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Public funding of innovation: Exploring applications and allocations of the European SME Instrument

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A B S T R A C T

Financial constraints can severely limit the development of small and medium size enterprises (SMEs) and are very likely to affect innovative firms. In order to lower the barriers to firm growth, in 2014 the European Commission introduced the SME Instrument with the specific aim to support businesses with high-growth potential in need of external finance. By exploiting the availability of information not only on grant awards but also on applications, this is the first study that examines which types of firms apply to the scheme and which ones are selected for the two main rounds of funding. The evidence suggests that the scheme is successful at attracting SMEs with high-growth potential, and that – in line with signalling theory – patenting and prior venture capital funding are strong predictors of awards.

1. Introduction

The financing of innovative small and medium-size enterprises (SMEs) has attracted significant attention among economists and policy makers. While SMEs can be key sources of innovation, structural change and industrial renewal (Schumpeter, 1934; Acs and Audretsch, 1990; Christensen, 1997), their potential is often limited by several constraints, among which scarcity of financial resources is often the most binding (Storey, 1994; Cosh et al., 2009). Financial constraints arise when firms are unable to access external capital and cannot exploit available growth opportunities because of information asymmetries between investor and investee that distort optimal capital allocations and induce inefficiency in the investment process (Jensen and Meckling, 1976; Stiglitz and Weiss, 1981).

Comparative studies highlight the geographical breadth and depth of the investment problem (see for example Bond et al., 2003), and with specific reference to European firms, recent evidence indicates that European SMEs lag behind their US peers: Hall et al. (2016) and Cincera et al., 2016 document a clear negative relationship between financial constraints and R&D investment among innovative European firms. Cincera et al., 2016 also show that European innovators are more financially constrained than their US counterparts, and this effect is stronger among young leading innovators.

In order to support the growth ambition of European SMEs, in 2014 the European Commission launched the SME Instrument. Originally funded by the European Union (EU) under the H2020 Framework Programme for Research and Technological Development, and now part of the European Innovation Council pilot remit, the SME Instrument targets the finance gap experienced by small and young innovative firms while they try to push new ideas to market. The scheme has a budget of around €3 billion to be invested over the period 2014–2020 and responds to the need to ease the financial constraints experienced by SMEs during the process of exploitation and scaling up, rather than exploration and pre-commercial development. To date, no systematic

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econometric analysis has been carried out to investigate what types of firms apply to the SME Instrument and what types of firms are awarded the funds. To the best of our knowledge, this is the first study of this kind. While at the time of writing it is premature to estimate the performance effects of the whole policy instrument, an analysis of the co-determinants of funding is now possible. This is, on the one hand, an important exercise to understand how the scheme is working, and on the other, a necessary step towards future evaluations of the policy outcomes.

The paper is structured as follows. In the next section we review the literature on firm financial constraints and innovation (Section 2). We then present in more detail the SME Instrument (Section 3), and the data and methods of analysis (Section 4). In Section 5 we show and discuss the results of the econometric estimations. Section 6 concludes with a summary of our results and their implications.

2. The financial constraints of innovative SMEs

Relative to larger firms, SMEs provide more difficult investment propositions in general (i.e. independently of their innovativeness) because they may have no obvious track record, they are unlisted, have little or no collateral, and might carry out unique activities that are difficult to evaluate from the outside. As investment risk increases, external capital is only accessible at a premium. The resulting 'wedge' between the cost of external and internal funds means that some projects are only viable if they can be financed through internal funds (Berger and Udell, 2006; Revest and Sapio, 2012). Yet, internal finance might not be available through retained earnings if the firm is not only small but also young (Storey, 1994; Myers, 2000; Cosh et al., 2009).

A further set of problems is associated with innovation activities (Dosi, 1988; Hall, 2009; Coleman and Robb, 2012). Innovation investments are highly uncertain and hard to evaluate without specific knowledge; information about their success or failure emerges slowly over time; and, finally, innovation tends to involve idiosyncratic intangible capital (for example intellectual property rights) rather than tangible capital with greater secondary marketability. Therefore, innovation significantly increases information asymmetries between the firm and external investors, and exacerbates firm financial constraints (Hall, 1992; Brown and Petersen, 2009; Bond et al., 2010). Relatively few traditional lenders (i.e. banks) are willing and able to manage the technological and market uncertainty characterising small innovative firms. This is typically the function attributed to venture capitalists (Gompers and Lerner, 2001, Kortum and Lerner, 2000), even though VC is not available in large supply nor does it suit every investment proposition.

Two important aspects of the innovation investment problem must be added to the picture. The first one concerns the significant heterogeneity within SMEs populations: there is robust evidence that the positive contribution of SMEs to employment and output growth is highly concentrated among a minority of firms displaying disproportionately strong entrepreneurial performances (Shane, 2009; Coad and Nightingale, 2014; Haltiwanger et al., 2013).[1] The second aspect concerns the fact that while financial constraints can affect R&D expenditures, successful R&D projects can themselves be sources of financial constraints because the commercialisation of innovation is often costly at near-to-market stages (Mancusi and Vezzulli, 2014; D'Este et al., 2012; Hottenrott and Peters, 2012; Lahr and Mina, 2020). It is therefore important to focus not only on the resources that are needed in the R&D process, but also on the inputs, including finance, that firms require in the exploitation phase of product and service innovation.

All in all, the empirical literature is rather clear on the effects of (small) firm size and (young) age on the likelihood that firms experience financial constraints (Carpenter and Petersen, 2002a; 2002b; Canepa and Stoneman, 2008; Czarnitzki and Hottenrott, 2011).[2] Moreover, high-tech firms seem more likely to be financially constrained than medium- and low-tech firms (Himmelberg and Petersen, 1994; Guiso, 1998; Canepa and Stoneman, 2008), arguably because the former are engaged in frontier research and undertake investments that are riskier and more prone to asymmetric information problems (Carpenter and Petersen, 2002a; Canepa and Stoneman, 2008). A higher probability of observing constraints for innovative firms is consistent with evidence coming from tests of the R&D sensitivity of cash flow (in line with Fazzari et al., 1988), despite well-known methodological problems associated with the identification of financial constraints in this literature (Kaplan and Zingales, 2000; Coad, 2010; Farre-Mensa and Ljungqvist, 2016).

In studying these investment processes, one fundamental problem is the analytical separation of finance seeking behaviours from observations of investments that are the results of successful selection (Cosh et al., 2009; Fraser, 2009). On the rare occasions when separate observations are available for the demand for external finance and success at obtaining it, the evidence is that finance seeking behaviours tend to be related to capital requirements and the capacity to generate internal resources, while success at obtaining finance resides in the availability of signals of quality that can aid the selection of investment propositions (Cosh et al., 2009; Mina et al., 2013). Innovation signals are at the same time an indication of greater investment risk, but also stronger potential returns. Moreover, there may be certification effects in the form of access to complementary sources of finance that can reduce information asymmetries. Prior investment by knowledgeable funders (such as VC) and patents can function as strong signals of quality in an investment framework (Spence, 2002) and should favour the likelihood of success at obtaining external finance especially at an early stage of business development (Baum and Silverman, 2004; Mann and Sager, 2007; Häussler et al., 2012; Conti et al., 2013a, 2013b; Hsu and Ziedonis, 2013, Lahr and Mina, 2016).

3. The SME Instrument

Innovation policy can ease the barriers to growth of SMEs in several ways, including through supply-side measures, institutional change initiatives as well as demand-side interventions.[3] In the specific case of SMEs, many government support schemes have often overlooked the fact that, considering the heterogeneity of the overall SME sector, the *median* small business is not the engine of growth and structural change envisaged by Schumpeter, and is not an innovative firm (Coad and Nightingale, 2014). From a policy viewpoint, this becomes problematic when the only condition for funding eligibility under a government

[1] For a more general discussion of firm heterogeneity and its implications, see Dosi et al. (2010).

[2] Czarnitzki and Hotternrott (2011) use the 1992–2002 data of the Mannheim Innovation Panel to examine R&D and capital investment among German manufacturing firms. They uncover a negative causal relationship between both internal constraints (measured by price-cost margin) and external constraints (measured by credit rating indices) and R&D investment. They also find that internal constraints were higher for R&D investment than they were for capital investments, and that the impact of external constraints on R&D investment becomes greater with decreasing firm size.

