecessor, the SME Instrument. Utilizing applicant data from both programs, the study assesses the EIC's effectiveness in targeting firms that align with its objectives of driving breakthrough innovation. The research reveals that the EIC Accelerator pilot attracts younger and smaller firms, in comparison to its predecessor. A significantly higher proportion of applicants are high tech and medium hightech, indicating a strategic shift towards supporting cutting-edge technologies. Despite this shift, the analysis of funding determinants demonstrates a consistent pattern across both programs, emphasizing the influence of firm size, age, and patent portfolio. Further, a regression discontinuity design analysis is used to estimate the impact of funding during the EIC accelerator pilot on firm-level outcomes, such as patenting, revenue, or employment growth. However, the very recent launch of the program shrinks both the observations and the ex-post window, and due to large standard errors the point estimates are not significant at conventional levels.

JEL classification: O3, O31, O32, O38, L25, L26.

Keywords: Innovation Policy, Industrial policy, deep-tech, start-up, regression discontinuity, patent, firm growth

Acknowledgments. The views expressed here are of the authors only and do not necessarily reflect those of the respective institutions, such as the European Commission. This work includes analysis based on data from the European and Innovation Council & Small and Medium Enterprises of the European Commission, to whom we are very grateful. For this we would like to thank specially Stèphane Ouaki, Keith Sequeira, Nichita Lavrentiev, Luis Sanchez Alvarez and Aminata Sissoko. We also acknowledge insightful comments from Andreas Konstantinidis, Giovanni La Placa and Pietro Santoleri, Anne-Marie Sassen. Marco Grazzi gratefully acknowledges support from the Fulbright Commission and from the Nanovic Institute for European Studies at the Keough School of Global Affairs, and the Center for Italian Studies at the College of Arts and Letters, University of Notre Dame. Views and information presented are his own and do not represent the Fulbright Program, the U.S. or the Italian government. Miriam Russ gratefully acknowledges support from the University of Bonn and in particular from Prof. Clara Brandi.

1 Introduction

Those approaching for the first time the broad field of innovation, as well as those more accustomed to it might have overlooked the - indeed not so - recent surge of attention on industrial policies (among the many others Criscuolo et al., 2019; Pianta et al., 2020; Chang and Andreoni, 2020; Aiginger and Rodrik, 2020; Bloom et al., 2019).

Let us briefly recall the reason of such attention. In OECD countries, GDP growth, in per capita terms, is fuelled in large part by productivity growth, and this evidence is confirmed at each edition of the Compendium of Productivity Growth (OECD, 2023). Although productivity growth can be spurred by several channels, from organizational change all the way to learning-by-doing; innovation, intended as technological change, continues to be the main driver of productivity growth (see Cohen, 2010, and the references therein). Having dusted off the critical role of innovation as a driver of economic growth, let us consider why this is particularly biting in Europe.

First, growth has been stagnating in EU in the last decade. Although we would retain from framing this as a competitive race among countries, EU poor performance is a matter of fact. According to data from the World Bank (2024), in 2011 the EU had the same level of GDP (current US$) as the US and twice that of China. In 2022, US GDP is roughly twice that of EU and in the meantime time, China's GDP is roughly equal that of the European Union. *Second*, the EU appears to be lagging behind in its ability to generate competitive advantage and aggregate growth from research and innovation. Recent empirical works have dispelled the belief of a EU's superior performance in science and basic research, the so-called 'European Paradox' (see among the many others, Dosi et al., 2006; Bonaccorsi, 2007; Rodríguez-Navarro and Narin, 2018). However, if one considers the broad EU ecosystem for science, technologies and their industrial exploitation it is apparent that, in relative terms, EU is comparatively much worse at generating value from innovation than it is at producing basic research and scientific publications. As imperfect and partial as the indicator is, over the total cumulated number of 1520 unicorns[1] worldwide, around 49% are US based; 18% and 6% are respectively Chinese and Indian, while only 7% are based in the European Union (Crunchbase, 2024).

It is against such a background that in this work we investigate the effect of a shift in EU policy to support innovation. In particular, and to our knowledge for the first time, we focus on the difference brought about by a change from the SME instrument (see among the others Mina et al., 2021) to the new EIC accelerator instrument phase characterized by the emergence of the European Innovation Council (EIC) work program, under Horizon Europe (HEU). Far from being a simple re-labeling, the new EIC has changed the approach to providing resources for innovation in a number of ways that we address in this work.

The EIC has been established in 2021 with a budget of 10.1 billion euro for the years 2021 to 2027 and it is managing 70% of the total budget for small and medium enterprises (SMEs)[2] of Horizon Europe (EC, 2021). Its goal is to support innovations with potential breakthrough nature with a focus on deep-tech innovation (for a tentative definition of deep-tech, refer to Basilio et al., 2022;

[1] Typically defined as a private VC-financed startups with valuations of over $1 Billion.

[2] At the European level, small and medium-sized enterprises are defined as firms with fewer than 250 employees and either a maximum total turnover of €50 million or a maximum balance sheet total of €43 million (EC, 2003).

EISMEA, 2020). It supports technologies with scaleup potential that may be too risky for private investors. One of its funding schemes, the EIC accelerator, can be considered as the direct successor of the SME Instrument. The latter was aimed at funding SMEs in the Horizon 2020 programme (the research and innovation framework programme preceding Horizon Europe) with no focus on deeptech as such (see also EISMEA, 2022).

The questions that we will address in this work are aimed at exploring if, and to what extent, the switch from SME to the new funding scheme has resulted in a change of the features of the pool of applicants. Then, we will investigate the characteristics of the companies receiving fundings from EIC, and finally, although the time span for the ex-post analysis only allows for an exploration, we will consider the impact of fundings on the selected companies. As a result, our empirical analysis can be split in two parts. The first looks at the *ex-ante* period, the process of application for fundings and its outcome; the second focuses on the *ex-post* period, the years after the award of the fundings. Notice that the launch of EIC is very recent as it took place only in 2021. Even though it was preceded by a pilot phase covering the years 2018-2020, it is hard to expect that the EIC activities have already produced their complete effect, due to the long time development that is required for deeptech.

In the first part of this work, the central research question develops around the effectiveness of the EIC Accelerator pilot in targeting firms that align with its stated goals of supporting deep technology and breakthrough innovation. In this perspective, we analyze applicant pool samples to find out if differences in selection criteria have had an effect on the type of firms applying. The exploratory, non-parametric analysis is complemented by more standard probit analyses purported at identifying the determinants of being funded and how they differ between the two programs, SME instrument and EIC. Our results suggest that firms applying to an EIC accelerator pilot grant are in average younger, smaller in terms of employees, but bigger in terms of assets and have filed less patents so far, than the firms applying to the SME instrument. Further, the share of high tech[3] and medium high tech applicants is significantly larger in the EIC pilot, jumping from around 5% high-tech firms and 8% medium high tech firms in the SME instrument, to 13% and 29% respectively in the EIC pilot phase. In this respect, our findings point to the effectiveness of the EIC program in shifting the focus on deep-tech and breakthrough innovation. In addition, the program appears to be successful in targeting technology oriented firms in an earlier entrepreneurial phase.

The firm-level characteristics associated to a higher probability of success show some degree of similarity across the two programs. Size (as proxied by the number of employees) when significant, display a positive sign, suggesting that relatively larger firms are more likely to be awarded the grant. Patents display a positive sign in both programs while, interestingly, a younger age has proven to be an advantage only during the EIC pilot. In addition, two further details are worth mentioning: first, firms that engage in multiple applications markedly boost their chances of securing funding in both programs. Second, although being categorized as high-tech appears to be a detrimental factor during the SME Instrument phase, this characteristic does not influence the selection during the EIC pilot phase, decreasing barriers for high tech firms to be funded.

In the second part of the analysis (section 6), the focus shifts to estimating the impact of funding

[3] High tech and medium high tech firms are identified according to the OECD taxonomy of sectors based on R&D intensity (Galindo-Rueda and Verger, 2016).

on firm-level outcomes. As traditional in this field of literature (Bronzini and Piselli, 2016; Santoleri et al., 2022) we employ a regression discontinuity design, leveraging the fact that firms need to attain a specific evaluation score in order to be admitted to the interview phase, where funding decisions are made. By comparing firms just below the threshold with those just surpassing it, the analysis aims to assess the local average treatment effect of funding on different indicators of firm performance one, two, and three years after application. The research question underlying this framework is: does receiving funding through the EIC Accelerator pilot translate into tangible firm-level advancements in innovation and success, as displayed by patent filings and other key performance indicators, in the years following the application? In this respect our analysis is substantially limited by the recent launch date of the EIC. The implications are twofold: the total number of funded firms that we can observe in the *ex-post* phase is small; if we want to have three years of observation after the event of funding, the sample further shrinks. Our preliminary evidence on this is neither a significant effect of being funded on innovation, proxied by the filing of patents in the years after application, nor on firm level outcomes such as assets, profitability and the number of employees.

Our work is structured as follows. In section 2 we review recent studies on the topic and section 3 describes the institutional setting of the European Innovation Council. Section 4 describes the data sources and reports some descriptive statistics. The following two sections then focus on the analysis of the EIC pilot. First, in a comparison with the SME instrument, the characteristics of applicants and determinants of funding are analyzed in section 5. Secondly, section 6 assesses the impact of EIC funding on the firms in a regression discontinuity design. We finally discuss our findings.

2 *Literature Review*

The consensus for policy interventions to support innovation is almost unanimous. As already noted by Arrow (1962) perfect competition is unable to provide the socially optimal level of innovation, because of the riskiness, non-appropriability and non-divisibility of the outputs of innovation. Spence (1984) added that innovation is likely to generate positive externalities in the form of (knowledge) spillover effects. When a company generates something truly groundbreaking, that knowledge can spill over to other firms that either copy or learn from the original research without having to pay the full cost of R&D. Even with well functioning institutions to protect intellectual property, ideas and knowledge might spread beyond the firm's boundaries, making it impossible for the company in which the innovation was originally developed to fully appropriate the economic value associated to the new idea or product. Thus the existence of knowledge spillover, in absence of appropriate countervailing policies, would keep innovation below a socially desirable level (see also Bloom et al., 2019). At a more fundamental level, the very uncertain and serendipitous nature of the innovation process make it apparent that innovation levels of private companies would be always too low (Dosi and Nelson, 2010).

Small and medium sized enterprises can play a major role in driving innovation, but at the same time they are facing major financial constraints (Mina et al., 2021). Therefore, public support for innovative SME's is in place in most developed countries, in various formats, such as tax reliefs, public procurement, and grants. All of these can have significant positive effects on innovation. According to Dechezleprêtre et al. (2023) more than 80% of OECD countries had tax reliefs for research and development expenditures in place in 2018, regardless of size, and the figures keep raising (OECD, 2021). Analyzing the tax regime in the UK, Dechezleprêtre et al. (2023) find that being under the more generous tax regime for SMEs increases patenting activity and R&D expenditure significantly. de Rassenfosse et al. (2019) show that the US government spends around 50 billion dollar per year on public procurement of innovation, accounting for one third of all federal spending on R&D in the US. Further, around 1.5% of the procurement contracts have led to at least one patent, with these contracts accounting for more than 35% of the total contract value.

Within the field, the literature on R&D subsidies is one of the richest and oldest (see among the others, Busom 2000 on Spain, Lach 2002 on Israel, Sissoko 2013 on France). However, while tax incentives are untargeted measures and procurement contracts are used when agencies want to buy products for their own use (de Rassenfosse et al., 2019), public grants can be used to target support to specific firms and specific sectors according to a public purpose and strategic goals, such as the green or digital transition (see also Bloom et al., 2019).

In the US, the Small Business Innovation Research (SBIR) program, acting at the federal level, is one of the main programs supporting innovative SME's through research and development grants. According to Howell (2017) the award of a SBIR grant has large positive impacts on patenting, revenue, and future private venture capital investments. The counterpart to the SBIR program in Europe has been the SME instrument, 2014-2020. Bellucci et al. (2023) compare the characteristics of applicants and beneficiaries of the EU SME instrument at the time of application to companies that got private venture capital using a propensity score matching. While they find that publicly funded SMEs are on average smaller, older and have been less innovative before being funded than privately funded firms, Mina et al. (2021) find that the SME instrument scheme attracts firms with high-growth potential when comparing them to firms that did not apply, and that patenting and prior private venture capital funding are predictors of getting funded after application.

As far as the ex-post effects of the SME Instrument are concerned, Santoleri et al. (2022) use a regression discontinuity design to compare firms that just got funded under the SME instrument to firms that were right below the threshold of getting funded. They find that public grants have sizable impacts on different firm level outcomes, increasing private equity, patents and employment, as well as decreasing the probability of failure.

In recent years, both aiming to improve on previous funding scheme, and also in response to pressing societal challenges, there has been an increasing focus on so-called *deep tech* (Basilio et al., 2022). As described in Section 3, the EIC Accelerator pilot is specifically aimed at fostering deep tech and breakthrough innovation. Nonetheless, the concept of deep tech remains somewhat nebulous and does not fall in standard economic categories. We refer here to the definition in Basilio et al. (2022), according to which the main characteristic of deep tech is that it is based on cutting-edge science and technology. The authors argue, that although current deep tech includes fields such as AI, material science, and biotechnology, a classification based on industry sectors is inadequate due to the dynamic character of deep tech. As research frontiers progress, the sectors and activities belonging to deep tech evolve as well. Consequently, Basilio et al. (2022) aim for a definition of deep tech based on the specifc barriers to entry in these fields due to asymmetric information and capital intensity. Multi-dimensional uncertainties and risks, such as market, technological, regulatory, and scale-up risks, lead to strong information asymmetries between the scientists, who possess private information and beliefs about their projects' value, and potential investors, who must base their decisions on publicly available information.

