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Innovation coherence, financial slack, and SMEs' success in competitive innovation policies: Evidence from the EU SME-instrument

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ABSTRACT

Innovation policies are a key instrument to support small and medium-sized companies in overcoming financial constraints and pursuing high-risk and cutting-edge innovation projects. Yet, the mechanisms through which internal capabilities and innovation resource configurations influence success in such competitive arenas remain underexplored. In this scenario, this study explores how innovation coherence – the alignment between a firm's new project and its existing patent portfolio – and available financial slack shape the likelihood of securing public innovation funding. Funding evaluations are critical policy tools, as they not only improve access to resources but also act as market signals of technological quality and implementation capacity during the competitive evaluation process. Against this backdrop, we test our framework in the context of the EU Horizon 2020 SME Instrument, one of the most competitive innovation policy scheme in Europe, using a novel measure of innovation coherence derived from text analysis of firms' patent portfolios and project proposals, and combining its effect with financial slack. Innovation coherence and financial slack are found to strongly and positively influence evaluation outcomes, offering both theoretical and practical contributions for SMEs and policymakers engaged in competitive innovation policy initiatives.

1. Introduction

Small and medium-sized companies (SMEs) are widely recognized as key actors in fostering innovation and driving economic development, thanks to their organizational agility, market proximity and ability to adapt to technological change (Storey, 2016; Sáez-Martínez et al., 2014; Acs et al., 1999). However, their innovation activities are often constrained by structural limitations and financial barriers (Ulvenblad and Barth, 2021; D'Este et al., 2012; Carpenter and Petersen, 2002), which are particularly relevant in high-risk and technology-intensive projects (Testa et al., 2019; Mancusi and Vezzulli, 2014; Hoegl et al., 2008), that increasingly entail discontinuities in R&D activities (Schumpeter, 1934) driven by technological progresses (Radicic and Petković, 2023).

Although SMEs have improved their ability to innovate independently (Kim et al., 2023; Hall, 2009), the high costs and risks of innovation (Zimmermann and Thomä, 2016; Hölzl and Janger, 2014) - combined with the intangible and combinatorial nature of innovation assets (Yoruk et al., 2023; Teece, 2018) - create persistent financing constraints (Lerner and Nanda, 2020; García-Quevedo et al., 2018; D'Este et al., 2016).

To mitigate these constraints, public R&D initiatives aim close the gap between the social and private returns on innovation (Chiappini et al., 2022; Montmartin and Massard, 2015; Veugelers, 2008) and to reduce the underinvestment caused by information asymmetries and adverse selection (David et al., 2000; Akerlof, 1978). Such measures are particularly relevant for younger and more innovative SMEs, that usually lack collateral, established track record and stable revenue streams (Wang et al., 2022; Lahr and Mina, 2021; Banerjee, 2014), making them most exposed to credit rationing and markets' frictions (Casey and O'Toole, 2014; Stiglitz and Weiss, 1981).

Despite their policy relevance, there is still limited understanding of the antecedents that determine which SMEs succeed in securing such competitive funding, where the decision-making process heavly relies on ex-ante evaluations of that applicants' technological quality and readiness to execute innovation projects (Hottenrott et al., 2016; Henningsen et al., 2015).

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While prior literature has extensively examined the impacts of public funding on firms' innovation performance and growth (Bellucci et al., 2025; Zheng et al., 2023) - often in terms of innovation output, economic performance, and behavioral additionality – we still lack a nuanced understanding of factors shaping funding success before awards are granted (Bellucci et al., 2019).

As summarized by Dvouletý et al. (2021), most empirical studies focus on structural firm characteristics or on the broader policy design (Noh et al., 2018), mainly considering post-award effects rather than on the ex-ante factors that can influence the evaluators' allocation decisions. This leaves unexplored how, in competitive funding schemes where applicants share comparable baseline eligibility (Iori et al., 2023) but show heterogeneous success rates (e.g., Bellucci et al., 2025; Marullo et al., 2024; Mascarini et al., 2023), strategic and organizational factors drive differences in evaluation outcomes. That is, understanding such within-applicant heterogeneity is essential to uncovering who gets funded and why.