[3] For a general classification of innovation policy designs see Steinmueller (2010).

support scheme is firm size: if only a minority of small firms produce high impact, then vast unqualified government support channelled indiscriminately into all SMEs involves a high risk of deadweight losses. Appropriate policy may therefore need a greater degree of selectivity in order to address the funding gaps of firms with growth opportunities.

This principle is reflected in the design of the European Union's SME Instrument.[4] Announced by the European Commission in December 2010, this is the largest SMEs support scheme now active in the region.[5] It is administrated by the Executive Agency for Small and Medium-sized Enterprises (EASME), which has mandate to spend about €3 billion on innovative SMEs over the period 2014–2020. The objectives of the Instrument are described by the Commission as follows: "*The SME Instrument addresses small and medium-sized enterprises (SMEs) with a radically new idea underpinned by a business plan for rolling out marketable innovation solutions and with ambitions to scale up*. *It supports high-risk, high-potential SMEs to develop and bring to market new products, services and business models that could drive economic growth*".[6]

The SME Instrument is a novel scheme within the European innovation policy. Until its introduction there was no dedicated policy tool at the pan-European level aimed at directly supporting technological entrepreneurship of young and small companies. In fact, EU innovation policies have been traditionally focused on cooperative R&D projects bringing together science and business partners institutionally to promote technological innovation. In this regard, SMEs could indirectly benefit from policy support only as part of larger consortia.[7] On the contrary, the SME Instrument allows individual SMEs to apply for support alone.

The policy design of the SME Instrument has been inspired by the US Small Business Innovative Research (SBIR) program. In light of its success in providing early-stage financing to young innovative firms (Mazzucato, 2013; Howell, 2017), the discussion of introducing a SBIR-like program in the EU has been object of a long-standing debate among scholars and policy-makers (Encaoua, 2009; Connell, 2006; Grilli, 2014). The SME Instrument mimics the SBIR 3-phase structure, with a focus on technology commercialization while budget allocation is considerably lower (roughly 1/5 of the US SBIR).[8]

EASME is responsible for selecting awardees. Eligible firms are for-profit SMEs[9] which are legally established in the EU-28 or in a country associated to Horizon 2020. The grants are assigned after a committee of four independent experts appointed by EASME assesses the projects.[10] The evaluation process covers and assign a score to three aspects of the project: impact, excellence, and quality and efficiency of implementation.[11] Only projects deemed to be sufficient in each aspect (i.e. above a certain threshold for each criterion, the maximum score is 5 for each criterion), and which are above an overall threshold (calculated by adding up the median scores of all three criteria) are considered eligible to receive the grants. among this set of eligible firms, grants are allocated by EASME based on budgetary constraints.

The SME Instrument is expected to play an important role in facilitating innovation and commercialisation through resourcing and expert advice. It covers a broad range of possible uses[12] and consists of three consecutive phases. A firm can submit an application for a Phase I award. In Phase I the agency can award the firm a lump sum of €50,000 to determine the technical feasibility and commercial potential for breakthrough innovation. In Phase II the agency can award the firm between €500,000 and €2.5million to develop further the idea towards investment readiness and market launch. In the forthcoming Phase III the firm will receive no SME instrument funds, but support measures and services to commercialise its resulting product. Thus, a key feature of this financing instrument is that it complements the 'hard' financial side of the capital contribution with a 'soft' non-financial side consisting of mentoring and monitoring. In addition, with the steady increase in the number of applications and the limited Horizon 2020 budget, the European Commission created "the Seal of Excellence" certificate. The recipients are proposals worthy of funding under the scheme but not funded because of Horizon 2020 budget limits.

To date, €882 million have been awarded to 2457 SMEs participating in 2344 projects, with €93 million invested in 1864 Phase I projects and €789 million in 480 Phase II projects. In terms of success rates, the scheme is very competitive: as of 2017, after three years, the overall success rate of the programme is 8.4% for Phase I and 5.5% for Phase II.[13]

[4] For information on the SME Instrument as well as early qualitative assessments concerning the characteristics of applicant firms, see European Commission (2018) and ACCESS4SME (2018).

[5] https://ec.europa.eu/easme/en/comment/5693.

[6] https://ec.europa.eu/easme/en/sme-instrument.

[7] Examples of this policy approach are the Fast-Track to Innovation (FTI) and the Eurostar II programs. The FTI, as the SME Instrument, offers close-to-market support to speed up market delivery of innovation. Unlike the SME Instrument, the FTI does not target exclusively SMEs; nor does it allow single applicants to submit proposals but it is addressed to consortia of limited size (European Commission, 2019). The Eurostar II scheme, differently from the SME Instrument, provides funding for transnational, collaborative projects led by R&D performing SMEs in participating EUREKA countries. Hence, it is not targeted at individual SMEs (European Commission, 2018). See Section 2.2. in Di Minin et al. (2016) where the SME Instrument is put in historical perspective within the European innovation policy.

[8] For a full-fledged comparison between the SME Instrument and the SBIR, see Di Minin et al. (2016). Note also that early attempts at emulating the US SBIR program have been carried out by individual European countries such as the UK (see Coad and Tredgett, 2015) and the Netherlands (i.e. SBIR-NL). From a broader perspective, in recent years great emphasis has been put on alleviating market frictions for young and small innovative companies in individual EU members. Some examples are the Young Innovative Companies programs in Finland (Autio and Rannikko, 2016) and in France, and the Start-up Act in Italy (Menon et al. 2018).

[9] SMEs are defined by the European Commission as having less than 250 persons employed, an annual turnover of up to 50 million euros, or a balance sheet total of no more than 43 million euros.

[10] The appointment of the expert evaluators follows the criteria stated in Article 40 of the Rules for Participation of Horizon 2020 (EASME, 2016). Experts can apply to be evaluators through a call for expression of interest. The EU selects experts on the basis of educational attainment, professional experience and knowledge of the SME Instrument "topics". Until 2018, the SME Instrument has in fact been structured around 13 different thematic areas and firms competed among each other within a specific field (e.g. ICT, nanotechnology, space research and development, biotechnology, sustainable agriculture, etc.) (European Commission, 2018). To avoid conflict of interest, experts are obliged to sign a code of conduct. In case of violations, the European Commission invalidates his/her work and apply sanctions. The entire pool of evaluators is constituted by around 1500 experts. Most of them come from the private sector (75%) and represent almost 60 different nationalities. The pool is subject to a yearly rotation of 20% every year to ensure an impartial treatment of the projects submitted. The evaluators selected by the EU are assigned to a specific "topic" and receive proposals in their subject of expertise based on key words indicated in the application. Each eligible project is evaluated by four different experts. Each evaluator works independently as there are no contacts between the four evaluators (EASME, 2016). Hence, manipulation from the experts is unlikely since they work remotely, they do not know the scores of the other evaluators, nor the number of awards that will be granted in advance.

[11] Note that the object of evaluation is the project, not the firm. These criteria are also used by most policy instruments within the framework of the European Union Horizon 2020 program.

[12] The scheme supports prototyping, miniaturisation, scaling-up, design, performance verification, testing, demonstration, development of pilot lines, validation for market replication, and other activities 'aimed at bringing innovation to investment readiness and maturity for market take-up' (EC, 2018: https://ec.europa.eu/programmes/horizon2020/en/h2020-section/sme-instrument)

[13] Accelerating Innovation in Europe: HORIZON 2020 SME Instrument Impact Report, 2017 Edition.