Additionally, deep tech is focused on high risk and long-term projects, whose outcome is a physical product (software can be embedded in the hardware), which makes the scale-up process more capital-intense than in sectors like digital tech. As a result, deep tech ventures require substantial external capital not only during the research and development phase but also during subsequent market entry and scale-up stages. Clearly such project require an eco-systemic approach.

This framework emphasizes why public innovation funding in the deep tech sector is especially important, as deep tech is inherently characterized by the uncertainties and risks that make private funding difficult. Ideally, in such a scenario, public funds can lead to the de-risking of the technologies, serve as an additional certification and thus decrease information asymmetries and ultimately crowd-in private investors.

At the same time, such a "procedural" definition of deep tech makes a sectoral classification difficult. Thus, to categorize projects based on the European Classification of Economic Activities (NACE), we refer to the OECD taxonomy of economic activities (Galindo-Rueda and Verger, 2016). The taxonomy divides economic activities into five principal groups of different technology levels based on sectoral R&D intensity. For this analysis, a binary indicator was implemented for firms operating within the first (high tech) and second (medium high tech) levels of this classification.

To estimate the maturity of innovation, the EU employs the concept of technological readiness levels (TRL's) which provide a standardized framework, ranging from 1 to 9, to discuss and assess the phases of the innovation cycle from initial concept to market entry, with 9 indicating full maturity.

3 *The EIC and the evolution of the institutional setting*

Research and innovation funding at the European level is organized in framework programs (FP), a series of funding initiatives established by the EU to promote and advance research and innovation within Europe. Such programs, which have been the primary financial vehicles for supporting R&D activities across various sectors and themes, have changed significantly since the inception of the first Framework Programme in 1984 both in scope and budget, culminating in the most recent "Horizon Europe" program, covering the period from 2021 to 2027 (Reillon, 2017).

The current FP has a total budget of approximately €95.5 billion and is structured in three pillars, Excellent Science, Global Challenges and Innovative Europe. The European Innovation work programme is located in pillar 3 and has a budget of approximately €10 billion for 2021-2027, it manages approximately 10% of the total funds of Horizon Europe and it is administered by the European Innovation Council and SMEs Executive Agency (EISMEA) (refer to EC Europa EU, 2021a, for a more detailed description of the program).

Table 1 summarizes changes in key elements that occurred in the evolution from SME instrument, the initial EIC pilot phases, all the way to the fully-fledged EIC. We underline a shift from generic, incremental, R&D activities in the SME, to deep tech and breakthrough innovations; in addition to major procedural changes between the phases and in the selection process. Table 1 also reports the number of applications and successful applications. As one can see, all funding programs are highly competitive with success rates between 2 and 5 percent.

In this work we focus our attention on the SME Instrument and the EIC Accelerator Pilot A and B (Columns 1-3), whereas the ongoing EIC accelerator funding scheme, one of the three funding instruments at the EIC and the successor of the EIC accelerator pilot phase, cannot be investigated as it started only two years ago and data is not yet available.

Stage	**SME Instrument**	**EIC Accelerator Pilot A**	**EIC Accelerator Pilot B**	**EIC Accelerator**
Timeframe	2014-2017	2018 - 09/2019	10/2019 - 2020	2021-2027
Key Focus	General SME support	Deep tech focus, breakthrough innovations		
Major Changes	Initial implementation	Introduction of interviews, bottom-up approach, proactive management	Phase 1 abolished, blended finance, monobeneficiaries focus	Establishment of EIC, program managers, continuous applications (challanges)
Procedure interview	Single-step remote evaluation	2-step process with interviews	Continued two-step process with interviews	Three-step process: short proposal, full proposal, interview
Quality threshold	12	13	13	13
Applications	18497	12229	13791	ongoing
N. of grants	860	505	293	ongoing
Success Rate	4.6%	4.1%	2.1%	ongoing
Grants	€1.4 billion	€0.6 billion	€1 billion + €0.7 billion equity	ongoing

Table 1: Evolution of the SME Instrument and the EIC Accelerator

3.1 SME Instrument: 2014-2017

The SME Instrument (SMEI), column 1 of table 1, established under the 8th European framework program for Research and Innovation, Horizon 2020, was designed to support innovative SMEs developing not only breakthrough but also incremental innovation. Managed by the European Agency for Small and Medium Enterprises (EASME) and endowed with a €3 billion budget, it drew inspiration from the US Small Business and Innovation Research (SBIR) program (Howell, 2017; Mina et al., 2021). Similarly to SBIR, the SMEI provided support to small and medium-sized enterprises in three phases: the first, covering for concept and feasibility assessment, allowed firms to receive a grant of €50,000 for market analysis and preliminary business and technological plan, preparing them for a phase 2 grant ranging from €0.5 million to €2.5 million, with a focus on R&D, demonstration, and market replication. The third phase consisted of indirect support activities aimed at facilitating access to private capital (EU Council, 2013).

Eligibility for funding required the firm to be a for-profit SME and to be legally established in an EU member state or a Horizon 2020 associated country (Mina et al., 2021). Firms could directly apply to any of the three phases, though phase 1 was specifically intended to prepare an application for phase 2. Notably, firms could apply as single entities, marking a significant deviation from other European policies. The SME Instrument was structured around calls within specific thematic areas, such as space, healthcare, or energy, encompassing 27 topics in total, and aimed at supporting internationally oriented SMEs with a profile of high risk and high potential (EC, 2015, 2017a). The selection procedure involved a remote evaluation by four experts who assessed projects in three categories: impact, excellence, and implementation.

Funding decisions were subsequently made based on a budgetary threshold. Budgets were allocated individually for each thematic area, meaning the threshold effectively leading to funding varied for each topic and cohort, applying at a specific cut-off date, and was decided ex-post after the evaluations.

3.2 EIC pilot: 2018-2020

In 2017, the interim evaluation of Horizon 2020 reported an increased need to foster breakthrough innovation and market creation (EC, 2017b). Therefore, it was decided to launch a new pilot initiative in the remaining time of Horizon 2020 preparing the implementation of a fully fledged European innovation council in the succeeding framework program, Horizon Europe, starting in 2021. This also represented a strong shift towards focusing on radically new ideas and non-incremental innovation.

The SME Instrument was integrated into a pilot phase for the EIC work program in 2018. The SME instrument was renamed as EIC accelerator pilot, one out of two new funding schemes at the EIC Pilot, alongside the Pathfinder Pilot instrument. While the Pathfinder Pilot instrument was aimed at early-stage scientific innovation projects at low TRLs (1-3) conducted by interdisciplinary consortia, the Accelerator Pilot instrument was aimed at close-to-market projects with higher TRLs of mono beneficiaries. The Transition funding scheme targets project with intermediate TRL. Hence, as a result, the EIC funding schemes now cover the whole spectrum of TRL space.

Several procedural and institutional changes were implemented in two steps, with the start of the EIC Pilot in 2018, and starting at the cut-off date in October 2019 (column 2 and 3 of table 1, respectively).

Already in the pilot phase A, the overall quality threshold was increased from 12 points in the SME instrument to 13 points for the remote expert evaluation. Furthermore, and noteworthy, an interview phase was added after remote evaluation. In the interview phase, an expert panel makes the final funding decisions. Indeed, not all projects admitted to interview are guaranteed funding but roughly only one third. Quite remarkably, interview phase significantly impacts funding outcomes: funded firms are evenly distributed across all score terciles among interviewees (see figure 1). This indicates that the interview phase introduces a comprehensive reassessment, leading to a more varied selection of funded firms that may not strictly align with their initial score-based ranking. Further, there was a transition from topic-specific calls in the SME instrument to a bottom-up approach, enabling all firms to participate in open calls. Exceptionally, at two cut-off dates, a focus on specific topics was kept: a Green Deal-focused call in 2019 and an allocation of funds for Covid-related projects in 2020.

Starting in October 2019, additional changes were made, leading to Pilot phase B. From then onward, firms could only apply individually as mono-beneficiaries and the phase 1 grants of the

SME instrument were discontinued.

Furthermore, projects with high TRL could apply for additional equity of up to €15million in the form of blended finance (EC, 2020). This approach combines grants for innovation with equity investments for market scaling: a complete novelty for the EU scenario.[4] The EIC fund, established in 2020, was in charge of the implementation of the equity component of the blended finance awarded by the EIC. This includes an additional legal and financial due diligence by the European Investment Bank (EIB). If these checks are successful, there is a further condition to be met in order to receive equity from EIC: the awardee must be able to find a lead investor that is committing with more than 50% of the finance for that investment round. Clearly the very design of the blended funding scheme is aimed at generating crowding-in effect.[5] In total, 163 applicants were selected for blended finance on the 5 cutoff dates starting in October 2019 until the end of the pilot phase end of 2020. However, as the first funding agreement was only signed in January 2021 (EC Europa EU, 2021b), marking a significant operational delay in the implementation of the equity component, it is not possible to evaluate heterogeneous effects between firms with and without equity investment by the EIC fund. This remains an important next step in the analysis of the EIC.

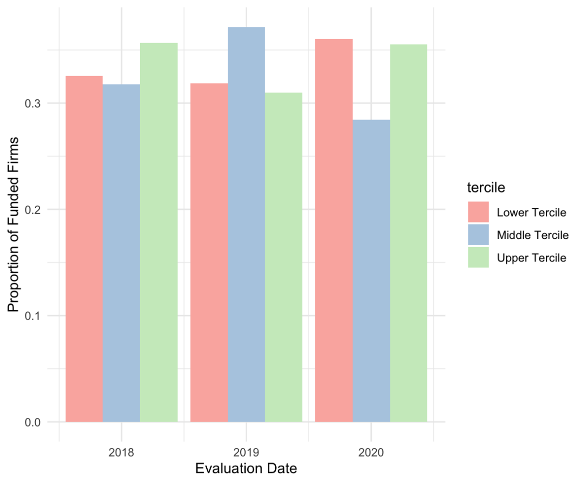


Figure 1: Distribution of funded firms on the evaluation score terciles in the interview phase.

3.3 Fully-flegded EIC: 2021-2027

In March 2021, the fully-fledged European Innovation Council work program managed by the new EISMEA was inaugurated (column 4 of table 1), succeeding the EIC pilot and introducing three principal funding schemes: Pathfinder, Transition, and Accelerator. The selection procedure of the EIC accelerator foresees continuous applications with a preliminary short proposal, followed by the full application at designated cut-off dates. The advent of Program Managers marked a significant advancement in the proactive management of innovation at the EIC. This evolution facilitated the

[4] Although, we were not able to find explicit references to the work of Mariana Mazzucato on the Entrepreneurial state, we find that this "equity involvement", is at least reminiscent of the policies suggested in Mazzucato (2011) and following works. More general, the equity component makes the EISMEA a new and relevant player in the governmental venture capital (GVC) panorama (see among the many others Lerner, 2000; Cumming and Johan, 2019; Audretsch et al., 2020).

[5] According to EISMEA (2023b) each euro invested by the EIC has attracted 3.5 additional euros by other investors.

introduction of topic-specific challenges, supplementing the open call. These challenge calls, written by the program managers and approved by the EIC program and steering committee, are open to proposals in predefined topics that have been identified in areas where breakthrough technologies or game-changing innovations developed by start-ups or SMEs can have a major impact on EU objectives. For a comprehensive overview of the funding instruments and the topic-specific challenges we refer to EISMEA (2023a) and EISMEA (2023b).

4 Data

The empirical work we present here, mostly relies on two datasets: E-Grants Data Warehouse, ex-CORDA (COmmon Research DAta Warehouse) database from the European Innovation Council, providing application data for the SME Instrument and the EIC Accelerator Pilot, and the Bureau van Dijk's Orbis (BvD Orbis) database for firm characteristics. More information can be found in the annual impact report EISMEA (2022, 2023b).[6]

Table 2: Descriptive statistics for the full sample and the BvD matched sample of firms across all years and programs.

	Full Sample	Matched Sample
Number of Firms	44517.0	37012.0
Funded Firms	3.7	3.8
Seal of Excellence	35.0	36.3
Mean Score	11.6	11.7
Median Score	12.2	12.3
SD Score	2.3	2.1
Number of Applications	1.7	1.7

The applicant dataset from CORDA and the EIC includes all applications to the SME Instrument Phase 2 and the EIC Accelerator Pilot from 2014 to 2020. Quite relevant for our analysis, it reports scores from the remote evaluation of each project and the binary decision (Go/No Go) from the interview phase, enabling to identify three mutually exclusive groups: projects receiving funding; projects advancing to the interview phase but not receiving funding; and unsuccessful firms that were either rejected or withdrew their applications. The data also report information on the size of the recommended grant and equity. As the funding threshold for the SME Instrument and the interview phase threshold during the EIC Pilot vary slightly across different cut-off dates, the analysis employs a normalized threshold, calculated as the difference from the score and the cutoff-specific threshold. Consequently, projects with a normalized threshold of zero or higher are directly funded in the SMEI and advance to the interview in the EIC Pilot, while those below zero are definitively unfunded. Until 2019, consortia comprising multiple firms were eligible to apply for the SME instrument, allowing for projects that involved more than one firm. In the analysis at hand each firm is treated as

[6] We gratefully acknowledge support from the Joint Research Centre of the EU Commission (JRC) that has provided the match between firms' information, as appearing in CORDA, and BvD identifiers. The data analysis was carried out using Python and R, for the regression discontinuity design the 'rdd' package in R was used.

one observation, as we are interested in firm level characteristics, both as determinants for funding (Section 5) and as outcome variables after funding (section 6).