To address this gap, we adopt a dual theoretical perspective. From a signaling perspective, project proposals convey information about underlying applicants' capabilities and competencies that are not directly observable to evaluators under conditions of asymmetric information (Feng et al., 2021; Antonelli and Crespi, 2013; Meuleman and De Maeseneire, 2012). In particular, we argue that the two dimensions of innovation coherence - defined as the degree of technological proximity between a firm's proposal and its existing patent portfolio (Pugliese et al., 2019; Teece et al., 1994) - and financial slack – defined as the level of liquid resources that a firm can flexibly reallocate across strategic activities (Marlin and Geiger, 2015; Voss et al., 2008) act as signals of project quality and feasibility, and risk mitigation (Hottenrott and Lopes-Bento, 2016), thus jointly shaping the perceived and actual ability to deliver high-quality innovation and ultimately influencing funding decision.

From a RBV perspective, these factors represent embedded SME-specific advantages that influence innovation outcomes. In this view, innovation coherence reflects the strategic alignment of new research projects with existing technological competences, enabling resource leveraging and increasing implementation and commercialization success rates (Leten et al., 2007). Similarly, financial slack plays a dual role: as a tangible resource enhancing the firm's ability to experiment and execute research projects, and as a market signal of financial robustness and of additional readiness to undertake innovation initiatives (Zona, 2012; Herold et al., 2006).

Empirically, we examine these relationships in the empirical context of the EU Horizon 2020 SME Instrument, a competitive grant program explicitly designed to provide financial support to SMEs aiming to commercialize high-potential innovations.

Specifically, we leverage confidential data on applicants' rankings and project proposals, combining them with firm-level patent data, and employ a mixed-method approach that combines advanced text-mining techniques, like Latent Dirichlet Allocation (LDA) applied to SMEs' patent portfolio and funding proposals, and multivariate regression models (ordinary least square and multinomial logit) to assess the impact of innovation coherence and available financial slack on grant allocation decisions. Based on these data, we were able to capture the nuanced relationships underlying the observed within-applicants heterogeneity, ultimately answering the call for more research on innovation policy, with a pronounced focus on SMEs' innovations outcomes themselves rather than on R&D inputs (Zheng et al., 2023; Martin et al., 2018). In doing so, our contributions are threefold. First, we contribute to the advancement of literature on innovation funding, by providing a coherent framework combining signaling and resource-based view theories that explain the antecedents of grant allocation in competitive policy settings (e.g., Marullo et al., 2024; Bellucci et al., 2023; Barbieri et al., 2020; Martin, 2016). Second, our study also adds to the literature on financial constraints and innovation funding, and on where available financial resources have a differential impact depending on the degree of innovation coherence embodied in innovative research projects (Agrawal et al., 2018; Yang et al., 2014; Hoegl et al., 2008). Third, by empirically testing our research hypotheses based on a novel, objective and scalable measure of innovation coherence, we provide robust evidence that informs both SME strategies for competing in grant-based funding schemes and policymaker understanding of how evaluation criteria align with firm capabilities and competencies, thus contributing to more effective allocation of scarce resources.

The paper is organized as follows. Section 2 reviews the theoretical background, discussing how innovation coherence and financial slack shape SMEs' innovation capacity and interact with public R&D subsidies, with a specific focus on the SME Instrument. Section 3 presents the research strategy, data, and methodological approach. In Section 4 we present the empirical findings, while in Section 5 discussions are presented. Section 6 concludes by providing evaluable managerial and policy implications, as well as outlining limitations and avenues for future research.