4. Research strategy, data and methods

4.1. Research strategy

The aim of this study is to investigate 1) what types of firms apply to the SME Instrument and 2) which ones are successful at obtaining the funds. A particularly important objective is the identification of determinants of SME Instrument awards, controlling for the probability that firms apply to the scheme. The study is made possible by the rare opportunity to work not only with the list of winners, but also with the list of applicants that are not successful in the selection process. Then an essential part of the research strategy is the construction of relevant counterfactuals to which the SME Instrument winners and applicants can be compared. The design of the study therefore involves the groups of firms that were awarded Phase I funding, Phase II funding, the Seal of Excellence (SoE), firms that applied but received no award nor SoE, and a further control group of SMEs that did not apply. among relevant firm characteristics, beyond basic demographic information, we are especially interested in *financial indicators* that may account for the need of external capital (leverage, profit margins, cash flow and long-term debt signals) and indicators that capture signals of firm quality such as *prior growth, patenting,* and *venture capital backing.*[14] The following paragraphs describe in detail the data, the construction of control groups, the variables used in the analysis, the estimation strategy and the sensitivity analyses that corroborate the robustness of our results.

4.2. Data

The main data sources for this study are the 2014, 2015, 2016 and 2017 of the H2020 SME Instrument (CORDA) database and ORBIS Bureau van Dijk's company database. In the impossibility to access country-specific business registers, ORBIS represents the best data source for comparable cross-country firm-level data (David et al., 2020). Yet, although coverage has improved in recent years, ORBIS still does not provide optimal representativeness especially for young and small firms (Kalemli-Ozcan et al., 2015).

We collected from ORBIS balance-sheet and patent applications of all applicants to SME Instrument calls in years 2014–2017.[15] We further match the data with information on VC investments extracted from the Thomson Reuters Eikon database, integrated, where information was missing, with investments records extracted from Crunchbase.

The total SME Instrument sample includes four categories of firms, described in Table 1: 1) all firms that received Phase II awards to November 2017; 2) all firms that only received the SoE in a Phase II; 3) all firms that received Phase I awards to November 2017; and 4) a large sample of firms that did not receive any award (including Phase I awards and SoE status). SMEs that never presented admissible proposals for SME Instrument in the first four program cycles were excluded from the analysis.

We matched SME Instrument data through company names and countries with Bureau van Dijk's ORBIS records.[16] After the exclusion of records of firms with balance-sheet information in conflict with the policy eligibility criteria,[17] and companies without an active status, we obtained from the matching with ORBIS the following percentage of coverage: 74.8% of applicants, 88.2% of Phase II winners, and 81.1% of Phase II or Phase I winners.

Table 1
SME Instrument applicants' groups definition, acronym and sample size.

SME Instr. group	Definition	Acronym	Sample size (SME Instr.-ORBIS data)
Winners of Phase II	SMEs that received at least once Phase II award in first four program cycles. For SMEs applying multiple times, we collected data with reference to the year these SMEs won a Phase II grant for the first time.	WinPh2	578
Phase II Seal of Excellence	Received at least once the Seal of Excellence for a Phase II in first four program cycles, but never received a Phase II award. For SMEs applying multiple times, we collected data with reference to the year these SMEs have been elected Seal of Excellence for the first time.	SoE	1854
Winners of Phase I	SMEs that received at least once Phase I award in first four program cycles, but were never received a Phase II award nor received a S.o.E. For SMEs applying multiple times, we collected data with reference to the year these SMEs won a Phase I grant for the first time.	WinPh1	1007
Below Threshold	SMEs that did not received Phase I, Phase II awards, and S.o.E. in first four program cycles. For SMEs applying multiple times, we collected data with reference to the year these SMEs applied to the SME Instrument for the first time.	BT	9967
Inadmissible	SMEs that never presented admissible proposals for SME Instrument in the first four program cycles	Inadm	Excluded

4.3. Control group

Starting from the population of all SME Instrument applicants, we selected the non-applicants control group from ORBIS by implementing a matching algorithm. The choice of selective matching vs. the extraction of a random sample ensures bias and variance benefits (Stuart and Ialongo, 2010). The matching procedure resulted in a balanced

[14] A further factor that could increase the likelihood of applying or receiving public support is the prior receipt of a grant. It is important to stress that we do not have data on prior receipt of public funding at regional, national or supranational level and we are not able to test whether this is a determinant of application and/or receipt of the SME Instrument grant. The interpretation of our findings should take this aspect into account.

[15] We use patent applications filed up until 2018. The underlying information source for patent-related information in ORBIS is the PATSTAT database, established and maintained by the European Patent Office (EPO). PATSTAT is a worldwide database containing bibliographical data on the majority of patents currently in force. The match between ORBIS and PATSTAT is carried out by Bureau van Dijk under a mutual agreement with the OECD (Organisation for Economic Cooperation and Development). Squicciarini and Dernis (2013) show that the share of successfully matched patents between PATSTAT and ORBIS is above 90% for selected OECD countries.

[16] To link SME Instrument applicants with ORBIS records we employed the BvD's Batch Search string functionality. In more detail, the search was performed using applicants' name and country. To adopt a conservative approach and avoid false positives, we only retained those matches featuring the highest quality possible, that is, those with "excellent" quality according to ORBIS (>= 95% correspondence). A manual check was also operated to further test the quality of the matching.

[17] After linking EASME data with ORBIS records, we performed a check on the eligibility criteria of the SME Instrument. In particular, we verified whether the number of employees (and revenues) where in compliance with the SME definition of the EU. We therefore discarded 22 firms that presented employees (and/or revenues) in excess of the SME definition. In order to adopt a conservative approach, we excluded them from the analysis.

treated/non-treated sample and was based on the following dimensions: location (country), size (number of employees), sector (NACE Rev.2 primary code, first 3 digits). Countries featuring applicants with non-missing variables were automatically excluded from the analysis.[18] We used a 1:1 nearest neighbour matching method with the propensity score defining the distance between units. The distance choice was supported by the presence of a large amount of covariates, after appropriate dichotomization of the variables location and sector (Stuart, 2010).[19] We implemented the nearest neighbour propensity score matching algorithm by country because of the large cross-country variations in the number of applications. An in-depth description of the matching protocol is provided in Appendix. We are aware of the limitations of propensity score matching to assess causal inference, as reported in King and Nielsen (2018) and our matching procedure is not aimed to obtain causal estimation of treatment effects, but rather to select comparable samples and correctly estimate likelihood of treatment. Moreover, as pointed out by the same authors (King and Nielsen, 2018), it is good practice to check that propensity score matching is applied so as to reduce imbalance in the sample and in the control group: this is indeed the goal we achieve with its application (see Appendix).

After the exclusion of duplicate units in the control group (the same control unit can be matched as nearest neighbour of multiple treated units), the final sample contains 23,176 companies: 13,406 applicants (3439 successful, 9967 unsuccessful) and 9770 non-applicants.

4.4. Variable definitions and descriptive statistics

We extracted from ORBIS the following variables, reported in Table 2 with full names and the labels used in the econometric results tables.

4.4.1. Dependent variables

The first dependent variable indicates whether a firm applied to the SME Instrument in a certain year (*D_APPLY*). This is coded as 1 if the firm applied to the programme and 0 otherwise. The second dependent variable indicates whether a firm received a Phase I grant and, in a separate set of estimations, Phase II grant in a certain year (*D_WIN_PH1* and *D_WIN_PH2* respectively). This variable takes value 1 in the year the grant was awarded and 0 otherwise.

4.4.2. Explanatory variables

We include as explanatory variables: *Firm size*, indicated by number of employees; *Firm age* defined as the difference between 2017 and the year of incorporation; an *Employment-based High-growth* dummy variable coded as 1 if the firm belongs to the fourth quartile of firm size average growth rate distribution over the last 3 years, and 0 otherwise; a *Revenue-based High-growth* dummy variable coded as 1 if the firm belongs to the fourth quartile of the revenue average growth rate distribution over the last 3 years; *Cash flow* weighted by total assets,; Leverage (*debt over equity*), calculated as the ratio between long term debts and shareholder funds; *Profit margin*, that is earnings as a percentage of revenues; *Sales*, weighted by total assets; *Long term debt over assets*; a *Manufacturing* dummy variable coded as 1 if the firm operates in manufacturing sectors (according to the NACE Rev. 2 classification) and 0 otherwise; a *High-tech* dummy coded as 1 if the firm operates in high-tech or knowledge-intensive services (according to standard OECD/Oslo Manual classification) and 0 otherwise; a *VC* dummy variable, coded as 1 if the firm received VC between 2010 and the year of SME Instrument status achievement (0 otherwise) for the applicants group, and coded as 1 if the firm received prior VC and 0 otherwise for the control group; a *Patents* dummy variable if the firm has at least one patent, and 0 otherwise; *Number of Patents; Country* dummies and *year of SME Instrument* achievement status dummies.