As described above, the CORDA data has been merged to Orbis IDs to create a dataset with firm-level characteristics. Around 83% of the applicants could be attributed an Orbis ID. These percentages vary only slightly between the SME Instrument and the EIC pilot, and also between funded and non-funded firms (see table 8). Table 2 shows the descriptive statistics of the full applicants sample and the matched sample of firms with Orbis IDs.

Even though firms with Orbis IDs tend to obtain a relatively higher score in the remote evaluation, the percentage of successful firms does not differ substantially in the matched sample. Table 9 shows the applications by country for the full sample and for the sample with matched BvD identifiers (matched sample).[7]

Although BvD Orbis is the best option to work with firm-level data from different countries, its limitations and imperfect coverage are also well known, especially for smaller firms and startups (for a detailed analysis, refer to Bajgar et al., 2020). For what concerns our work, these limitations also take the form of a data coverage that changes with the variables of interest. Table 13 in the appendix shows the data coverage for the whole sample of firms with Orbis IDs for some firm level variables. Notwithstanding such problems, BvD Orbis is the unique alternative for this sort of study, as shown also in Mina et al. (2021) and Santoleri et al. (2022).

A noticeable feature of the funding schemes that we are investigating that has not received attention so far, is that, over the years, firms apply multiple times for the same funding scheme. In fact, more than 50% of the firms in the sample have applied to funding from the SME Instrument and the EIC pilot at least twice, with over 30% applying more than three times. This indicates the importance of considering multiple applications when selecting the sample. Since the number of applications might affect the chances of obtaining funding and each application can be viewed as a distinct observation, we will include the count of applications as an independent variable in the ex-ante part of the analysis, when using the entire, unrestricted sample.

For the second part of the analysis, which examines the impact of funding, it is crucial to classify each firm annually as either treated or untreated. This is done, because firm-level outcome variables remain constant across multiple applications within the same year. To achieve this, if a firm received funding in a given year, its other applications in the same year are excluded, effectively treating the firm as funded for the entire year.

5 *Comparing the SME Instrument and the EIC Pilot*

In the first part of our empirical investigation we conduct a comparative analysis of firm selection between the SME Instrument and the EIC Pilot programs. To identify the distinct features and strategic orientation of the EIC Pilot in contrast to the SME Instrument, we begin by examining the applicant pools in both programs to discern whether the EIC Pilot's unique emphasis on deep technology succeeded in attracting the attention of different profile of applying firms. We then proceed in

[7] Countries with fewer applicants also tend to be have a lower coverage with Orbis IDs, leading to a underrepresentation in the matched sample.

section 5.1 by focusing on the determinants of funding success, analyzing the criteria that underpin the allocation of resources within these initiatives.

SME Instrument: Applicants				
	mean	sd	median	N
age	9.9	10.9	6.0	13960
employees	20.6	32.1	9.0	7913
assets (in thousands)	2702.3	7246.0	404.9	10537
N. of patents	9.9	38.6	0.0	14132
N. of patents last 3 years	3.9	12.8	0.0	14132
D patent	28.3	45.0	0.0	14132
D hightech	5.1	22.0	0.0	14132
D medium hightech	8.3	27.6	0.0	14132
D manufacturing	26.2	44.0	0.0	14132
SME Instrument: Funded Firms				
	mean	sd	median	N
age	10.5	10.8	7.0	654
employees	23.3	34.6	11.0	387
assets (in thousands)	3934.1	9202.3	922.3	527
No. patents	14.9	68.4	1.0	662
No. patents 3 years	5.9	13.9	0.0	662
D patent	39.9	49.0	0.0	662
D hightech	3.0	17.1	0.0	662
D medium hightech	4.7	21.1	0.0	662
D manufacturing	31.3	46.4	0.0	662

Table 3: Descriptive Statistics for the SME Instrument.

Table 3 and Table 4 present the descriptive statistics for the SME Instrument and the EIC Pilot Phase, respectively. In this respect, our exploratory analysis reveals that firms applying during the EIC Pilot Phase tend to be younger, smaller, and have filed fewer patent applications, likely attributable to their younger age. Notably, the proportion of high tech firms increases from approximately 5% in the SME sample to around 13% in the EIC Pilot sample.[8] Additionally, the EIC Pilot applicants also display a higher percentage of medium high tech.

In table 5 we proceed to verify whether such differences also have some level of statistical significance. The Welch's two-sample t-test, assessing the mean differences in continuous variables (Variables 1–4), confirms the statistical significance of these differences. This test, like the t-test, assumes normal distributions but accommodates unequal variances in the two samples. A Chi-squared test is used to determine the significance of differences in the proportions of binary variables (Variables 5-8).

The t-tests for age, assets, employees and patents show statistically significant differences in means (p-value = 0.00), suggesting that the average values of these variables differ significantly between the groups being compared and also the Chi-squared tests for the dummy variable indicate

[8] We recall that as discussed in section 2, in the absence of precise taxonomy to identify deep-tech firms or sector, we proxy such activities with the classification provided by Galindo-Rueda and Verger (2016).

EIC Pilot: Applicants				
	mean	sd	median	N
age	7.8	8.4	5.0	21337
employees	14.8	27.0	6.0	13223
assets (in thousands)	382.8	11110.3	1.1	14588
No. patents	4.6	29.7	0.0	21848
No. patents last 3 years	1.6	10.3	0.0	21848
D patent	10.2	30.2	0.0	21848
D hightech	13.3	33.9	0.0	21848
D medium hightech	29.4	45.6	0.0	21848
D manufacturing	20.2	40.2	0.0	21848
EIC Pilot: Funded Firms				
	mean	sd	median	N
age	7.1	8.1	5.0	679
employees	15.0	21.3	8.0	461
assets (in thousands)	260.4	1227.5	1.6	476
N. of patents	6.9	25.2	0.0	693
N. of patents last 3 years	3.6	14.6	0.0	693
D patent	19.2	39.4	0.0	693
D hightech	17.2	37.7	0.0	693
D medium hightech	26.7	44.3	0.0	693
D manufacturing	26.8	44.3	0.0	693

Table 4: Descriptive Statistics for the EIC Pilot scheme

significant differences in frequencies across the two samples for these variables. Figure 2 further illustrates that, while there is a notable increase in the proportion of high-tech firms towards the end of the SME phase, the introduction of the EIC accelerator pilot marks a pronounced and sustained increase in their prevalence.

The results underscore the significant impact of the EIC Pilot's in attracting interests from a different pool of companies *vis-a-vis* SMEI. Although deep tech and high tech are not synonymous, the emphasis on deep technology and radical innovation has apparently attracted younger, smaller, and more technology-oriented firms. Of course, we do not attribute a direct causal evidence from the change in policy program, from SMEI to EIC, to a change - and its direction - in the observed pool of applicants; however the descriptive results *per se* provide corroborating evidence towards the desired direction.

To further check the robustness of the results, table 10 in the appendix reports the outcomes of a Fligner-Policello test. This test, a member of rank-based tests, assesses the median equality in two samples, circumventing strict distributional assumptions (Fligner and Policello, 1981). It extends the Mann-Whitney-Wilcoxon Test, which requires continuous distributions with identical shapes for median equality testing. The Fligner-Policello test only assumes symmetric distributions to validate median equality. Nonetheless, it retains relevance even under asymmetric distributions by facilitating stochastic dominance evaluation (for an application in a similar context, refer among

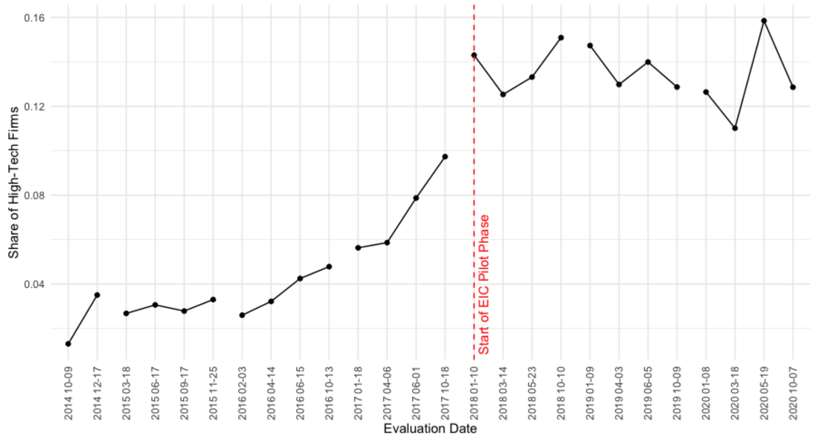


Figure 2: Share of applicants high tech over time. Dots referring to calls of the same year are connected by a line.

Table 5: Sample Difference Tests for Applicants.

	Test Statistic	p-Value	Type
Age	19.47	0.00	T-test
log(Assets)	100.86	0.00	T-test
log(Employees)	16.47	0.00	T-test
Patents in last 3 years	17.32	0.00	T-test
D patents	1970.56	0.00	Chi-Squared
D hightech	635.66	0.00	Chi-Squared
D medium hightech	2300.68	0.00	Chi-Squared
D manufacturing	173.63	0.00	Chi-Squared

the others to Bottazzi et al., 2011).[9] In the case at hand, stochastic dominance in terms of age, for example, would mean, that if one randomly selects one applicant from the SMEI and one applicant from the EIC pilot phase, the probability that the applicant from the SME instrument is older exceeds $\frac{1}{2}$. One advantage of the Fligner-Policello test is that the sign of the test-statistic also indicates the direction of the stochastic dominance. Here we can see that indeed, the probability of firms in the EIC pilot sample being younger and smaller than in the SME instrument, both in terms of assets and employees, exceeds 50%. In general, the results of the Fligner-Policello test corroborate the analysis before.

5.1 Comparing the Determinants of Selection

The evidence collected so far suggests that firms applying to the EIC pilot phase are on average younger, smaller and more technology-oriented than firms that applied to the SME instrument. This is in line with the shift towards deep tech and breakthrough innovation of the EIC pilot phase.

We move now to a more standard parametric analysis to investigate the determinants of selection

[9] Stochastic dominance of distribution F_A over F_B is defined according to Bottazzi et al. (2011). Given random variables X_A and X_B with corresponding distribution functions F_A and F_B, F_A dominates F_B, if the probability $\mathbb{P}[X_A > X_B]$ exceeds $\frac{1}{2}$.

into funding, in the two different programs. In the remainder of this section, the *dependent variable* is the binary variable 'funded', which is 1 if the firm got a grant in the respective year and 0 if the firm was not successful. As *explanatory variables*, we employ the age of the firm in the year of application, computed as the difference between application year and incorporation year; the number of employees (in log) as a proxy for size; a patent dummy, as a proxy for innovation in the years before application, taking value 1 if the firm filed at least one patent in the last three years before funding, and zero otherwise. As a lot of firms apply several times to the programs, a counter is also used to track the number of applications of the same firm. The counter is continuous over both instruments, that is, if a firm has already applied twice to the SME Instrument, it will have a counter of three if it applies for the first time to the EIC pilot. Then, the high tech and medium high tech dummies are used, and an additional dummy for manufacturing based on the NACE sectors. As standard in this field of literature (see among the others Mina et al., 2021) we also try to account for the financial sustainability of the firms employing a series of indicators: cash-flow scaled by total assets (cash_totass), ratio of debt and equity (debt_equity), and ratio of debt and total assets (debt_totass). Clearly, due to coverage issues of BvD Orbis recalled above in section 4 and also discussed in Bajgar et al. (2020), the inclusion of additional variables to the regression reduces the size of the sample.

A probit model is used to estimate the determinants of funding both for the SME Instrument and the EIC pilot individually. Further, a model with interaction terms is used to allow for a more direct comparison between the two programs. Probit models are used to estimate the probability for a binary dependent variable, here funding, to be 1, conditional on the independent variables $X \in \mathbb{R}^k$. This is called the response probability and is defined as

$$P(x) = \mathbb{P}[Y = 1|X = x] = \mathbb{E}[Y|X = x] \tag{1}$$

We then have the following regression framework

$$Y = P(x) + e, \text{ with } \mathbb{E}[e|X] = 0 \tag{2}$$

In a probit model $P(x)$ is linked via a standard normal distribution function Φ to the regressors, that is $P(x) = \Phi(x'\beta)$. The coefficients are then estimated via Maximum Likelihood Estimation.

It is important to note that the coefficients cannot be interpreted directly as marginal effects, instead the marginal effects are given by

$$\frac{d}{dx}P(x) = \beta g(x'\beta) \tag{3}$$

where g is the density of Φ. As the link function Φ is not linear, the marginal effects are not constant in x.

Thus, we estimate variations of the following equation individually for the SME Instrument and the EIC Pilot

$$Y_{t,i} = P(x_{t-1,i}) + e_{t,i} = \Phi\left(\beta^0 + \beta^1 x^1_{t-1,i} + \cdots + \beta^k x^k_{t-1,i}\right) + e_{t,i} \tag{4}$$

where $Y_{t,i}$ is 1 if firm i got funded at evaluation date t and 0 otherwise, $x^j_{t-1,i}$ are firm-level characteristics as described in 5.1 in the year $t-1$, that is one year before funding, and $e_{t,i}$ is the error term.