2. Theoretical background and research hypotheses development

Innovation funding is critical for SMEs willingness to survive and achieve sustainable growth (Boccaletti et al., 2025; Dvouletý et al., 2021; Cecere et al., 2020), but succeed in competitive schemes depends less on declared financial need or size alone and more on how evaluators perceive and are able to assess firms' capabilities in uncertain and high competitive environments (Marullo et al., 2024; Neufeld et al., 2013). In this scenario, the evaluation process through a panel of expert reviewers assumes a crucial role, as they are tasked with evaluating proposals under conditions of informational asymmetry and filtering out less feasible or impactful projects objectively and appropriately (Criscuolo et al., 2017; Bornmann et al., 2008). To this end, standard criteria such as potential impact and innovation are commonly used to determine overall research merit (Gallo et al., 2018), while ensuring objective and appropriate evaluations (e.g., Murray et al., 2016; Marsh et al., 2008). However, decisions concerning funding outcomes of more competitive proposals has been shown to be opaque and far from linear, often relying on heuristics, sectoral familiarity and interpretative cues (Hug and Aeschbach, 2020). Prior empirical work has mainly focused on firm-level characteristics as predictors of funding success, such as firm size, R&D intensity, cash flow, or sectoral affiliation (e.g., Falk and Svensson, 2020; Cantner and Kösters, 2012), considered as reliable proxies of firms' absorptive capacity and ability to manage high-risk innovation projects (Huergo and Trenado, 2010). Beyond these structural determinants of evaluation success, the evaluation of potential knowledge spillovers has been positively associated with positive assessments (Feldman and Kelley, 2006), with evaluators perceiving projects embedded in collaborative networks as more likely to generate broader returns (Marullo et al., 2024) and boost innovation propensity (Audretsch et al., 2025). Additionally, Li and Agha (2015) show that panel of experts often favor "big names" with strong reputations and established track record over high novel and risky projects. At the same time, radical and novel proposals are often penalized due to a perceived trade-off between novelty and feasibility (Gallo et al., 2018; Boudreau et al., 2016). Adding further complexity, evaluators often face difficulties in assessing the multilevel performance potential of such research projects, especially with seemingly similar technological potential. This is even more true in competitive funding schemes, where the project performance extends beyond product innovation to encompass operational performance, competitive advantage and organizational quality (Blindenbach-Driessen et al., 2010), thus requiring subjective judgments.

In light of this increasing level of subjectivity and the strategic nature of evaluations, firms are not only required to present valid projects but also to convince evaluators of technological maturity of their proposals, their organizational implementation ability, and the significance of the expected impact (Steigenberger et al., 2025; Meuleman and De Maeseneire, 2012; Connelly et al., 2011). From a signaling perspective, one relevant construct is innovation coherence, which refers to the extent to which a firm's technological portfolio is internally consistent and built around interconnected knowledge bases (Leten et al., 2007; Breschi et al., 2003). That is, high innovation coherence indicates the firms' ability to recombine existing assets into feasible innovation outcomes (Kim et al., 2023; Makri et al., 2010). This implies signaling the evaluators the capability of capitalizing on interconnected technological capabilities (Pugliese et al., 2019; Chen and Chang, 2012) and shared knowledge (Kim et al., 2016). Proposals grounded in prior competencies and capabilities and established technological trajectories (Dibiaggio and Nesta, 2005; Foss and Christensen, 2001) tend to be perceived more solid and less risky (Hottenrott and Lopes-Bento, 2016). Adding to this, from a resource-based view perspective, firms with appreciable higher innovation coherence are more likely to explore complementaries across technologies (Foss and Christensen, 1996), learning mechanisms and spillovers (Van Looy et al., 2005; Dosi et al., 1992), and economy of scope (Yoo and Lee, 2023; Cantwell and Piscitello, 2000). For evaluators, this may indicate technological maturity and lower risk of execution failure, contributing to enhancing the firm's absorptive capacity (Cohen and Levinthal, 1990), and ultimately making the project more attractive in competitive review processes. Given these premises, innovation coherence could effectively communicate expected superior project feasibility, performances (Christensen, 2005; Nesta and Saviotti, 2005; Piscitello, 2004) and competitive positioning (Leten et al., 2016; Valvano and Vannoni, 2003), further reinforcing perception of strategic strength.

In light of these arguments, innovation coherence closely aligns with the goals and key evaluation criteria of funding policies, aimed at discriminated between high-potential competitive R&D projects. Therefore, the following hypothesis is formulated:

H1 –. *SMEs' innovation coherence positively affects funding success.*

While innovation coherence provides a strategic signal of feasibility, evaluators also seek signs that the firm has the internal capacity to implement the proposed project. In that respect, we focus on the availability of financial slack, defined as the stock of excess resources that can readily redeployed across strategic activities (Marlin and Geiger, 2015; George, 2005), helping firms to adapt to internal and external pressures (Voss et al., 2008).

Unlike intangible forms of slack (such as human resources or routines), financial slack is directly observable at firm level, and thus provides strong signaling value in high-risk and capital-intensive domains (Shaikh et al., 2018). According to signaling theory, financial slack can be leveraged in competitive funding contexts to signal evaluators financial robustness and resilience (Tyler and Caner, 2016; Hoegl et al., 2008), reducing evaluators' perceived risk, while also increasing perceived continuity of project execution (Paeleman and Vanacker, 2015). According to signaling theory, this makes financial slack a credible indicator of a firm's capacity to buffer shocks (Du et al., 2022; Zona, 2012) and reduces coordination costs and risks (e.g., Liang et al., 2023; Lu and Wong, 2019).