Table 2
Variables names and acronyms.

Name		Acronym
Number of employees		N_EMP
Age	Year of incorporation minus 2017	AGE
Dummy high-growth company in employees	1 = the firm belong to the fourth quartile of the employment average growth rate distribution over the last 3 years; 0 = otherwise	D_HG_EMP_Q
Dummy high-growth company in revenues	1 = the firm belong to the fourth quartile of the revenues average growth rate distribution over the last 3 years; 0 = otherwise	D_HG_REV_Q
Cash flow over total assets	Cash flow / Total assets	CASH_ TOTASS
Debt / Equity	Long term debts / Shareholder funds	DEBT_EQUITY
Profit margin	Earnings as% of total revenues	PROFIT_MARGIN
Sales over total assets	Sales / Total assets	SALES_TOTASS
Long term debts over total assets	Long term debts / Total assets	LT_DEBTS_TOTASS
Dummy manufacturing	1 = the firm operates in manufacturing sectors (according to the NACE Rev. 2 classification); 0 = otherwise	D_MANUFACT
Dummy high-tech	1 = the firm operates in high-tech manufacturing sectors or knowledge-intensive services; 0 = otherwise	D_HT
Dummy VC-backed	SME Instrument applicants group 1 = the firm received VC between 2010 and the year of SME Instrument status achievement (see Table 1) 0 = otherwise Control sample 1 = the firm received VC funding in the period 2010–2017; 0 = otherwise	D_VC_PRE
Number of patents	Number of patent applications filed	N_PATENTS
Dummy patents	1 = the firm has filed a patent application; 0 = otherwise	D_PATENTS
Country	Country where firm is located	COUNTRY
Year of SMEi status achievement		YEAR_SMEI

Table 3 reports the descriptive statistics of the sample. To reduce the potential influence of outliers in our estimations, we have winsorized all our continuous variables at the 1% level on both sides of the distribution. As expected, firms in our sample tend to be small and young featuring a median number of employees around 6 and a median age of 9 years old. Around 21% of all firms operate in the manufacturing sector whereas a sizable share belongs to high-tech industries.[20] Only 3% of firms has received VC while roughly 17% has filed at least one patent application.

4.5. Estimation method

We use probit modelling to estimate the probability that a firm ap-

[18] These are all Horizion2020 associated countries: Anguilla, Armenia, Greenland, and Georgia.

[19] We also tried to apply the Mahalanobis as distance function, but convergence was not possible given the large number of variables.

[20] Among them, the majority operates in knowledge intensive business services. In more detail, the applicants mainly belong to sectors such as computer programming activities (NACE 62), engineering activities and related technical consultancy (NACE 70), business and other management consultancy activities (NACE 71), research and experimental development on natural sciences and engineering (NACE 72), wholesale of pharmaceutical goods (NACE 46). This is mainly due to the fact that a sizable share of the SME Instrument competitions refer to technology areas such as ICTs (European Commission, 2018).

plies to the SME Instrument. We then model the likelihood that firms are awarded funding, conditional on the probability that they apply to the scheme. Assuming that firms are aware of the existence of the SME Instrument, winning the grant is only observed for firms that choose to participate in the program. The sample is thus censored because the dependent variable of interest is only observed for a subsample of firms. This generates a potential endogeneity problem, which can be addressed through a Heckman sample selection approach.[21] Binary models with sample selection can be estimated by specifying two distinct equations, one for the selection into sample and one for the binary response:

$$y_1 = 1[\mathrm{x}_1\boldsymbol{\beta}_1 + u_1 > 0] \qquad \textit{Binary response equation}$$

$$y_2 = 1[\mathrm{x}\ \boldsymbol{\delta}_2 + v_2 > 0] \qquad \textit{Sample selection equation}$$

where y_1 is the binary response variable and y_2 is the binary variable indicating the selection indicator; x_1 and x are the matrixes containing the explanatory variables for the response variable and the selection indicator, respectively; $\boldsymbol{\beta}_1$ and $\boldsymbol{\delta}_2$ are the vectors of coefficients for the response variable and the selection indicator, respectively; and u_1 and v_2 are the error terms. Importantly, y_1 is observed only when $y_2 = 1$ and it is assumed that x is always observed. Binary models with sample selection can be estimated by assuming that the latent errors are normal and independent of the explanatory variables (Wooldridge, 2010). Hence, assuming that $(u_1, v_2) \perp \mathrm{x} \sim \mathrm{N}(0, 1)$, the density of y_1 conditional on x and $y_2 = 1$ can be expressed as:

$$P(y_1 = 1 | y_2 = 1,\ \mathrm{x}) = E[P(y_1 = 1 | v_2,\ \mathrm{x}) | y_2 = 1,\ \mathrm{x}] = E\left\{\Phi\left[(\mathrm{x}_1\boldsymbol{\beta}_1 + \rho v_2) \big/ \left(1-\rho^2\right)^{1/2}\right] | y_2 = 1,\ \mathrm{x}\right\}$$

$$= \frac{1}{\Phi(\mathrm{x}\boldsymbol{\delta}_2)} \int_{-\mathrm{x}\boldsymbol{\delta}_2}^{\infty} \Phi\left[(\mathrm{x}_1\boldsymbol{\beta}_1 + \rho v_2) \big/ \left(1-\rho^2\right)^{1/2}\right] \varphi(v_2) \mathrm{d}v_2$$

where $\Phi(z) \equiv \int_{-\infty}^{z} \varphi(w)\mathrm{d}w$, with $\varphi(\cdot)$ being the standard normal density, and the parameter ρ is the correlation between u_1 and v_2. The Heckman two-step procedure consists of the estimation of $\boldsymbol{\delta}_2$ with a probit model of y_2 on x (first step) and then the estimation of $\boldsymbol{\beta}_1$ and ρ using the conditional density $P(y_1 = 1 | y_2 = 1,\ \mathrm{x})$ together with $P(y_1 = 0 | y_2 = 1,\ \mathrm{x})$ (second step). To ensure model identification, the procedure requires the existence of at least one variable that affects the selection but does not determines the response, i.e. a variable in x that is not also in x_1 (the exclusion restriction).

We estimate one model with the observations of Phase I awards and one with the observations of Phase II awards. The exclusion restriction is *Profit margin*: in all models this has strong predictive power in the selection step (application), but does not determine the outcome (win). In the Online Supplementary Materials that accompany the paper we present the estimation of independent equations to show that the instrument is always valid.

We approach the estimations in a step-wise manner, by running a baseline model with the variables *number of employees, age, dummy for high-growth in employees, dummy for high-growth in revenues, cash-flow over total assets, debt/equity, profit margin, sales over total assets, dummy for manufacturing, dummy for high-tech, country dummies* and *dummy for year of SME Instrument status achievement* (for all applicants). We then include the variables *VC* and *patents* to observe their effects in the results and performance of the models. We also include interaction terms of the *high-tech* dummy, *VC* and *patents* variables with firm *size* and *age*. All independent variables are measured for the period prior to the event that is predicted. All estimations include country and year dummies.

Bivariate correlations (Table 4) and also variance inflation factors (VIF, available in the Online Supplementary Materials, Table A2-1) show that multicollinearity is not an issue in our estimations. The mean VIF value as well as individual VIFs all feature magnitudes well below the commonly accepted threshold of 10.

Table 3
Descriptive statistics.

Variable	Mean or Proportion (*)	Median	Min	Max
N_EMP	16.8	6	0	142
AGE	12.6	9	1	54
D_HG_EMP_Q	0.16	0	0	1
D_HG_REV_Q	0.16	0	0	1
CASH_TOTASS	0.022	0.056	−1.93	0.79
DEBT_EQUITY	0.58	0	0	18.8
PROFIT_MARGIN	1.64	2.70	−88.9	76.8
SALES_TOTASS	1.38	1.00	0.000002	9.21
LT_DEBTS_TOTASS	0.16	0	0	2.11
D_MANUFACT	0.21	0	0	1
D_HT	0.61	1	0	1
D_VC	0.031	0	0	1
D_PATENTS	0.17	0	0	1
N_PATENTS	0.70	0	0	17

Notes: all continuous variables are winsorized at the 1% level on both sides of the distribution.