Additionally to be able to compare funding determinants between the two samples directly, we also estimate a probit model for both samples together, with a dummy indicating if a firm is from the EIC pilot sample or not. Then, the interaction terms allow to assess quantitatively the difference in coefficients between the SME instrument baseline and the EIC pilot phase:

$$\begin{aligned} Y_{t,i} =& \Phi\Big(\beta^0 + \beta^1 x^1_{t-1,i} + \cdots + \beta^k x^k_{t-1,i} \\ &+ \mathbb{1}_{EIC} + \beta^{k+1} x^1_{t-1,i}\mathbb{1}_{EIC} + \cdots + \beta^{2k} x^k_{t-1,i}\mathbb{1}_{EIC}\Big) + e_{t,i} \end{aligned} \tag{5}$$

Table 6 and table 7 report the results for the two separate probit models for the SME Instrument and the EIC pilot phase; then tables 14 and 15 in the Appendix report the marginal effects.

Table 6: Probit model results for the SME Instrument phase

	Dependent variable: Probability of being funded									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(employees + 1)	0.073***	0.078***	0.080***	0.069**	0.067**	0.070**	0.068**	0.043	0.089**	0.094**
	(0.022)	(0.025)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.034)	(0.043)	(0.043)
age		−0.001	−0.001	−0.0004	−0.0004	−0.001	−0.003	−0.003	−0.005	−0.005
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
counter			0.049***	0.045***	0.046***	0.049***	0.051***	0.042**	0.049*	0.050**
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.020)	(0.025)	(0.025)
D_patents				0.272***	0.278***	0.286***	0.273***	0.266***	0.289***	0.289***
				(0.056)	(0.056)	(0.057)	(0.057)	(0.067)	(0.085)	(0.085)
D_HT					−0.365***	−0.402***	−0.424***	−0.453***	−0.366**	−0.376**
					(0.131)	(0.132)	(0.132)	(0.152)	(0.180)	(0.181)
D_MHT						−0.372***	−0.394***	−0.361***	−0.294**	−0.281**
						(0.107)	(0.108)	(0.122)	(0.137)	(0.137)
D_Manufacturing							0.136**	0.122*	0.080	0.096
							(0.063)	(0.074)	(0.091)	(0.091)
cash_totass								0.001	0.0004	0.001
								(0.001)	(0.001)	(0.001)
debt_equity									−0.0001	−0.0003
									(0.004)	(0.004)
debt_totass										−0.344
										(0.225)
Constant	−1.886***	−1.890***	−1.833***	−1.895***	−1.869***	−1.806***	−1.818***	−1.238**	−1.359**	−0.873
	(0.211)	(0.212)	(0.221)	(0.222)	(0.223)	(0.221)	(0.221)	(0.625)	(0.631)	(0.669)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,789	7,783	6,452	6,452	6,452	6,452	6,452	4,661	3,379	3,379
Log Likelihood	−1,489.211	−1,489.030	−1,261.948	−1,250.238	−1,245.836	−1,238.946	−1,236.619	−895.308	−543.121	−541.748
Akaike Inf. Crit.	3,052.422	3,052.060	2,599.896	2,578.475	2,571.671	2,559.892	2,557.239	1,862.616	1,160.242	1,159.495

Note: *p<0.1; **p<0.05; ***p<0.01

For the SME instrument important predictors of funding are the number of employees and having filed at least one patent in the last three years. Both have a positive impact on the probability of funding, while the coefficient for the high tech dummy is negative and significant. Age is not statistically significant in the SME instrument phase. This is in line with the existing literature on the determinants of funding for the SME instrument by Mina et al. (2021). An important new insight that we provide for the SME instrument is that repeated applications significantly increase the chance of getting funded.

Table 7: Probit model results for the EIC pilot phase

	Dependent variable: Probability of being funded									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
employees_log	0.053**	0.078***	0.073**	0.067**	0.067**	0.071**	0.070**	0.058	0.069	0.070
	(0.025)	(0.028)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.044)	(0.047)	(0.047)
age		−0.007*	−0.009**	−0.010**	−0.010**	−0.010**	−0.011***	−0.020***	−0.019***	−0.019***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
counter			0.053***	0.044***	0.044***	0.044***	0.044***	0.052***	0.059***	0.058***
			(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)	(0.015)
D_patents				0.210**	0.206**	0.202**	0.196**	0.216**	0.199*	0.201*
				(0.084)	(0.085)	(0.085)	(0.085)	(0.107)	(0.113)	(0.113)
D_HT					0.037	0.015	−0.016	0.019	0.041	0.040
					(0.072)	(0.075)	(0.077)	(0.108)	(0.115)	(0.115)
D_MHT						−0.063	−0.085	−0.016	−0.008	−0.009
						(0.061)	(0.062)	(0.090)	(0.098)	(0.098)
D_Manufacturing							0.114*	0.184**	0.160*	0.161*
							(0.064)	(0.091)	(0.096)	(0.096)
cash_totass								0.0001	0.0001	0.0001
								(0.0002)	(0.0002)	(0.0002)
debt_equity									−0.018	−0.018
									(0.033)	(0.033)
debt_totass										−0.008
										(0.019)
Constant	−1.782***	−1.783***	−1.891***	−1.883***	−1.887***	−1.872***	−1.889***	−6.043	−6.252	−6.257
	(0.153)	(0.153)	(0.160)	(0.160)	(0.160)	(0.161)	(0.162)	(253.689)	(412.593)	(412.021)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,692	9,680	9,525	9,525	9,525	9,525	9,525	5,140	4,407	4,407
Log Likelihood	−1,327.190	−1,325.082	−1,277.425	−1,274.431	−1,274.297	−1,273.750	−1,272.204	−585.426	−499.193	−498.968
Akaike Inf. Crit.	2,726.380	2,724.163	2,630.850	2,626.863	2,628.594	2,629.499	2,628.407	1,250.851	1,080.385	1,081.935

Note: *p<0.1; **p<0.05; ***p<0.01

For the EIC pilot phase, the number of employees is not a significant determinant of funding, but age has a significant negative impact on the probability of being funded. The coefficient of the patent dummy is significant, but only at the 10% level. Interestingly, the high tech and medium high tech dummies become not statistically significant, whether they were negative and significant for SME instrument.[10] The counter accounting for multiple times applicants is significant, indicating that having applied before either to the SME instrument or the EIC pilot increases the chances of being selected in the EIC pilot as well.

Overall, the results of the individual probit models show, that having filed patents in the last three years, and having applied before have a consistent and positive impact on the probability of being funded in both phases, whereas being a high tech firm decreases the chances of being funded only in the SME instrument and the number of employees is not consistently significant for the EIC pilot phase.

The probit model results with interaction terms, comparing the determinants of funding success

[10] In a sense, the shift to deep tech (as proxied by high tech) has already occurred, thanks to the effectiveness of EIC in attracting a pool of applicant firms that are already more inclined to deep tech.

between the EIC pilot and the SME Instrument phase, are shown in Table 16 in the appendix. They are consistent with the results of the individual probit estimations. The baseline is the SME instrument and the interacted terms show the differential influence of the independent variable for the EIC pilot phase. A negative coefficient for an interaction term suggests that the effect of that variable on the likelihood of being funded is more negative for the EIC sample compared to the SME phase, whereas a positive coefficient suggests a more positive effect for the EIC sample than for the SME phase. Whenever, the interaction term is not significant, the variable has similar effects in both programs. Hence, one can see that the most notable difference lies in the fact that in the EIC pilot phase being a high tech or medium high tech firm does not decrease the probability of getting funded. As above, we attribute this difference to the remarkable shift in the pool of applicant towards high-tech firms that occurred in moving from SME instrument to EIC. As reported in tables 3 and 4 the share of high tech applicant increased from around 5% to 13%

Together, the greater share of applications from technology-oriented firms and the differences in the selection lead to a striking difference of 15 percentage points between the shares of high tech firms being funded in the SME instrument and the EIC pilot (see tables 3 and 4).

6 *The impact of EIC funding on firms*

From an innovation policy point of view, it is clearly important that each funding program is able to attract applications from the categories of companies it wants to target. But it is at least as important that the financing has the desired effect. In this respect, we recall that, as discussed in section 1, our analysis is partially limited by the recent start of the EIC program, we then emphasize the preliminary nature of these findings.

To identify the effect of funding on firm level outcomes, we exploit the fact that funding is partly determined by the evaluation scores, that have to be above a certain threshold for the firm to be admitted to the interview phase. This makes it possible to apply a fuzzy regression discontinuity design based (Imbens and Lemieux, 2008; Hansen, 2022), which is mainly based on the assumption that near to the threshold it is random whether firms are above or below the threshold. Therefore, by estimating the difference in outcomes for firms that are just above and just below the threshold, taking into account the differential funding probabilities, it is possible to estimate a local average treatment effect for the treated. In this respect, the fact the companies admitted to the interview have roughly the same chances of being awarded the funding, independent of their scores in the previous selection round (see figure 1) further confirms for the adopted technique.

A setting where a regression discontinuity design is applicable is determined by an institutional framework, where the treatment is at least party determined by a running variable being at one side of a predetermined threshold. Using the Potential Outcome Framework, an individual is treated if $T = 1$ and is not treated if $T = 0$. The potential outcome for an individual is then Y_1 and Y_0 respectively and the observed outcome $Y = TY_1 + (1-T)Y_0$. Let X be the covariate that determines treatment, called the running variable. In a sharp regression discontinuity design, treatment is determined by X being higher or lower than a threshold c, that is $T = \mathbb{1}_{X>c}$. In a fuzzy regression discontinuity design, as we have it here, there is only a discontinuity in treatment probabilities at the cutoff, i.e. the conditional probability of treatment given that the running variable is x, written as $p(x) = \mathbb{P}[T = 1|X = x]$ is discontinuous for $x = c$. In the case at hand being above the normalized threshold of 0, increases the treatment probability from 0% to around 35%, see Figure 3.

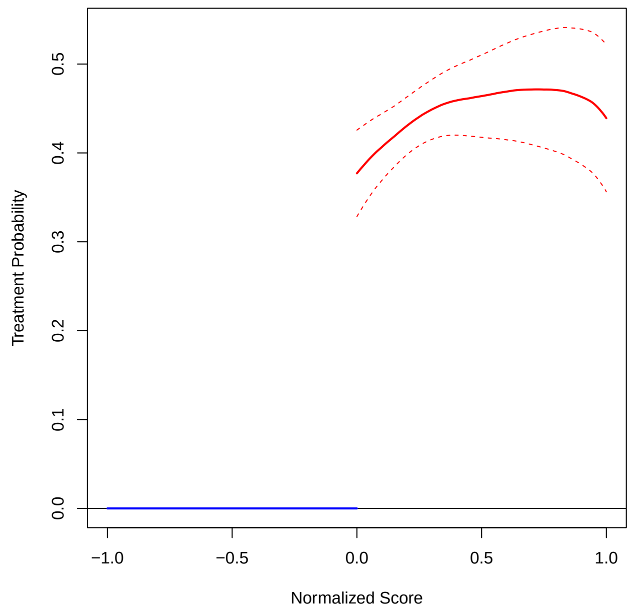


Figure 3: Probability of getting funded by the normalized evaluation score. Firms above the threshold advance to the interview phase. Blue and red lines show local linear regressions on each side of the threshold, emphasizing the discontinuity. Dashed lines indicate confidence intervals.

Given that we have the outcome function $m(x) = \mathbb{E}[Y|X = x]$, and potential outcome functions $m_0(x) = \mathbb{E}[Y_0|X = x]$ and $m_1(x) = \mathbb{E}[Y_1|X = x]$ the average treatment effect for individuals with $X = x$ is $\theta(x) = m_1(x) - m_0(x)$. Let $m(c+)) = \lim_{z\downarrow c} m(z)$ and $m(c-) = \lim_{z\uparrow c} m(z)$, denote the limits of the outcome function from above and below to c, and $p(c+)$ and $p(c-)$ denote the limits of the conditional probability of treatment towards c. Then the identification theorem that we resort to for the fuzzy regression discontinuity design is that provided in Hahn et al. (2001). Referring to their work, suppose that $m_0(x)$ and $m_1(x)$ are continuous at $x = c$, $p(x)$ is discontinuous at $x = c$ and T is independent of θ for X near c. Then

$$\theta(c) = \frac{m(c+) - m(c-)}{p(c+) - p(c-)} \tag{6}$$

The theorem states that the average treatment effect at the threshold is the ratio between the differences in outcomes and the differences in probabilities of treatment at the cutoff. This gives us the possibility to consistently estimate $\theta(c)$ by estimating $m(c+)$, $m(c-)$, $p(c+)$, and $p(c-)$ and taking the ratio of the differences, given the assumptions are met. It is important to note that we can only estimate $\theta(c)$, which is a local average treatment effect at the threshold and that it is inherent to a regression discontinuity design to be suffering from low external validity, because the treatment effect cannot be generalized (Cattaneo et al., 2021).