Further, from a resource-based perspective, financial slack becomes a valuable asset that enhances a firm's ability to engage in experimentation (Yang et al., 2014) and capitalize on R&D efforts (Ashwin et al., 2016; Lee and Wu, 2016; Kim et al., 2008). In this sense, financial slack complements innovation coherence by reflecting a firm's forward-looking strategic orientation aimed at better aligning technological trajectories and organization purposes (Bentley and Kehoe, 2020; Teirlinck, 2020), to boost performances (Guo et al., 2020; Rafailov, 2017). Building on this, we argue that financial slack amplifies the value of innovation coherence, making it more credible in the eyes of evaluators. Accordingly, we propose the following hypothesis:

H2 –. *SMEs' available financial slack positively moderates the relationship between innovation coherence and funding success.*

3. Research design

3.1. Empirical setting: The EU SME-instrument

In this paper we examine the SME Instrument Program, announced in 2010, which is the largest SMEs support scheme, aimed at prompting the development of innovation capacity of those for-profit SMEs[1] located in the EU-28 or associated to Horizon 2020.

In the lens of Ergas (1987), the SME Instrument can be categorized as a diffusion-oriented innovation policy, supporting the generation and dissemination of new know-how by reinforcing firms' innovation capabilities. As stated by the European Commission, "*the objective of the SME-I is to develop and capitalise on the potential of SMEs by filling the gap in funding for early-stage high-risk research and innovation and increasing private-sector commercialisation of research results. It is targeted at SMEs showing a strong ambition to grow and internationalise and shall be provided for all types of innovation where each activity has a clear European added value*" (ECA, 2020). Furthermore, SME-I provides financial tools and expert support across different stages of the innovation process, encompassing a wide plethora of possible applications such as "*prototyping, miniaturization, 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*" (European Commission, 2020). The program is expected to play an important role in boosting innovation, especially for firms with higher abilities to craft and capitalize on their existing resource bases (Zheng et al., 2023). Although it has been compared to the US Small Business Innovative Research (SBIR) program, particularly in its function as an early-stage funding mechanism (Howell, 2017), the SME Instrument differs in terms of budget scale and its focus on supporting individual technological entrepreneurial initiatives (Di Minin et al., 2016). Previous studies have shown that the SME-I's awarded firms tend to be high-growth potential SMES with prior patenting activity and access to venture capital funding (Mina et al., 2021). These firms are typically more profitable and rely more on short-term deb instruments (Bellucci et al., 2025). Interestingly, they are less like to engage in Open Innovation strategies (De Marco et al., 2020; Costa et al., 2023), suggesting a preference for internalized R&D strategies. Operationally, the SME-Instrument consists of three distinct phases, each aligned with a different stage of innovation lifecycle:

- SME-I Phase 1 (*Concept and Feasibility assessment*), to support the development of proof of concept, feasibility studies, and initial assessment of the commercial potential of innovative ideas. It establishes that the total eligible cost is €71,249, the co-finance rate is of 70 %, and the total amount of funsind is set at €50,000.
- SME-I Phase 2 (*Demonstration and Market Replication R&D*) offers larger grants ranging between €500,000 and €2.5 million, covering up to 70 % of eligible costs (exceptionally, 100 % where a research institution is present) for innovation activities closer to market deployment.
- SME-I Phase 3 (*Commercialisation*) does not entail direct financial suport but facilitate commercial exploitation of innovations resulting from SMEI Phases 1 and 2.

Details are summarized in Table 1. This articulate design of the SME-Instrument clearly reflects a deliberate collective policy response to address market failures affecting SMEs. Indeed, the co-financing requirement itself acts as a commitment signal, reducing moral hazard

[1] According to the European Commission definitions, SMEs are enterprises with 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.

Table 1
Overview of the SME-Instrument Phases and Funding Structure.