4.6. Robustness checks

In order to assess the absence of sensitivity of the results to the construction of the control sample of SME Instrument non applicants, as a robustness check we replicated the whole analysis for two alternative control samples, both extracted from the population of eligible non-applicant firms contained in ORBIS. The first alternative control group was extracted with random sampling (random control group). More specifically, we proceeded to extract at random five firms for each applicant, by country (i.e. the random sampling procedure was replicated for each country presenting at least one SME Instrument applicant). After the exclusion of duplicate units, the random control group contained 48,168 non-applicants. The second alternative control group was selected through a 5:1 nearest neighbour matching method with the propensity score distance measure (NN PS 5:1 matching control group). While the first sensitivity test is important as a benchmark for the use of matching, selecting more than one comparison unit for each SME Instrument applicant firm might be considered as a refinement of the 1:1 case (Stuart and Ialongo, 2010). We implemented the 5:1 nearest neighbour propensity score matching algorithm by country and, after the exclusion of duplicate units, the NN PS 5:1 matching control group contained 18,852 non-applicants. The detailed protocol of control samples building construction is reported in the Appendix.

The replication of the analysis on the two alternative control groups (available in the Online Supplementary Materials) shows that results are

[21] As an alternative to the two-step procedure one can also estimate the models using a maximum likelihood approach. Yet, given that they are significantly more computational demanding, we have opted for using the two-step procedure.

Table 4
Correlation table.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
[1] N_EMP	1.000													
[2] AGE	0.300	1.000												
[3] D_HG_EMP_Q	0.008	−0.151	1.000											
[4] D_HG_REV_Q	−0.087	−0.226	0.296	1.000										
[5] CASH _TOTASS	0.039	0.040	0.001	0.024	1.000									
[6] DEBT_EQUITY	0.000	−0.029	0.028	0.002	−0.006	1.000								
[7] PROFIT_MARGIN	0.034	0.079	−0.014	−0.008	0.498	−0.038	1.000							
[8] SALES_TOTASS	0.042	−0.069	0.009	−0.007	0.046	−0.069	0.091	1.000						
[9] LT_DEBTS_TOTASS	−0.007	−0.038	0.019	0.018	−0.122	0.335	−0.148	−0.105	1.000					
[10] D_MANUFACT	0.170	0.234	−0.066	−0.065	0.001	0.032	0.007	−0.093	0.014	1.000				
[11] D_HT	−0.157	−0.224	0.052	0.092	0.003	−0.029	−0.019	−0.106	0.002	−0.517	1.000			
[12] D_PATENTS	0.173	0.109	−0.014	0.044	−0.060	0.019	−0.110	−0.168	0.065	0.201	−0.024	1.000		
[13] N_PATENTS	0.239	0.155	−0.024	0.002	−0.059	0.007	−0.086	−0.114	0.040	0.164	−0.030	0.645	1.000	
[14] D_VC	0.017	−0.090	0.064	0.089	−0.137	0.000	−0.205	−0.098	0.071	−0.031	0.097	0.160	0.135	1.000

fully consistent.

5. Results

Table 5 reports the results of the selection equation; Table 6 reports the results of the outcome 'Phase I award' equation; Table 7 shows the results of the outcome 'Phase II award' equation. All tables include the computation of marginal effects. We first examine the results of the selection equation.

Estimation of a baseline selection (application) equation (Model 1) shows a positive and significant effect of size on the probability of application and a negative effect for age (Table 5).[22] The effects of growth indicators (dummies for the firm being in the top quartile of the growth rates distribution) have the expected positive sign in both dimensions of employment and revenue. among the financial variables, leverage, profit margins, and sales over assets exert a negative effect, while long-term debt appears to have a positive and sizable effect. However, leverage becomes insignificant when tested alongside all the main effects (Model 5), while the effects of profit margins, sales and long-term debt remain significant. Manufacturing firms and high-tech firms are more likely to apply, a possible indication of greater need of external finance due to greater capital intensity.[23] Being a high-growth firm by revenue, active in manufacturing, and high-tech company, are the characteristics producing the largest marginal effects, increasing the probability of applying by 10, 17 and 19% respectively.

In Model 2, firm size and age are interacted with the high-tech dummy: being active in high-tech sector may amplify the positive effect of size and negative effect of age (younger high-tech firm are more likely to apply). When we test for the effects of having obtained VC prior to the application (Model 3) we obtain a positive and significant result. Also positive and strongly statistically significant is the effect of being patent-active (Model 5). The marginal effects on the decision to apply are substantial (40% probability for VC and 43 for patenting). Both results indicate greater need for finance. As for the effect of VC, this is no substitute for SME Instrument funding and might also capture greater alertness to the availability of complementary sources of external capital. Interacting first VC (Model 4) and then patenting (Model 5) with size and age only generates a positive and significant effect for patenting and size, suggesting that larger firms with patents seem to be more likely to apply (the economic effect is, however, small).

Results from the outcome equation for Phase I awards produce interesting insights into the first successful step of the award selection process (Table 6).

Being in the top quartile of the revenue growth rates distribution is positively associated with the award. Positive and significant effects are also recorded for the manufacturing dummy (Model 1). Experience of VC investment does not make a statistically significant contribution (Model 4), whereas patents are the strongest determinants of winning a Phase I award and increase the probability of funding by just below 10% (Model 5).

Results from the outcome equation for Phase II awards (Table 7) highlight the factors that determined success at the most selective step of the evaluation process, and the one associated with the largest rewards in terms of funding.

In the baseline model (Model 1), being a high-growth firm is a strong predictor, but only as far as the top quartile employment performance is concerned. The effect of the revenue-related variable is not significant. among the financial indicators, sales have a clear and statistically significant negative effect. This is plausible when we consider that the SME Instrument addresses a finance gap for firms which might not yet be at the stage where they reap the benefits of full-scale production and commercialisation. The variable 'high tech' has a strong negative effect. However, the relative effect of this variable weakens substantially with the inclusion of the patenting variable (Model 5, where 'high tech' is not statistically significant). Most interestingly, firms that have already received VC-backing are more likely to win Phase II awards (Model 3). An even clearer effect is recorded for patents (Model 5). The marginal effects are smaller relative to the same variables in the selection equation, but the results are stable and statistically strong.

All the estimations have been tested also by adding one interaction term at the time and results do not change from those that are synthetically presented in Tables 5–7. When we use the number of patents instead of the dichotomous variable (patents yes/no) there is no improvement in the results: consistently with extant literature (Lahr and Mina, 2016), the important difference is between patent active and patent inactive firms.

6. Conclusion

Innovative SMEs have long been considered as fundamental components of the processes of economic growth and industrial transformation. among the heterogeneous population of SMEs, the more innovative firms tend to have a strong growth orientation. However, in the absence of internal finance – this is typically the case of young firms

[22] In unreported tests (available upon request) we have also verified the robustness of our results to the inclusion of squared terms in age and size. Results do not support a non-linear relation between these covariates with SME Instrument application or win.

[23] We have also verified the sensitivity of our results to the use of more fine-grained sectoral dummies (i.e. 2-digit NACE rev. 2). Results (available upon request) are practically unaltered. Point estimates from these models reveal that the sectors with higher chances of applying and winning R&D grants are pharmaceuticals (NACE 21), manufacture of computer, *electronic* and optical products (NACE 26), and scientific research and development (NACE 72). In contrast, firms in accommodation (NACE 55), food and beverage service activities (NACE 56), residential care activities (NACE 87) systematically display lower propensities.