To understand what exactly is measured by $\theta(c)$, it is helpful to introduce the concept of compliance status. We can divide our sample into 4 groups, compliers, always-takers, never-takers and defiers. Compliers are units that are treated when above the threshold and not treated below the threshold. Whereas always-takers are always treated (this case is excluded in our sample) and never takers are never treated even when when they make it above the threshold. Defiers are also excluded in our sample due to the selection mechanism, these are the units that would get treatment below the threshold and no treatment above the threshold. In the case of a sharp regression discontinuity design, the whole sample consists only of compliers, in the case of the fuzzy regression discontinuity design at hand however, we have at least compliers and never-takers. Only the units that, given they are above the score threshold, make it through the interview phase and get funding are compliers, whereas the units that do not get funding even though they made it to the interview phase are never-takers. As already stated there are no always takers or deniers in the sample, as all units below the threshold can succesfully be excluded from treatment (Cattaneo et al., 2021).

Arguing for the validity of a fuzzy regression discontinuity design is always difficult, as the assumptions of equation 6 can never be proven, but only made plausible by a convincing argumentation based on the institutional setting and by unsuccessful falsification tests.

The first assumption that needs to be discussed is the assumption of continuity of the potential outcome functions at the threshold. As it is difficult to argue for continuity only at the threshold, normally it is argued for continuity in general. A possible violation of this assumption is due to the manipulation of the running variable to obtain treatment. This might lead to bunching just above the threshold. In the case at hand however, this is highly unlikely, because evaluation is done by external experts that do not know the threshold that will lead to a pass-through to the interview phase, as this is only determined after the evaluation of the projects based on budgetary constraints. One could expect bunching at the quality threshold at a score of 13, but as the final score is the median of 4 evaluation it is also unlikely to find proper bunching at the quality threshold, because of coordination difficulties. McCrary (2008) has introduced a density test to detect manipulation of the running variable. The test is insignificant for the normalized score with a p-value of 0.45, suggesting no manipulation of the running variable. Figure 4 provides graphical evidence in this respect.

The second assumption that needs to hold in the case of a FRD design is the independence of treatment T and treatment effect θ at the threshold c. It means that treatment must be randomly assigned around the threshold, and units cannot select into or be selected into treatment, because then units with a higher treatment effect might be selected more often than units with a lower treatment effect (Hansen, 2022). In the case at hands it would be surprising if treatment assignment is completely independent from the treatment effect, as the interview phase aims to do a further selection of high-potential start-ups. If this indeed leads to the selection of projects with high treatment effects, then θ does not give the local average treatment effect anymore, but only an upper bound for the treatment effect. However, the difference around the threshold is still meaningful, because it shows the combined effect of the selection procedure and the funding.

Overall, employing a Fuzzy Regression Discontinuity (FRD) design is a plausible approach for this study.

Once we are reassured about the possibility to employ a FRD, let us examine the effects of

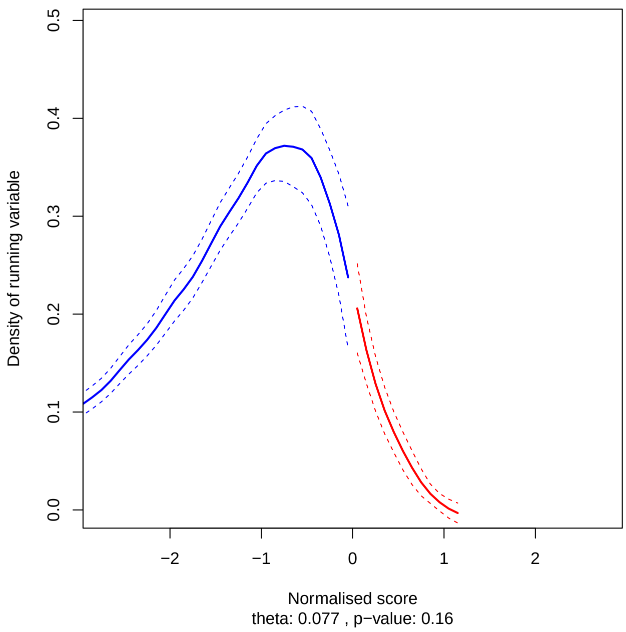
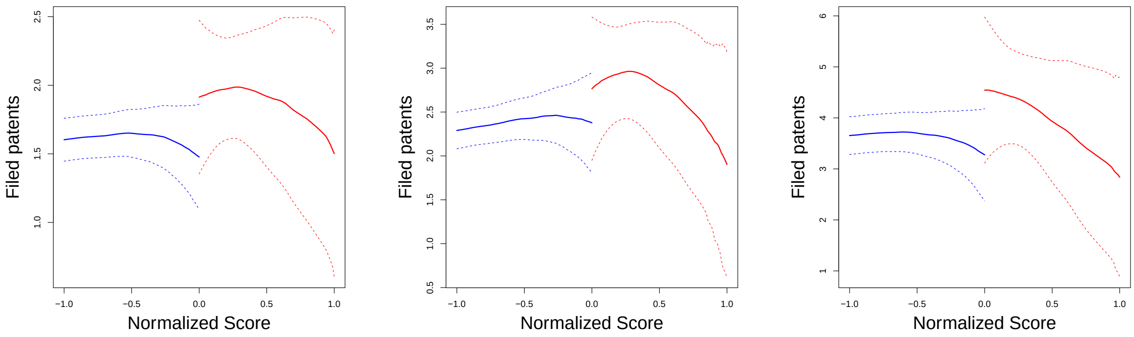


Figure 4: McCrary test for continuity of the normalized evaluation score at the threshold. Blue and red lines show local linear regressions on each side of the threshold. Dashed lines indicate confidence intervals.

being funded on several firm-level outcomes, that serve as proxy both for the innovativeness and the growth potential of the firms. Figures 5, 6, 7 and 8 report the graphical evidence for the regression discontinuities for four outcomes over three years after application. The plots present the estimated local polynomial regressions on either side of the cutoff score, where dots represent observed data points, and the solid line indicates the estimated relationship between the grant and the outcomes. Dashed lines are confidence intervals. The regression tables can be found in Appendix C. The graphs display the estimates using the optimal bandwidth as calculated based on Imbens and Kalyanaraman (2012). Additionally, the tables provide estimates for bandwidths that are doubled and halved in size. The results do not provide statistical evidence that, to date, on the limited time span available, funding by the EIC has a significant effect on these firm level outcomes. However, some trends could potentially be derived from the data.

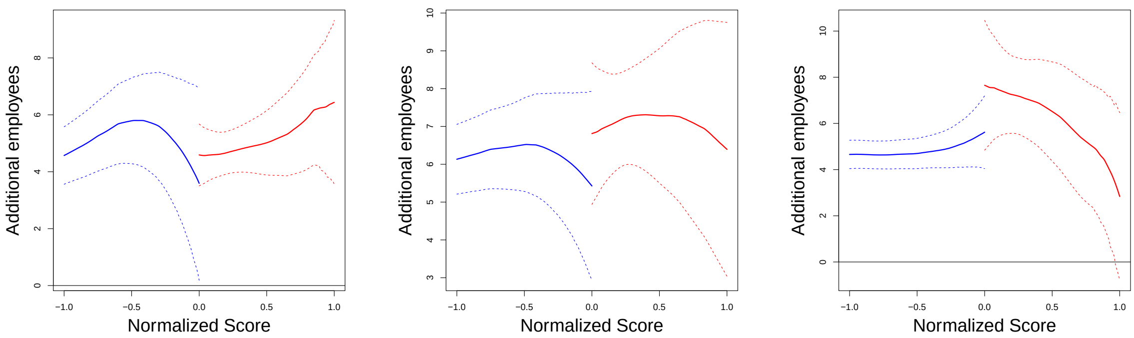
Patent filings subsequent to the competition serve as proxies for innovation. It is common in the literature to weight patents by citation count to reflect the heterogeneity in patent quality (see among the others, in a similar setting Santoleri et al., 2022). However, given the recent nature of the patents in question, filed between 2019 and 2022, citations are expected to be scarce. Moreover, firms from earlier competitions rounds inherently have a greater likelihood of accruing citations. Consequently, this analysis employs a cumulative patent count within the first n years post-funding, rather than citation-weighted patents. Figure 5 visually reports the impact of funding on patent filings within the initial three years following the competition and table 18 provides the corresponding regression outcomes. Across all bandwidth and time horizon there is a consistently positive point estimate at an economic meaningful level, suggesting a positive influence of funding on patent filings and thus innovative activity. However, the standard errors are very large and therefore the confidence intervals



Year 1 after application   Year 2 after application   Year 3 after application

Figure 5: Regression Discontinuity graphs for patents over three years. Blue and red lines show local linear regressions on each side of the threshold, emphasizing the discontinuity. Dashed lines indicate confidence intervals.

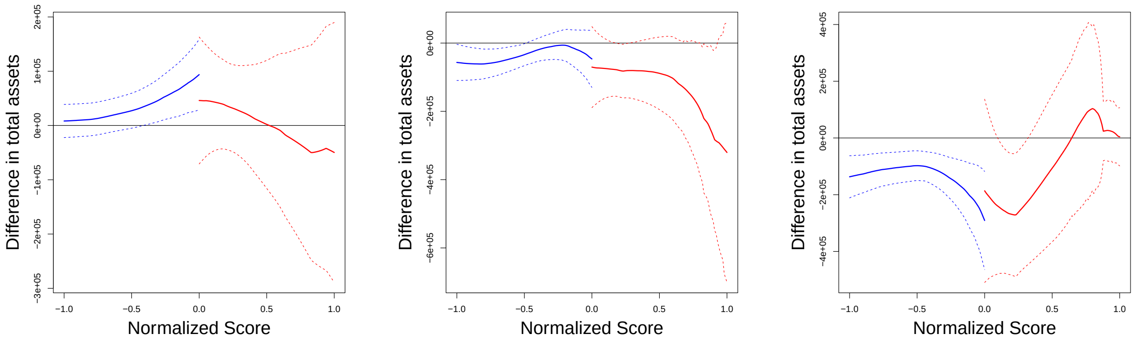
are wide, such that the effect is not statistically significant at conventional intervals.



Year 1 after application   Year 2 after application   Year 3 after application

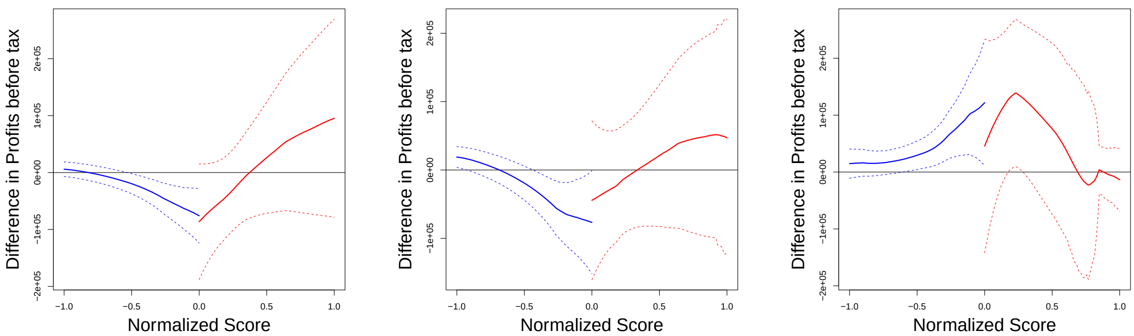
Figure 6: Regression Discontinuity graphs for employees over three years. Blue and red lines show local linear regressions on each side of the threshold, emphasizing the discontinuity. Dashed lines indicate confidence intervals.

To evaluate firm growth, this study measures the changes in employee count and total assets. The growth effect for year n post-competition is quantified by the difference in the number of employees (and similarly, total assets) between year $t+n$ and year $t-1$ (the year preceding the competition). The corresponding regression discontinuity plots are depicted in figures 6 and 7, and the regression outcomes are reported in tables 19 and 20, respectively, in the appendix. For employee growth, the estimates are uniformly positive, yet they lack statistical significance. The data for assets present a more ambiguous picture, particularly in subsequent years, where there appears to be a general decrease in assets. From these findings, it is not feasible to discern an indication for a trend. Similarly, also the analysis of profitability does not allow to draw clear conclusions.



Year 1 after application　Year 2 after application　Year 3 after application

Figure 7: Regression Discontinuity graphs for assets over three years. Blue and red lines show local linear regressions on each side of the threshold, emphasizing the discontinuity. Dashed lines indicate confidence intervals.



Year 1 after application　Year 2 after application　Year 3 after application

Figure 8: Regression Discontinuity graphs for profits before tax over three years. Blue and red lines show local linear regressions on each side of the threshold, emphasizing the discontinuity. Dashed lines indicate confidence intervals.

7 *Conclusions by way of discussion*

The nature and uncertainties characterizing the innovation process have traditionally been addressed resorting to a variety of policy instruments, from direct financing of basic research, to public procurement, especially in the defense industry, to tax incentives and innovation grants. In this work we have analyzed the impact of a relevant change in EU innovation policy due to the shift from SME Instrument to EIC accelerator.

The SME Instrument 2014-17 (also refer to table 1 of section 3.1), was designed to support innovation activities, also non-radical, by SMEs. It was endowed with around €3 billion budget and drew inspiration from the US Small Business and Innovation Research (SBIR) program (Howell, 2017; Mina et al., 2021). Similarly to SBIR, the SMEI provided support to SMEs by covering for concept and feasibility assessment, with a grant of €50,000 for market analysis and preliminary business and technological plan, preparing them for a phase 2 grant ranging from €0.5 million to €2.5 million, with a focus on R&D, demonstration, and market replication.