Table 5
Results of the selection equation.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
D_APPLY												
N_EMP	0.006***	(0.000)	0.005***	(0.001)	0.005***	(0.001)	0.005***	(0.001)	0.002***	(0.001)	0.002**	(0.001)
AGE	−0.011***	(0.001)	−0.003**	(0.002)	−0.003**	(0.002)	−0.003**	(0.002)	−0.007***	(0.002)	−0.006***	(0.002)
D_HG_EMP_Q	0.062**	(0.031)	0.063**	(0.031)	0.057*	(0.032)	0.056*	(0.032)	0.085**	(0.033)	0.087**	(0.033)
D_HG_REV_Q	0.288***	(0.032)	0.281***	(0.032)	0.267***	(0.032)	0.267***	(0.032)	0.207***	(0.034)	0.208***	(0.034)
CASH_TOTASS	0.069	(0.064)	0.071	(0.065)	0.107	(0.066)	0.105	(0.066)	0.117*	(0.066)	0.116*	(0.066)
DEBT_EQUITY	−0.001	(0.006)	−0.000	(0.006)	0.001	(0.006)	0.001	(0.006)	0.004	(0.006)	0.004	(0.006)
PROFIT_MARGIN	−0.006***	(0.001)	−0.006***	(0.001)	−0.006***	(0.001)	−0.006***	(0.001)	−0.005***	(0.001)	−0.005***	(0.001)
SALES_TOTASS	−0.254***	(0.015)	−0.253***	(0.015)	−0.245***	(0.015)	−0.246***	(0.015)	−0.207***	(0.014)	−0.206***	(0.014)
LT_DEBTS_TOTASS	0.358***	(0.068)	0.356***	(0.068)	0.341***	(0.069)	0.342***	(0.069)	0.334***	(0.069)	0.335***	(0.069)
D_MANUFACT	0.478***	(0.034)	0.469***	(0.034)	0.469***	(0.034)	0.470***	(0.034)	0.300***	(0.036)	0.298***	(0.036)
D_HT	0.538***	(0.030)	0.746***	(0.046)	0.723***	(0.046)	0.725***	(0.046)	0.668***	(0.048)	0.665***	(0.049)
D_HT * N_EMP			0.003***	(0.001)	0.003***	(0.001)	0.003***	(0.001)	0.004***	(0.001)	0.005***	(0.001)
D_HT * AGE			−0.018***	(0.002)	−0.017***	(0.002)	−0.017***	(0.002)	−0.017***	(0.003)	−0.017***	(0.003)
D_VC					1.141***	(0.136)	0.774**	(0.308)	0.779**	(0.323)	0.773**	(0.323)
D_VC * N_EMP							0.010	(0.008)	0.013	(0.009)	0.012	(0.009)
D_VC * AGE							0.026	(0.036)	−0.018	(0.041)	−0.017	(0.041)
D_PATENTS									1.352***	(0.043)	1.353***	(0.075)
D_PATENTS * N_EMP											0.003**	(0.001)
D_PATENTS * AGE											−0.005	(0.003)
Constant	−0.097	(0.250)	−0.193	(0.259)	−0.230	(0.261)	−0.232	(0.261)	−0.541*	(0.326)	−0.570*	(0.336)
COUNTRY FE	Yes		Yes		Yes		Yes		Yes		Yes	
Number of obs	11,761		11,761		11,761		11,761		11,761		11,761	
Wald chi2	1205.27		1242.57		1245.28		1250.96		1949.31		1912.57	
Log likelihood	−7260.73		−7228.74		−7178.36		−7176.82		−6583.52		−6579.89	
Marginal effects												
N_EMP	0.0023***	(0.0002)	0.0017***	(0.0002)	0.0016***	(0.0002)	0.0016***	(0.0002)	0.00073***	(0.0002)	0.00050**	(0.0002)
AGE	−0.0038***	(0.0004)	−0.0012**	(0.0005)	−0.0011**	(0.0005)	−0.0011**	(0.0005)	−0.0022***	(0.0005)	−0.0020***	(0.0005)
D_HG_EMP_Q	0.022**	(0.01)	0.022**	(0.01)	0.020*	(0.01)	0.020*	(0.01)	0.027**	(0.01)	0.028**	(0.01)
D_HG_REV_Q	0.10***	(0.01)	0.099***	(0.01)	0.093***	(0.01)	0.093***	(0.01)	0.066***	(0.01)	0.067***	(0.01)
CASH_TOTASS	0.024	(0.02)	0.025	(0.02)	0.038	(0.02)	0.037	(0.02)	0.037*	(0.02)	0.037*	(0.02)
DEBT_EQUITY	−0.00026	(0.002)	−0.000060	(0.002)	0.00039	(0.002)	0.00039	(0.002)	0.0012	(0.002)	0.0012	(0.002)
PROFIT_MARGIN	−0.0021***	(0.0002)	−0.0021***	(0.0002)	−0.0019***	(0.0002)	−0.0019***	(0.0002)	−0.0015***	(0.0002)	−0.0015***	(0.0002)
SALES_TOTASS	−0.090***	(0.005)	−0.089***	(0.005)	−0.086***	(0.005)	−0.086***	(0.005)	−0.066***	(0.004)	−0.066***	(0.004)
LT_DEBTS_TOTASS	0.13***	(0.02)	0.13***	(0.02)	0.12***	(0.02)	0.12***	(0.02)	0.11***	(0.02)	0.11***	(0.02)
D_MANUFACT	0.17***	(0.01)	0.17***	(0.01)	0.16***	(0.01)	0.16***	(0.01)	0.096***	(0.01)	0.095***	(0.01)
D_HT	0.19***	(0.01)	0.26***	(0.02)	0.25***	(0.02)	0.25***	(0.02)	0.21***	(0.01)	0.21***	(0.02)
D_HT * N_EMP			0.0012***	(0.0003)	0.0012***	(0.0003)	0.0011***	(0.0003)	0.0013***	(0.0003)	0.0015***	(0.0003)
D_HT * AGE			−0.0065***	(0.0008)	−0.0060***	(0.0008)	−0.0061***	(0.0008)	−0.0054***	(0.0008)	−0.0054***	(0.0008)
D_VC					0.40***	(0.05)	0.27**	(0.1)	0.25**	(0.1)	0.25**	(0.1)
D_VC * N_EMP							0.0034	(0.003)	0.0041	(0.003)	0.0040	(0.003)
D_VC * AGE							0.0091	(0.01)	−0.0057	(0.01)	−0.0053	(0.01)
D_PATENTS									0.43***	(0.01)	0.43***	(0.02)
D_PATENTS * N_EMP											0.0011**	(0.0004)
D_PATENTS * AGE											−0.0015	(0.001)

Notes: Results obtained using a probit estimator. The dependent variable is a dummy indicating with 1 whether a firm has applied to the SME Instrument. All explanatory variables are taken with one year lag. Robust standard errors reported in parentheses. All continuous variables have been winsorized at the 1% level on both sides of the distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table 6
Results of the outcome 'Phase I award' equation.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
D_WIN_PH1												
N_EMP	−0.001	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.002*	(0.001)	0.002*	(0.001)
AGE	0.005**	(0.002)	0.003	(0.003)	0.003	(0.003)	0.003	(0.003)	−0.001	(0.002)	−0.002	(0.003)
D_HG_EMP_Q	0.035	(0.052)	0.036	(0.052)	0.037	(0.052)	0.037	(0.052)	0.086*	(0.048)	0.085*	(0.048)
D_HG_REV_Q	0.163**	(0.053)	0.162**	(0.053)	0.162**	(0.053)	0.160**	(0.053)	0.238***	(0.047)	0.238***	(0.047)
CASH_TOTASS	0.091	(0.096)	0.090	(0.096)	0.090	(0.097)	0.091	(0.097)	0.047	(0.088)	0.047	(0.088)
DEBT_EQUITY	−0.015	(0.011)	−0.015	(0.011)	−0.015	(0.011)	−0.015	(0.011)	−0.010	(0.010)	−0.010	(0.010)
SALES_TOTASS	−0.028	(0.035)	−0.026	(0.035)	−0.026	(0.035)	−0.025	(0.035)	−0.152***	(0.027)	−0.153***	(0.027)
LT_DEBTS_TOTASS	−0.010	(0.117)	−0.010	(0.117)	−0.010	(0.117)	−0.008	(0.117)	0.168	(0.109)	0.167	(0.109)
D_MANUFACT	0.171**	(0.064)	0.164**	(0.064)	0.164**	(0.064)	0.162**	(0.064)	0.306***	(0.056)	0.305***	(0.056)
D_HT	−0.017	(0.061)	−0.043	(0.085)	−0.043	(0.085)	−0.053	(0.085)	0.335***	(0.071)	0.333***	(0.071)
D_HT * N_EMP			−0.002	(0.001)	−0.002	(0.001)	−0.001	(0.001)	0.000	(0.001)	0.000	(0.001)
D_HT * AGE			0.004	(0.004)	0.004	(0.004)	0.004	(0.004)	−0.006*	(0.004)	−0.006	(0.004)
D_VC					−0.002	(0.103)	0.296	(0.193)	0.476**	(0.197)	0.478**	(0.197)
D_VC * N_EMP							−0.003	(0.004)	−0.003	(0.005)	−0.003	(0.005)
D_VC * AGE							−0.029	(0.021)	−0.031	(0.022)	−0.032	(0.022)
D_PATENTS									0.679***	(0.046)	0.671***	(0.069)
D_PATENTS * N_EMP											−0.001	(0.001)
D_PATENTS * AGE											0.002	(0.003)
Constant	−0.741**	(0.377)	−0.758**	(0.380)	−0.757**	(0.381)	−0.746**	(0.378)	−1.882***	(0.339)	−1.864***	(0.338)
COUNTRY FE	Yes		Yes		Yes		Yes		Yes		Yes	
YEAR SMEi FE	Yes		Yes		Yes		Yes		Yes		Yes	
Number of obs	11,784		11,784		11,784		11,784		11,784		11,784	
Censored obs	5996		5996		5996		5996		5996		5996	
Wald chi2	5217.40		4762.17		4759.18		4742.03		38,364.59		36,327.79	
Log pseudolikelihood	−8587.84		−8587.06		−8587.06		−8585.43		−8573.79		−8573.53	
Rho	−0.389		−0.396		−0.397		−0.398		0.998		0.998	
Wald test indip. eqns (Prob>chi2)	0.000		0.000		0.000		0.000		0.005		0.007	
Marginal effects												
N_EMP	−0.00020	(0.0002)	0.0000062	(0.0003)	0.0000061	(0.0003)	0.000024	(0.0003)	0.00025*	(0.0001)	0.00030*	(0.0002)
AGE	0.0012**	(0.0006)	0.00080	(0.0007)	0.00080	(0.0007)	0.00080	(0.0007)	−0.00017	(0.0003)	−0.00028	(0.0004)
D_HG_EMP_Q	0.0086	(0.01)	0.0091	(0.01)	0.0091	(0.01)	0.0092	(0.01)	0.012*	(0.007)	0.012*	(0.007)
D_HG_REV_Q	0.040**	(0.01)	0.040**	(0.01)	0.040**	(0.01)	0.040**	(0.01)	0.033***	(0.007)	0.033***	(0.007)
CASH_TOTASS	0.023	(0.02)	0.022	(0.02)	0.022	(0.02)	0.023	(0.02)	0.0065	(0.01)	0.0066	(0.01)
DEBT_EQUITY	−0.0038	(0.003)	−0.0038	(0.003)	−0.0038	(0.003)	−0.0038	(0.003)	−0.0013	(0.001)	−0.0014	(0.001)
SALES_TOTASS	−0.0071	(0.009)	−0.0065	(0.009)	−0.0065	(0.009)	−0.0062	(0.009)	−0.021***	(0.004)	−0.021***	(0.004)
LT_DEBTS_TOTASS	−0.0024	(0.03)	−0.0025	(0.03)	−0.0025	(0.03)	−0.0021	(0.03)	0.023	(0.02)	0.023	(0.02)
D_MANUFACT	0.043**	(0.02)	0.041**	(0.02)	0.041**	(0.02)	0.040**	(0.02)	0.043***	(0.008)	0.043***	(0.008)
D_HT	−0.0043	(0.02)	−0.011	(0.02)	−0.011	(0.02)	−0.013	(0.02)	0.047***	(0.010)	0.046***	(0.010)
D_HT * N_EMP			−0.00040	(0.0003)	−0.00040	(0.0003)	−0.00035	(0.0003)	0.0000099	(0.0002)	0.0000079	(0.0002)
D_HT * AGE			0.00097	(0.001)	0.00097	(0.001)	0.0011	(0.001)	−0.00083*	(0.0005)	−0.00081	(0.0005)
D_VC					−0.00049	(0.03)	0.074	(0.05)	0.066**	(0.03)	0.067**	(0.03)
D_VC * N_EMP							−0.00069	(0.001)	−0.00044	(0.0007)	−0.00042	(0.0007)
D_VC * AGE							−0.0072	(0.005)	−0.0043	(0.003)	−0.0044	(0.003)
D_PATENTS									0.094***	(0.007)	0.093***	(0.010)
D_PATENTS * N_EMP											−0.00012	(0.0002)
D_PATENTS * AGE											0.00024	(0.0005)