The new EU framework program "Horizon Europe" also marked the birth of the EIC work program in the explicit attempt to foster deeptech innovation and market creation (EC, 2017b). The implementation of a fully fledged EIC, starting in 2021 was preceded by a pilot phase from 2018 to 2020.

In this work we have been able to address some key features of the change in policy. The analysis of the first cohorts of applicants to EIC calls has revealed that the program has been able to attract the interest of firms in line with the stated purpose. With respect to SME instrument, a larger share of deep tech companies, identified here with their technological intensity, applied to the EIC calls, also refer to section 5. Another significant change that produced a relevant impact in the selection process has been the introduction of the interview phase, similarly to the venture capital approach of a pitch presentation. Under the SME instruments innovation grants were only assigned with remote evaluation score by a group of expert. A distinct feature of EIC is that remote evaluation score can only grant access to the interview: not all applicants admitted to the interview eventually receive funding, but roughly only one third. We can claim that the introduction of the interview was a relevant change because funded firms are evenly distributed across all score terciles among interviewees (see figure 1). This indicates that the interview phase introduced a comprehensive reassessment, leading to a more varied selection of funded firms *vis a vis* a remote only assessment. We have completed the analysis of the selection process, by casting comparison of the firm-level characteristics associated to success in the two programs, SME instrument and EIC. Again, a significant difference emerges in that the SMEI appeared to disfavor firms in high-tech sectors, whether we do not observe such effect anymore in EIC. Finally, having filed for patents is relevant in both programs, whether younger age comparatively has a role in EIC.

Due to the short time spam after treatment, we overlook recalling here the methodology employed and the results concerning the effects of funding (refer instead to section 6). Rather, we will discuss the avenues opened up by the emergence of EIC for both future research and policy considerations. *First*, we expect that the implementation of the equity component of the blended finance awarded by the EIC will re-ignite a lively discussion around the effectiveness of government venture capital (GVC) in the EU and outside (among the others, refer to Cumming et al., 2017; Grilli and Murtinu, 2014; Cumming and Johan, 2019; Colombo et al., 2016; Audretsch et al., 2020). *Second*, while a thorough assessment of the EIC funding schemes will require some additional years, in order to increase the number of treated firms and the length of the post-treatment window, nonetheless it is hard to overestimate its potential contribution across several and related directions. EU has been lagging behind in terms of its capacity to generate competitive advantage and aggregate growth from research and innovation and in view of the GDP level of EU, its VC market is very thin. To what extent the presence of EIC equity, also through the particular design to attract private capital, will contribute to the flourishing of a larger VC base? This is even more important in the deep tech, where technological uncertainties and longer time-to-market have scared off VCs globally (van den Heuvel and Popp, 2023; Gaddy et al., 2017).

References

AIGINGER, K. AND D. RODRIK (2020): "Rebirth of industrial policy and an agenda for the twenty-first century," *Journal of industry, competition and trade*, 20, 189–207.

ARROW, K. (1962): "Economic Welfare and the Allocation of Resources for Invention," in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, NBER Chapters, 609–626.

AUDRETSCH, D., A. COLOMBELLI, L. GRILLI, T. MINOLA, AND E. RASMUSSEN (2020): "Innovative start-ups and policy initiatives," *Research Policy*, 49, 104027.

BAJGAR, M., G. BERLINGIERI, S. CALLIGARIS, C. CRISCUOLO, AND J. TIMMIS (2020): "Coverage and representativeness of Orbis data," OECD Science, Technology and Industry Working Papers 2020/06, OECD Publishing.

BASILIO, O., F. MURRAY, AND L. FROLUND (2022): "What is 'Deep Tech' and what are Deep Tech Ventures," Tech. rep., Working Paper. MIT Global Programs.

BELLUCCI, A., G. GUCCIARDI, AND D. NEPELSKI (2023): "The determinants of Public Grants and Venture Capital financing: Evidence from Europe," Jrc technical report, JRC.

BLOOM, N., J. V. REENEN, AND H. WILLIAMS (2019): "A Toolkit of Policies to Promote Innovation," *Journal of Economic Perspectives*, 33, 163–184.

BONACCORSI, A. (2007): "Explaining poor performance of European science: Institutions versus policies," *Science and Public Policy*, 34, 303–316.

BOTTAZZI, G., M. GRAZZI, A. SECCHI, AND F. TAMAGNI (2011): "Financial and economic determinants of firm default," *Journal of Evolutionary Economics*, 21, 373–406.

BRONZINI, R. AND P. PISELLI (2016): "The impact of R&D subsidies on firm innovation," *Research Policy*, 45, 442–457.

BUSOM, I. (2000): "An Empirical Evaluation of The Effects of R&D Subsidies," *Economics of Innovation and New Technology*, 9, 111–148.

CATTANEO, M. D., L. KEELE, R. TITIUNIK, AND G. VAZQUEZ-BARE (2021): "Extrapolating Treatment Effects in Multi-Cutoff Regression Discontinuity Designs," *Journal of the American Statistical Association*, 116, 1941–1952.

CHANG, H.-J. AND A. ANDREONI (2020): "Industrial policy in the 21st century," *Development and Change*, 51, 324–351.

COHEN, W. M. (2010): "Fifty years of empirical studies of innovative activity and performance," *Handbook of the Economics of Innovation*, 1, 129–213.

COLOMBO, M., D. CUMMING, AND S. VISMARA (2016): "Governmental venture capital for innovative young firms," *The Journal of Technology Transfer*, 41, 10–24.

CRISCUOLO, C., R. MARTIN, H. G. OVERMAN, AND J. V. REENEN (2019): "Some Causal Effects of an Industrial Policy," *American Economic Review*, 109, 48–85.

CRUNCHBASE (2024): Accessed 22.02.2024 `https://news.crunchbase.com/unicorn-company-list/`.

CUMMING, D. AND S. JOHAN (2019): "Government venture capital research: fake science and bad public policy," *Venture Capital*, 21, 121–131.

CUMMING, D. J., L. GRILLI, AND S. MURTINU (2017): "Governmental and independent venture capital investments in Europe: A firm-level performance analysis," *Journal of corporate finance*, 42, 439–459.

DE RASSENFOSSE, G., A. JAFFE, AND E. RAITERI (2019): "The procurement of innovation by the U.S. government," *PLoS ONE*.

DECHEZLEPRÊTRE, A., E. EINIÖ, R. MARTIN, K.-T. NGUYEN, AND J. V. REENEN (2023): "Do Tax Incentives Increase Firm Innovation? An RD Design for R&D, Patents, and Spillovers," *American Economic Journal: Economic Policy*, 15, 486–521.

DOSI, G., P. LLERENA, AND M. S. LABINI (2006): "The relationships between science, technologies and their industrial exploitation: An illustration through the myths and realities of the so-called 'European Paradox'," *Research Policy*, 35, 1450–1464, triple helix Indicators of Knowledge-Based Innovation Systems.

DOSI, G. AND R. R. NELSON (2010): "Technological change and industrial dynamics as evolutionary processes," in *Handbook of the Economics of Innovation*, ed. by B. H. Hall and N. Rosenberg, Elsevier: Amsterdam, chap. 4.

EC, ed. (2003): *COMMISSION RECOMMENDATION of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises*, European Commission, OfficialJournaloftheEuropeanUnion.

EC (2015): "Horizon 2020 Work Programme 2014 – 2015. 7. Innovation in small and medium-sized enterprises," Tech. rep., European Commission.

——— (2017a): "Horizon 2020 Work Programme 2016 - 2017. 7. Innovation in SMEs," Tech. rep., European Commission.

——— (2017b): "Key findings from the Horizon 2020 interim evaluation," Tech. rep., Publications Office of the European Union.

——— (2020): "Horizon 2020 Work-Programme 2018-2020- Annex 12 Enhanced European Innovation Council (EIC) Pilot," Tech. rep., European Commission.

——— (2021): "Horizon Europe Budget," *Publications Office of the European Union*.

EC EUROPA EU (2021a): Accessed 31.01.2024 `https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe/how-horizon-europe-was-developed_en`.

——— (2021b): Accessed 21.02.2024 `https://ec.europa.eu/commission/presscorner/detail/en/IP_20_2530`.

EISMEA (2020): "Deep Tech Europe - European Innovation Council Pilot Impact Report 2020," Tech. rep., EISMEA - European Innovation Council and SMEs Executive Agency.

——— (2022): "The European Innovation Council Impact report 2022," Tech. rep., EISMEA - European Innovation Council and SMEs Executive Agency.

——— (2023a): "European Innovation Council (EIC) Work Programme 2024," Tech. rep., European Innovation Council.

——— (2023b): "The European Innovation Council Impact report 2023: Accelerating Deep Tech in Europe," Tech. rep., EISMEA - European Innovation Council and SMEs Executive Agency.

EU COUNCIL (2013): "COUNCIL DECISION of 3 December 2013 establishing the specific programme implementing Horizon 2020 - the Framework Programme for Research and Innovation (2014-2020) and repealing Decisions 2006/971/EC, 2006/972/EC, 2006/973/EC, 2006/974/EC and 2006/975/EC," Tech. rep.

FLIGNER, M. A. AND G. E. POLICELLO (1981): "Robust rank procedures for the Behrens-Fisher problem," *Journal of the American Statistical Association*, 76, 141–206.

GADDY, B. E., V. SIVARAM, T. B. JONES, AND L. WAYMAN (2017): "Venture Capital and Cleantech: The wrong model for energy innovation," *Energy Policy*, 102, 385–395.

GALINDO-RUEDA, F. AND F. VERGER (2016): "OECD Taxonomy of Economic Activities Based on R&D Intensity," OECD Science, Technology and Industry Working Papers 2016/4, OECD Publishing.

GRILLI, L. AND S. MURTINU (2014): "Government, venture capital and the growth of European high-tech entrepreneurial firms," *Research Policy*, 43, 1523–1543.

HAHN, J., P. TODD, AND W. VAN DER KLAAUW (2001): "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 69, 201–209.

HANSEN, B. (2022): *Econometrics*, Princeton University Press.

HOWELL, S. T. (2017): "Financing Innovation: Evidence from R&D Grants," *American Economic Review*, 107, 1136–1164.

IMBENS, G. AND K. KALYANARAMAN (2012): "Optimal Bandwidth Choice for the Regression Discontinuity Estimator," *The Review of Economic Studies*, 79, 933–959.

IMBENS, G. W. AND T. LEMIEUX (2008): "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 142, 615–635.

LACH, S. (2002): "Do R&D subsidies stimulate or displace private R&D? Evidence from Israel," *The journal of industrial economics*, 50, 369–390.

LERNER, J. (2000): "The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program," *The Journal of Private Equity*, 3, 55–78.

MAZZUCATO, M. (2011): "The entrepreneurial state," *Soundings*, 49, 131–142.

MCCRARY, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, 142, 698–714.

MINA, A., A. D. MININ, I. MARTELLI, G. TESTA, AND P. SANTOLERI (2021): "Public funding of innovation: Exploring applications and allocations of the European SME Instrument," *Research Policy*, 50.

OECD (2021): "OECD R&D tax incentives database," Tech. rep., OECD.

——— (2023): *Compendium of Productivity Indicators*, OECD Publishing.

PIANTA, M., M. LUCCHESE, AND L. NASCIA (2020): "The policy space for a novel industrial policy in Europe," *Industrial and Corporate Change*, 29, 779–795.

REILLON, V. (2017): "EU framework programmes for research and innovation- Evolution and key data from FP1 to Horizon 2020 in view of FP9," *EPRS | European Parliamentary Research Service*.

RODRÍGUEZ-NAVARRO, A. AND F. NARIN (2018): "European Paradox or Delusion—Are European Science and Economy Outdated?" *Science and Public Policy*, 45, 14–23.

SANTOLERI, P., A. MINA, A. DI MININ, AND I. MARTELLI (2022): "The Causal Effects of R&D Grants: Evidence from a Regression Discontinuity," *The Review of Economics and Statistics*, 1–42.

SISSOKO, A. (2013): "R&D Subsidies And Firm-Level Productivity: Evidence From France," LIDAM Discussion Papers IRES 2011002, Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES).

SPENCE, M. (1984): "Cost Reduction, Competition, and Industry Performance," *Econometrica*, 52, 101–121.

VAN DEN HEUVEL, M. AND D. POPP (2023): "The role of venture capital and governments in clean energy: lessons from the first cleantech bubble," *Energy Economics*, 124.

WORLD BANK (2024): Accessed 23.02.2024 `https://databank.worldbank.org/indicator/NY.GDP.MKTP.CD/1ff4a498/Popular-Indicators`.