Notes: The table reports results obtained using an Heckman two-step procedure. The dependent variable is a dummy indicating with 1 whether a firm was awarded a Phase I grant of the SME Instrument. All explanatory variables are taken with one year lag. Robust standard errors reported in parentheses. All continuous variables have been winsorized at the 1% level on both sides of the distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table 7
Results of the outcome ’Phase II award’ equation.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
D_WIN_PH2												
N_EMPLOYEES	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.003*	(0.001)	0.002	(0.002)
AGE	0.003	(0.003)	0.002	(0.004)	0.003	(0.004)	0.003	(0.004)	−0.001	(0.004)	0.000	(0.005)
D_HG_EMP_Q	0.149**	(0.067)	0.149**	(0.067)	0.143**	(0.068)	0.143**	(0.068)	0.188**	(0.071)	0.188**	(0.071)
D_HG_REV_Q	−0.031	(0.068)	−0.030	(0.068)	−0.035	(0.069)	−0.039	(0.069)	0.039	(0.074)	0.036	(0.075)
CASH _TOTASS	−0.050	(0.126)	−0.050	(0.125)	−0.017	(0.130)	−0.020	(0.131)	−0.055	(0.130)	−0.055	(0.131)
DEBT_EQUITY	−0.014	(0.012)	−0.014	(0.012)	−0.013	(0.012)	−0.014	(0.012)	−0.013	(0.013)	−0.013	(0.013)
SALES_TOTASS	−0.157**	(0.058)	−0.158**	(0.059)	−0.161**	(0.060)	−0.159**	(0.059)	−0.271***	(0.057)	−0.268***	(0.058)
LT_DEBTS_TOTASS	−0.247*	(0.149)	−0.246*	(0.149)	−0.249	(0.152)	−0.245	(0.152)	−0.105	(0.168)	−0.110	(0.169)
D_MANUFACT	−0.045	(0.083)	−0.048	(0.083)	−0.035	(0.083)	−0.039	(0.083)	0.079	(0.087)	0.075	(0.088)
D_HT	−0.333***	(0.079)	−0.389***	(0.110)	−0.396***	(0.111)	−0.409***	(0.112)	−0.123	(0.140)	−0.129	(0.141)
D_HT * N_EMP			0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.001	(0.002)	0.001	(0.002)
D_HT * AGE			0.004	(0.006)	0.004	(0.006)	0.005	(0.006)	−0.003	(0.007)	−0.003	(0.007)
D_VC					0.255**	(0.118)	0.477**	(0.220)	0.667**	(0.221)	0.663**	(0.223)
D_VC * N_EMP							0.000	(0.004)	0.000	(0.004)	0.000	(0.004)
D_VC * AGE							−0.026	(0.027)	−0.027	(0.027)	−0.027	(0.027)
D_PATENTS									0.644***	(0.124)	0.644***	(0.139)
D_PATENTS * N_EMP											0.001	(0.002)
D_PATENTS * AGE											−0.003	(0.005)
Constant	−0.583	(0.461)	−0.550	(0.463)	−0.594	(0.470)	−0.577	(0.469)	−1.584**	(0.513)	−1.583**	(0.519)
COUNTRY FE	Yes		Yes		Yes		Yes		Yes		Yes	
YEAR SMEi FE	Yes		Yes		Yes		Yes		Yes		Yes	
Number of obs	11,784		11,784		11,784		11,784		11,784		11,784	
Censored obs	5996		5996		5996		5996		5996		5996	
Wald chi^2	4688.69		4639.33		5696.38		5426.00		10,249.68		11,018.99	
Log pseudolikelihood	−7528.27		−7528.05		−7525.70		−7525.06		−7518.93		−7518.69	
Rho	−0.517		−0.520		−0.486		−0.487		0.417		0.369	
Wald test indip. eqns (Prob>chi2)	0.000		0.000		0.000		0.000		0.296		0.328	
Marginal effects												
N_EMP	0.00016	(0.0002)	0.00014	(0.0002)	0.00014	(0.0002)	0.00014	(0.0002)	0.00017*	(0.0001)	0.00012	(0.0001)
AGE	0.00054	(0.0005)	0.00037	(0.0006)	0.00039	(0.0006)	0.00040	(0.0006)	−0.000099	(0.0003)	0.000031	(0.0004)
D_HG_EMP_Q	0.023**	(0.01)	0.023**	(0.01)	0.021**	(0.01)	0.021**	(0.01)	0.013**	(0.005)	0.013**	(0.005)
D_HG_REV_Q	−0.0049	(0.01)	−0.0047	(0.01)	−0.0053	(0.01)	−0.0057	(0.01)	0.0026	(0.005)	0.0025	(0.005)
CASH_TOTASS	−0.0079	(0.02)	−0.0079	(0.02)	−0.0026	(0.02)	−0.0030	(0.02)	−0.0037	(0.009)	−0.0038	(0.009)
DEBT_EQUITY	−0.0022	(0.002)	−0.0022	(0.002)	−0.0020	(0.002)	−0.0020	(0.002)	−0.00086	(0.0009)	−0.00088	(0.0009)
SALES_TOTASS	−0.024**	(0.008)	−0.025**	(0.008)	−0.024**	(0.008)	−0.024**	(0.008)	−0.018***	(0.004)	−0.019***	(0.004)
LT_DEBTS_TOTASS	−0.038	(0.02)	−0.039	(0.02)	−0.037	(0.02)	−0.036	(0.02)	−0.0072	(0.01)	−0.0077	(0.01)
D_MANUFACT	−0.0071	(0.01)	−0.0075	(0.01)	−0.0053	(0.01)	−0.0058	(0.01)	0.0054	(0.006)	0.0052	(0.006)
D_HT	−0.052***	(0.01)	−0.061**	(0.02)	−0.059**	(0.02)	−0.061***	(0.02)	−0.0084	(0.01)	−0.0089	(0.01)
D_HT * N_EMP			0.000020	(0.0003)	0.000015	(0.0003)	0.000019	(0.0003)	0.000085	(0.0001)	0.000083	(0.0001)
D_HT * AGE			0.00057	(0.0010)	0.00063	(0.0009)	0.00073	(0.0009)	−0.00018	(0.0004)	−0.00019	(0.0005)
D_VC					0.038**	(0.02)	0.071**	(0.03)	0.046**	(0.02)	0.046**	(0.02)
D_VC * N_EMP							0.000049	(0.0006)	0.000029	(0.0003)	0.000032	(0.0003)
D_VC * AGE							−0.0039	(0.004)	−0.0018	(0.002)	−0.0019	(0.002)
D_PATENTS									0.044***	(0.006)	0.045***	(0.007)
D_PATENTS * N_EMP											0.000072	(0.0001)
D_PATENTS * AGE											−0.00019	(0.0004)

Notes: The table reports results obtained using an Heckman two-step procedure. The dependent variable is a dummy indicating with 1 whether a firm was awarded a Phase II grant of the SME Instrument. All explanatory variables are taken with one year lag. Robust standard errors reported in parentheses. All continuous variables have been winsorized at the 1% level on both sides of the distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

– their growth prospects can only be realised if firms are able to access external capital. While it is well established in the literature that innovative SMEs may be particularly sensitive to asymmetric information problems, and therefore more likely to experience financial constraints, policy responses have often neglected, on the one hand, the high concentration patterns of innovation, and on the other the need to support near-to-market innovation activities.

With specific reference to European SMEs, the empirical literature has identified more pronounced finance gaps relative to the US context (Cincera et al., 2016). An especially important difference appears to be the capacity of the US system to generate stronger support for entrepreneurial growth and to provide more resources for the development of new ideas with disruptive potential. This has been related to policy schemes such as the SBIR program, combined with the superior scale and efficiency of the venture capital market (Hughes, 2008).

The SME Instrument within Horizon 2020 aims to foster innovation and competitiveness in the European economy. It targets the finance gaps experienced by smaller innovative firms and provides resources to bridge the 'Valley of Death' investment problem. After a few years of operations, enough observations are now available for some systematic analyses of the program and in this study we have focussed on the characteristics of the companies that applied for SME Instrument funding and those that obtained Phase I and Phase II awards. The results indicate that the scheme is attracting companies that are in the top quartile of the growth distributions by employment and revenue but still have lower profit margins and lower sales. Applicants are more likely to be active in manufacturing and high-tech sectors (which are more capital-intensive sectors and therefore associated with greater need for external finance). Applicants are also more likely to have received VC support prior to the application and to have patents.

As far as the predictors of awards are concerned, the strongest determinants of funding success are in line with signalling theory (Spence, 2002) and are: a top quartile employment growth performance; VC 'certification' effects; and patenting. While being patent active is an accepted proxy for firm quality and growth opportunities, the results we obtain for the growth rate and VC-backing variables have more complex implications. It can be argued that growing firms and firms that have received some private equity investment before the SME Instrument grant may already have more resources to self-finance their innovation activities than other firms. However, these firms are not necessarily less financially constrained: growth may not generate enough cash flow when the quality of firm investment opportunities requires more – rather than less – financial resources over time (Hambrick and Crozier; 1985; Churchill and Mullins, 2001; Hottenrott and Peters, 2012; Lahr and Mina, 2020).[24] A second issue is that past growth, even though it is recent growth, may not be a good indicator of growth potential or a good predictor of future growth because growth process tend not to be persistent over time, but rather 'jumpy' and discontinuous, in populations of small and young firms (Hölzl, 2014; Daunfeldt and Halvarsson, 2015; Coad et al., 2018). This is certainly a point that is worth considering in future evaluations of post-grant outcomes of the scheme.

Despite the many open questions that can only be solved by future research, the results we have produced in this study help us to better understand some of the financing choices made by European SMEs, to shed light on the emergent use of the SME Instrument, and to prepare the ground for a future evaluation of the scheme. The Instrument aims to select SMEs with high-growth potential and is picking up signals of firm quality. It is, however, difficult at this stage to assess whether the scheme has been able to nurture a large enough number of high-quality firms to generate the desired impact on the European economy. Moreover, a comprehensive evaluation of the scheme's outcome will only be possible when enough data on post-award performances become available for a counterfactual analysis of the quantitative (growth-related) and qualitative (behavioural) effects produced by the Instrument. Further research should exploit application and award data to design a detailed evaluation of the policy as a quasi-experimental study that will make it possible to obtain fine-grained insights into the performance of the Instrument. Complementary case-study evidence could also be very useful to analyse the processes of learning that accompany the provision of finance under the scheme. Results from these further studies will be essential to fine-tune future policy interventions in this area in an adaptive policy-making framework.

[24] Testing the effects of interactions between the growth variables and indicators for cash, debt, profit margins, and long-term debt does not generate conclusive evidence one way or the other because estimation results are not statistically significant.

Credit author statement

Andrea Mina: Conceptualization, Methodology, Writing - Original draft, Writing - Review. **Alberto Di Minin**: Conceptualization, Writing - Original draft. **Irene Martelli**: Data curation, Formal analysis, Writing - Original draft. **Giuseppina Testa***:* Conceptualization, Writing - Original draft. **Pietro Santoleri**: Writing - Review, Formal analysis.

Declaration of Competing Interest

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

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Supplementary materials

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