A Descriptive Statistics

Table 8: Orbis Coverage for all applicants

	Total	SME Instrument	EIC Pilot
Total	83.0	80.7	84.7
Funded	85.3	82.1	88.7
Seal of Excellence	86.3	84.3	88.0
Rejected	81.2	78.4	83.0

Table 9: Percentage of Applications by Country in the Full and the Matched Sample

	Full Sample	Reduced Sample	Funded Firms (/w Orbis ID)
Spain	13.07	13.98	16.97
Germany	7.55	7.69	9.26
Italy	13.20	14.21	8.63
France	7.05	6.82	7.78
Denmark	3.42	3.53	5.87
Israel	6.50	7.00	5.73
Netherlands	4.29	4.78	5.73
Sweden	4.62	4.96	5.02
Finland	3.92	4.46	4.95
Ireland	2.20	2.45	4.60
Norway	2.32	2.62	4.31
Switzerland	2.89	3.22	3.18
Austria	1.80	2.06	2.48
Belgium	1.69	1.72	1.49
Portugal	1.73	1.62	1.34
Slovenia	1.30	0.87	0.99
Poland	1.60	0.98	0.92
Estonia	1.17	0.51	0.64
Iceland	0.62	0.57	0.64
Czechia	0.67	0.64	0.35
Hungary	2.53	1.07	0.35
Turkey	1.28	0.46	0.28
Latvia	0.55	0.51	0.21
Bulgaria	1.01	1.03	0.14
Malta	0.14	0.16	0.07
Romania	0.73	0.72	0.07
Slovakia	0.86	0.77	0.07
Ukraine	0.39	0.05	0.07
Bosnia...Herzegovina	0.16	0.15	0.00
Cyprus	0.32	0.37	0.00
Croatia	0.23	0.18	0.00
Lithuania	0.25	0.23	0.00
Luxembourg	0.23	0.21	0.00
Serbia	0.22	0.10	0.00

Table 10: Fligner-Policello test for the Applicants sample

	FP Statistic	p-Value
Age	-18.37	0.00
log(Assets)	-102.97	0.00
log(Employees)	-15.88	0.00
Patents in last 3 years	-41.42	0.00

Table 11: Fligner-Policello test for different finance types in the EIC pilot phase

	FP Statistic	p-Value	NA
Age	-1.40	0.16	FP-test
log(Assets)	-0.58	0.56	FP-test
log(Employees)	-0.67	0.50	FP-test
Patents in last 3 years	-0.91	0.36	FP-test
D patents	-0.85	0.40	FP-test
D hightech	0.01	0.99	FP-test
D medim hightech	-1.01	0.31	FP-test
D manufacturing	-1.62	0.11	FP-test

Table 12: T-test for different finance types in the EIC pilot phase

	Test Statistic	p-Value	Type
Age	3.69	0.00	T-test
log(Assets)	0.23	0.82	T-test
log(Employees)	0.88	0.38	T-test
Patents in last 3 years	0.86	0.39	T-test
D patents	0.85	0.40	T-test
D hightech	-0.01	0.99	T-test
D medim hightech	1.01	0.32	T-test
D manufacturing	1.61	0.11	T-test

Table 13: Coverage of firm level outcomes one year before application

eval year	status	age	ind. letter	NACE Rev2	TotProd Value	share capital	rev sales	sales	revenue	R&D expend	ebitda	rev turnover	P&L bef. tax	cash flow	total assets	current ratio	empl.	profit margin	lt debt	sh funds	orbis id count
2014	No	98.6	97.7	10.2	4.3	6.1	3.9	39.8	39.8	1.0	39.2	50.3	52.8	45.1	68.7	63.5	46.5	42.8	49.2	68.8	767.0
	SoE	98.4	97.9	8.9	10.0	13.7	9.5	30.0	32.1	0.0	30.0	46.3	51.1	42.1	73.2	64.7	43.7	36.8	48.4	72.6	190.0
	funded	97.6	98.4	13.5	5.6	9.5	5.6	31.7	33.3	2.4	35.7	47.6	50.0	46.0	77.8	71.4	49.2	36.5	46.8	77.8	126.0
2015	No	99.2	97.7	12.9	7.1	9.1	6.7	40.6	40.9	0.8	41.1	50.7	55.4	47.7	72.5	65.6	49.9	42.7	51.8	72.4	2015.0
	SoE	99.3	97.6	20.5	9.5	13.8	8.7	37.8	38.6	0.4	38.4	52.4	56.2	46.8	74.6	69.4	52.4	44.7	52.4	74.4	1209.0
	funded	99.3	97.9	24.1	11.3	17.0	10.6	39.0	39.0	0.7	40.4	57.4	61.7	53.9	84.4	76.6	57.4	48.9	53.2	84.4	141.0
2016	No	98.7	96.4	19.9	12.2	14.6	11.6	41.0	39.4	0.4	40.6	53.7	56.7	47.7	74.7	68.2	51.2	45.9	51.6	74.7	1892.0
	SoE	98.8	97.1	26.8	16.3	20.0	15.0	37.6	38.4	0.7	37.9	58.4	62.2	50.9	77.8	71.1	57.6	48.9	54.7	77.7	1643.0
	funded	98.3	98.9	15.3	9.6	11.9	7.3	36.7	40.1	0.6	41.8	58.8	63.8	55.4	79.1	71.2	58.8	42.4	55.9	79.1	177.0
2017	No	98.5	96.5	35.4	21.0	26.1	19.5	39.5	38.8	2.6	38.3	54.8	57.2	48.9	72.5	67.4	58.5	45.7	51.9	72.3	2846.0
	SoE	98.5	96.5	31.3	48.7	35.5	27.0	39.8	38.9	4.3	39.0	57.0	59.8	51.6	76.8	70.5	65.1	47.2	58.9	76.8	2674.0
	funded	99.5	98.2	20.2	9.2	12.4	8.3	35.3	36.2	4.6	32.6	59.6	62.4	52.3	78.0	72.9	64.2	45.0	50.0	77.5	218.0
2018	No	97.4	93.7	78.1	44.2	58.7	39.8	36.2	34.6	2.9	33.9	53.1	53.6	44.3	70.0	65.6	60.8	46.8	53.3	69.6	3183.0
	SoE	97.4	95.1	83.0	47.3	65.1	42.4	34.3	34.3	4.8	35.1	54.6	56.4	47.9	73.9	69.2	68.1	47.7	57.6	73.8	1955.0
	funded	98.6	96.8	88.1	41.1	63.5	37.4	32.4	38.8	7.8	33.8	48.9	56.6	43.4	75.8	69.4	68.9	41.6	60.3	75.8	219.0
2019	No	97.3	93.4	81.5	44.6	61.3	40.0	35.7	34.4	3.8	32.8	51.2	51.9	42.1	68.2	63.9	60.1	44.2	52.9	67.5	3656.0
	SoE	97.7	94.9	85.6	46.1	65.5	38.3	31.6	31.3	4.2	31.6	51.2	50.9	43.3	68.2	65.0	65.7	43.1	55.6	68.0	2406.0
	funded	97.9	95.0	91.1	43.3	71.3	34.0	26.2	27.3	4.3	30.9	46.8	45.4	37.6	67.7	64.2	69.1	37.2	52.1	67.7	282.0
2020	No	97.7	92.3	84.7	40.6	59.7	37.2	35.6	33.1	2.7	31.9	45.9	47.2	37.4	63.4	58.4	56.0	40.5	49.9	62.2	6865.0
	SoE	98.5	93.2	88.4	38.0	64.3	34.0	29.5	29.2	4.5	29.7	42.7	45.7	37.7	64.4	60.7	62.1	37.3	52.0	63.8	2839.0
	funded	97.4	94.8	84.9	29.7	60.9	28.6	30.7	29.7	6.8	28.1	36.5	41.1	29.2	62.0	58.9	59.9	30.2	50.5	61.5	192.0

B Additional Probit Specifications

Table 14: Probit model results for the SME Instrument phase - Marginal Effects

	Dependent variable: Probability of being funded									
	funded									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(employees + 1)	0.056	0.067	0.073	0.061	0.057	0.060	0.058	0.035	0.081	0.086
age		−0.0002	−0.0003	−0.0002	−0.0002	−0.0003	−0.0004	−0.0004	−0.0005	−0.001
		(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
counter			0.004**	0.004**	0.004**	0.004**	0.004***	0.003*	0.003	0.003
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
D_patents				0.028***	0.029***	0.029***	0.028***	0.028***	0.028***	0.028***
				(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
D_HT					−0.033**	−0.037***	−0.038***	−0.039**	−0.027*	−0.026*
					(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
D_MHT						−0.037***	−0.038***	−0.037***	−0.026**	−0.024**
						(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
D_Manufacturing							0.008	0.006	0.003	0.004
							(0.006)	(0.007)	(0.007)	(0.007)
cash_totass								0.0001	0.00004	0.0001
								(0.0001)	(0.0001)	(0.0001)
debt_equity									−0.00000	−0.00001
									(0.0003)	(0.0003)
debt_totass										−0.021
										(0.016)
employees										
		(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	−1.785***	−1.785	−1.828	−1.909	−1.887	−1.861	−1.867	−1.781	−2.017	−1.991
Observations	7,789	7,783	6,452	6,452	6,452	6,452	6,452	4,661	3,379	3,379
Log Likelihood	−1,535.347	−1,534.637	−1,307.244	−1,294.674	−1,291.227	−1,284.583	−1,283.725	−923.644	−563.685	−562.616
Akaike Inf. Crit.	3,074.693	3,075.275	2,622.487	2,599.348	2,594.454	2,583.166	2,583.451	1,865.288	1,147.369	1,147.232

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Probit model results for the EIC pilot phase - Marginal Effects

	Dependent variable: Probability of being funded							
	funded							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
employees_log	0.003	0.006***	0.006***	0.005***	0.005***	0.005**	0.006**	0.006**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age		−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
counter			0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
D_patents				0.013**	0.013**	0.013**	0.013*	0.013*
				(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
D_Manufacturing					0.005	0.010*	0.008	0.008
					(0.004)	(0.005)	(0.005)	(0.005)
cash_totass						−0.00000	−0.00000	−0.00000
						(0.00001)	(0.00001)	(0.00001)
debt_equity							−0.001	−0.001
							(0.002)	(0.002)
debt_totass								−0.0001
								(0.001)
Constant	−1.934***	−1.924	−2.026	−2.014	−2.024	−2.121	−2.167	−2.167
Observations	9,692	9,680	9,525	9,525	9,525	5,140	4,407	4,407
Log Likelihood	−1,370.807	−1,364.463	−1,319.148	−1,316.471	−1,315.743	−611.313	−524.200	−524.191
Akaike Inf. Crit.	2,745.615	2,734.926	2,646.296	2,642.943	2,643.485	1,236.625	1,064.401	1,066.381

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16: Probit model comparison of the SME and EIC phase

	Dependent variable: Probability of being funded							
	funded							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
employees_log	0.056^{***}	0.067^{***}	0.073^{***}	0.061^{**}	0.057^{**}	0.060^{**}	0.058^{**}	0.035
	(0.021)	(0.024)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)	(0.031)
age		−0.002	−0.003	−0.002	−0.002	−0.003	−0.004	−0.004
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
counter			0.041^{***}	0.036^{**}	0.038^{**}	0.042^{***}	0.042^{***}	0.032^{*}
			(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.019)
D_patents				0.268^{***}	0.275^{***}	0.280^{***}	0.272^{***}	0.267^{***}
				(0.053)	(0.053)	(0.054)	(0.054)	(0.064)
D_HT					-0.317^{**}	-0.352^{***}	-0.366^{***}	-0.373^{**}
					(0.128)	(0.129)	(0.129)	(0.149)
D_MHT						-0.355^{***}	-0.367^{***}	-0.358^{***}
						(0.104)	(0.104)	(0.118)
D_Manufacturing							0.079	0.059
							(0.060)	(0.071)
cash_totass								0.001
								(0.001)
eic	−0.117	−0.108	-0.159^{*}	−0.074	−0.099	−0.115	−0.114	-0.316^{***}
	(0.073)	(0.074)	(0.083)	(0.085)	(0.086)	(0.088)	(0.088)	(0.116)
employees_log:eic	−0.013	0.013	0.011	0.014	0.018	0.017	0.019	0.059
	(0.028)	(0.032)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.044)
age:eic		-0.008^{**}	-0.008^{**}	-0.009^{**}	-0.009^{**}	-0.008^{**}	-0.009^{**}	-0.011^{**}
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
counter:eic			−0.002	−0.008	−0.009	−0.014	−0.014	−0.004
			(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)
D_patents:eic				−0.009	−0.018	−0.025	−0.027	−0.054
				(0.079)	(0.079)	(0.079)	(0.080)	(0.099)
D_HT:eic					0.336^{**}	0.359^{**}	0.337^{**}	0.371^{**}
					(0.141)	(0.142)	(0.144)	(0.172)
D_MHT:eic						0.321^{***}	0.308^{***}	0.329^{**}
						(0.114)	(0.115)	(0.136)
D_Manufacturing:eic							0.045	0.095
							(0.079)	(0.099)
cash_totass:eic								−0.001
								(0.001)
Constant	-1.785^{***}	-1.785^{***}	-1.828^{***}	-1.909^{***}	-1.887^{***}	-1.861^{***}	-1.867^{***}	-1.781^{***}
	(0.056)	(0.056)	(0.066)	(0.068)	(0.069)	(0.069)	(0.069)	(0.083)
Observations	20,898	20,880	19,088	19,088	19,088	19,088	19,088	11,733
Log Likelihood	−3,528.959	−3,520.660	−3,227.190	−3,205.068	−3,201.568	−3,194.686	−3,190.942	−1,882.722
Akaike Inf. Crit.	7,065.917	7,053.321	6,470.381	6,430.136	6,427.135	6,417.373	6,413.884	3,801.443

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: Probit model comparison of the SME and EIC phase - Marginal Effects

	Dependent variable: Probability of being funded							
	funded							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
employees_log	0.004***	0.006***	0.007***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
age		−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
counter			0.004***	0.003***	0.003***	0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
D_patents				0.023***	0.023***	0.023***	0.023***	0.021***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
D_HT					−0.010*	−0.012**	−0.014**	−0.015**
					(0.005)	(0.005)	(0.006)	(0.007)
D_MHT						−0.014***	−0.016***	−0.016***
						(0.004)	(0.004)	(0.006)
D_Manufacturing							0.009***	0.009**
							(0.003)	(0.004)
cash_totass								0.00002
								(0.00003)
employees_log:eic	−0.054	−0.024	−0.038	−0.007	−0.010	−0.014	−0.012	−0.021
age:eic		−0.008	−0.008	−0.009	−0.009	−0.008	−0.009	−0.011
counter:eic			−0.013	−0.013	−0.016	−0.021	−0.021	−0.024
D_patents:eic				−0.018	−0.029	−0.038	−0.039	−0.082
D_HT:eic					0.317	0.333	0.313	0.304
D_MHT:eic						0.302	0.290	0.279
D_Manufacturing:eic							0.038	0.076
cash_totass:eic								−0.001
eic								
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	−1.855***	−1.849	−1.928	−1.957	−1.950	−1.933	−1.939	−1.947
Observations	20,898	20,880	19,088	19,088	19,088	19,088	19,088	11,733
Log Likelihood	−3,530.229	−3,521.732	−3,229.003	−3,205.436	−3,202.219	−3,195.532	−3,191.781	−1,886.385
Akaike Inf. Crit.	7,066.459	7,053.464	6,472.006	6,428.873	6,426.438	6,417.064	6,413.563	3,806.770

Note: *p<0.1; **p<0.05; ***p<0.01

C Regression Discontinuity Tables

	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
After 1 year						
LATE	0.991	4,363	0.995	0.850	1.171	0.242
Half-BW	0.495	2,340	1.143	1.079	1.059	0.290
Double-BW	1.982	6,853	0.772	0.747	1.033	0.302
After 2 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.857	3,925	0.888	1.274	0.697	0.486
Half-BW	0.428	2,054	0.817	1.751	0.466	0.641
Double-BW	1.713	6,403	0.897	1.083	0.828	0.408
After 3 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.961	2,608	2.607	2.029	1.285	0.199
Half-BW	0.480	1,429	2.400	2.921	0.822	0.411
Double-BW	1.921	3,920	2.037	1.744	1.168	0.243

Table 18: The effects on patent filing

	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
After 1 year						
LATE	0.896	4,259	2.739	3.232	0.847	0.397
Half-BW	0.448	2,156	7.311	3.777	1.936	0.053
Double-BW	1.792	7,081	-3.697	3.377	-1.095	0.274
After 2 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	1.215	4,956	3.632	3.562	1.020	0.308
Half-BW	0.607	2,826	8.087	4.926	1.642	0.101
Double-BW	2.429	7,405	1.323	3.507	0.377	0.706
After 3 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.813	2,170	4.557	4.726	0.964	0.335
Half-BW	0.407	1,148	3.769	7.713	0.489	0.625
Double-BW	1.626	3,520	5.753	3.544	1.623	0.104

Table 19: The effects on employees

After 1 year						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	1.120	5,689	-130,078.600	203,647.100	-0.639	0.523
Half-BW	0.560	3,069	-165,029.300	237,623.800	-0.694	0.487
Double-BW	2.240	9,021	-10,916.280	183,237.200	-0.060	0.952
After 2 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.678	3,322	-68,568.950	264,058.300	-0.260	0.795
Half-BW	0.339	1,654	274,128.900	436,277.100	0.628	0.530
Double-BW	1.356	5,872	-169,361.600	197,414.500	-0.858	0.391
After 3 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.649	1,975	261,922.000	458,157.500	0.572	0.568
Half-BW	0.324	984	1,021,706.000	914,040.900	1.118	0.264
Double-BW	1.297	3,384	-244,647.000	329,494.200	-0.742	0.458

Table 20: The effects on total assets

After 1 year						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	1.096	4,081	-29,136.410	155,791.200	-0.187	0.852
Half-BW	0.548	2,190	-40,096.770	194,325.100	-0.206	0.837
Double-BW	2.191	6,536	-97,183.840	131,349.600	-0.740	0.459
After 2 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.923	3,231	92,238.760	186,583.400	0.494	0.621
Half-BW	0.461	1,730	-121,995.400	159,236.900	-0.766	0.444
Double-BW	1.846	5,325	55,062.680	159,655.400	0.345	0.730
After 3 years						
	Bandwidth	Observations	Estimate	Std. Error	z value	Pr(>|z|)
LATE	0.616	1,442	-205,014.300	230,682.200	-0.889	0.374
Half-BW	0.308	745	-257,615.500	291,416.800	-0.884	0.377
Double-BW	1.233	2,476	31,417.110	187,562.100	0.168	0.867

Table 21: The effects on profitability

Quaderni del
Dipartimento di Politica Economica

1. *Innovation, jobs, skills and tasks: a multifaceted relationship.* M. Piva, M. Vivarelli. Vita e Pensiero, maggio 2018 (ISBN 978-88-343-3654-0)
2. *A bridge over troubled water: Interdisciplinarity, Novelty, and Impact.* M. Fontana, M. Iori, F. Montobbio, R. Sinatra. Vita e Pensiero, settembre 2018 (ISBN 978-88-343-3793-6)
3. *Concordance and complementarity in IP instruments*. M. Grazzi, C. Piccardo, C. Vergari. Vita e Pensiero, gennaio 2019 (ISBN 978-88-343-3879-7)
4. *Sustainable finance, the good, the bad and the ugly: a critical assessment of the EU institutional framework for the green transition*. L. Esposito, E.G. Gatti, G. Mastromatteo. Vita e Pensiero, febbraio 2019 (ISBN 978-88-343-3892-6)
5. *Technology and employment in a vertically connected economy: a model and an empirical test.* G. Dosi, M. Piva, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, giugno 2019 (ISBN digital edition [PDF]: 978-88-343-4008-0)
6. *Testing the employment impact of automation, robots and AI: A survey and some methodological issues.* L. Barbieri, C. Mussida, M. Piva, M. Vivarelli. Vita e Pensiero, settembre 2019 (ISBN digital edition [PDF]: 978-88-343-4052-3)
7. *A new proposal for the construction of a multi-period/multilateral price index*. C.R. Nava, A. Pesce, M.G. Zoia. Vita e Pensiero, ottobre 2019 (ISBN digital edition [PDF]: 978-88-343-4114-8)
8. *Lo Stato Sociale: da "lusso" a necessità*. L. Campiglio. Vita e Pensiero, febbraio 2020 (ISBN digital edition [PDF]: 978-88-343-4184-1)
9. *Robots and the origin of their labour-saving impact*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, marzo 2020 (ISBN digital edition [PDF]: 978-88-343-4196-4)
10. *Business visits, technology transfer and productivity growth*. M. Piva, M. Tani, M. Vivarelli. Vita e Pensiero, marzo 2020 (ISBN digital edition [PDF]: 978-88-343-4210-7)
11. *Technology, industrial dynamics and productivity: a critical survey*. M. Ugur, M. Vivarelli. Vita e Pensiero, settembre 2020 (ISBN digital edition [PDF]: 978-88-343-4406-4)
12. *Back to the past: the historical roots of labour-saving automation*. J. Staccioli, M.E. Virgillito. Vita e Pensiero, novembre 2020 (ISBN digital edition [PDF]: 978-88-343-4473-6)
13. *The present, past, and future of labor-saving technologies.* J. Staccioli, M.E. Virgillito. Vita e Pensiero, dicembre 2020 (ISBN digital edition [PDF]: 978-88-343-4479-8)
14. *Why Do Populists Neglect Climate Change? A Behavioural Approach*. L.A. Lorenzetti. Vita e Pensiero, dicembre 2020 (ISBN digital edition [PDF]: 978-88-343-4483-5)
15. *Relative wages, payroll structure and performance in soccer. Evidence from Italian Serie A (2007-2019)*. C. Bellavite Pellegrini, R. Caruso, M. Di Domizio. Vita e Pensiero, gennaio 2021 (ISBN digital edition [PDF]: 978-88-343-4490-3)
16. *Robots, AI, and Related Technologies: A Mapping of the New Knowledge Base*. E. Santarelli, J. Staccioli, M. Vivarelli. Vita e Pensiero, gennaio 2021 (ISBN digital edition [PDF]: 978-88-343-4499-6)
17. *Detecting the labour-friendly nature of AI product innovation*. G. Damioli, V. Van Roy, D. Vertesy, M. Vivarelli. Vita e Pensiero, aprile 2021 (ISBN digital edition [PDF]: 978-88-343-4600-6)
18. *Circular Economy Approach: The benefits of a new business model for European Firms*. C. Bellavite Pellegrini, L. Pellegrini, C. Cannas. Vita e Pensiero, luglio 2021 (ISBN digital edition [PDF]: 978-88-343-4817-8)
19. *The impact of cognitive skills on investment decisions. An empirical assessment and policy suggestions.* L. Esposito, L. Marrese. Vita e Pensiero, luglio 2021 (ISBN digital edition [PDF]: 978-88-343-4822-2)
20. *"Thinking of the end of the world and of the end of the month": the Impact of Regenerative Agriculture on Economic and Environmental Profitability*. L.A. Lorenzetti, A. Fiorini. Vita e Pensiero, ottobre 2021 (ISBN digital edition [PDF]: 978-88-343-4898-7)

21. *Labour-saving automation and occupational exposure: a text-similarity measure*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5089-8)
22. *Climate reputation risk and abnormal returns in the stock markets: a focus on large emitters*. G. Guastella, M. Mazzarano, S. Pareglio, A. Xepapadeas. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5092-8)
23. *Carbon Boards and Transition Risk: Explicit and Implicit exposure implications for Total Stock Returns and Dividend Payouts*. M. Mazzarano, G. Guastella, S. Pareglio, A. Xepapadeas. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5093-5)
24. *Innovation and employment: a short update*. M. Vivarelli. Vita e Pensiero, gennaio 2022 (ISBN digital edition [PDF]: 978-88-343-5113-0)
25. *AI technologies and employment. Micro evidence from the supply side*. G. Damioli, V. Van Roy, D. Vertesy, M. Vivarelli. Vita e Pensiero, gennaio 2022 (ISBN digital edition [PDF]: 978-88-343-5119-2)
26. *The Effect of External Innovation on Firm Employment*. G. Arenas Díaz, A. Barge-Gil, J. Heijs, A. Marzucchi. Vita e Pensiero, febbraio 2022 (ISBN digital edition [PDF]: 978-88-343-5146-8)
27. *The North-South divide: sources of divergence, policies for convergence*. L. Fanti, M.C. Pereira, M.E. Virgillito. Vita e Pensiero, maggio 2022 (ISBN digital edition [PDF]: 978-88-343-3524-4)
28. *The empirics of technology, employment and occupations: lessons learned and challenges ahead*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, novembre 2022 (ISBN digital edition [PDF]: 978-88-343-5383-7)
29. *Cognitive biases and historical turns. An empirical assessment of the intersections between minds and events in the investors' decisions*. L. Esposito, L. Malara. Vita e Pensiero, gennaio 2023 (ISBN digital edition [PDF]: 978-88-343-5420-9)
30. *Interaction between Ownership Structure and Systemic Risk in the European financial sector*. C. Bellavite Pellegrini, R. Camacci, L. Pellegrini, A. Roncella. Vita e Pensiero, febbraio 2023 (ISBN digital edition [PDF]: 978-88-343-5446-9)
31. *Was Robert Gibrat right? A test based on the graphical model methodology*. M. Guerzoni, L. Riso, M. Vivarelli. Vita e Pensiero, marzo 2023 (ISBN digital edition [PDF]: 978-88-343-5457-5)
32. *A North-South Agent Based Model of Segmented Labour Markets. The Role of Education and Trade Asymmetries*. L. Fanti, M.C. Pereira, M.E. Virgillito. Vita e Pensiero, maggio 2023 (ISBN digital edition [PDF]: 978-88-343-5529-9)
33. *Innovation and the Labor Market: Theory, Evidence and Challenges*. N. Corrocher, D. Moschella, J. Staccioli, M. Vivarelli. Vita e Pensiero, giugno 2023 (ISBN digital edition [PDF]: 978-88-343-5580-0)
34. *The Effect of Economic Sanctions on World Trade of Mineral Commodities. A Gravity Model Approach from 2009 to 2020*. R. Caruso, M. Cipollina. Vita e Pensiero, dicembre 2023 (ISBN digital edition [PDF]: 978-88-343-5686-9)
35. *Education and Military Expenditures: Countervailing Forces in Designing Economic Policy. A Contribution to the Empirics of Peace*. A. Balestra, R. Caruso. Vita e Pensiero, gennaio 2024 (ISBN digital edition [PDF]: 978-88-343-5757-6)
36. *Vulnerability to Climate Change and Communal Conflicts: Evidence from Sub-Saharan Africa and South/South-East Asia*. S. Balestri, R. Caruso. Vita e Pensiero, maggio 2024 (ISBN digital edition [PDF]: 978-88-343-5829-0)
37. *Assessing changes in EU innovation policy programs: from SME instrument to EIC accelerator for start-up funding*. M. del Sorbo, C. Faber, M. Grazzi, F. Matteucci, M. Ruß. Vita e Pensiero, luglio 2024 (ISBN digital edition [PDF]: 978-88-343-5860-3)