Phase	Stage	Funding Amount	Co-financing requirements	Eligible Activities
1	*Concept and Feasibility Assessment*	€50,000 (lump sum)	30 % (€21,249 of total €71,249)	Proof of concept, feasibility studies, commercial potential analysis
2	*Demonstration and Market Replication R&D*	€500,000 to €2.5 million	30 % (generally)	Prototyping, design, testing, performance verification, pilot lines, validation for market replication.
3	*Commercialization Support*	Non-financial support (no grants)	Not applicable	Investment readiness, access to finance, market uptake, business acceleration services

risks by ensuring that proponents are incentivized to undertake effort to successfully plan and execute innovation activities (Lepori, 2011). In parallel, the presence of a fixed grant ceiling not only limits public financial exposure but also discourages opportunistic behavior (Jensen and Meckling, 2019). In addition, the same multi-phase architecture of the SME-Instrument functions as an implicit filtering system that allows only the most feasible and technically sound projects to advance and reach the market, thus limiting firms' opportunistic behavior through the ex-ante evaluation of the proposals (Chiappini and Pommet, 2023; Masquin et al., 2011).

Further, the evaluation process of proposals for Phases 1 and 2 carried out by four independent experts on the three main proposal's criteria of impact, quality and efficiency of implementation, enhances the signaling effect of SME-instrument funding. That is, firms awarded with SME-I demonstrate technical and organizational merit, consequently reducing information asymmetries while increasing their attractiveness to private investors (Thompson et al., 2018; Chen et al., 2018). These design features offer a valuable framework for assessing how firm-level characteristics shape funding outcomes. Specifically, the degree of technological proximity- the alignment between a firm's project and its existing technological portfolio- together with the firms' excess financial resources, may play a critical role in influencing evaluation results and the likelihood of being awarded.

3.2. Research strategy and data

To empirically test the role of innovation coherence and financial slack in shaping evaluation outcomes under the SME Instrument, we exploit access to comprehensive and confidential data encompassing the set of firms that applied to the SME Instrument, building on SMEs that submitted at least one application between 2014 and 2019 (cutoffs 1–7). This unique dataset includes detailed proposal-level data (e.g., evaluation scores, requested and funding amounts, project summaries) matched to firm-level financial and patent data extracted from Bureau Van Dijk (BvD) ORBIS and the EPO PATSTAT databases, respectively.

Out of 72,973 proposals submitted during the selected period, to ensure data consistency and comparability, we restrict the focus to the 40,905 proposals submitted by active SMEs headquartered in the EU-28 Member States. Although the SME-I was open to SMEs from both EU Member States and Horizon 2020-associated countries, we exclude the latter due to substantial institutional differences in market conditions, intellectual property structures, and innovation support infrastructures (Archibugi and Filippetti, 2018; Grilli and Murtinu, 2014), which could impact on the reliability of our results. This restriction enhances the internal validity of our analysis by ensuring that all firms operate under comparable innovation policy environments, thus avoiding structural biases. We further refine the dataset by removing duplicate proposals, or near-identical proposals submitted by the same SME across different cutoffs, often with only minor changes (e.g., altered proposal name, acronym, or company name). For firms that submitted multiple proposals over time, we retained the most recent application (reducing the dataset to 31,149 proposals), while for multiple resubmissions within the same cutoff year, we keep the proposal with the highest evaluation score, further reducing the dataset of 14,027 duplicated proposals. These refinements result in a cleaned pool of 17,222 unique SME proposals, each corresponding to a distinct SME applicant.

For each of these SMEs, we retrieved standardized financial accounts from ORBIS, using unique identifiers (BvD Identification numbers) to merge with SME-I proposal data. In addition, we retrieved patenting records from PATSTAT, covering the period 1999–2016. Out of the 17,222 unique SMEs, only 2682 (15.57 %) had at least one active international patent at or prior to the time of their SME-I application, while the remaining 14,540 firms (84.43 %) had no active patents. It is worth noting that although in case of SMEs without patents, some intellectual property may nonetheless exist, as patents are often assigned to individual owners rather than firm (e.g., Balasubramanian and Sivadasan, 2011), this does not conflict with the core of our empirical design- as innovative performance is mainly linked to organization strategies and proposal-level innovation capabilities rather than to the specific legal ownership of patents (Ortega-Argiles et al., 2005)- and perfectly aligns with the firm-level application and evaluation process of the SME-I (European Court of Auditors, 2020).

As innovation coherence- our key independent variable-requires the existence of a technological portfolio, we further restrict our analysis to the subset of the 2682 patenting firms. This ensures the construct validity of our innovation coherence measure, which cannot be computed in the absence of a patent record. To assess the implications of excluding non-patenting SMEs, we conducted a comparative analysis between included and excluded SME-I applicants, based on observable characteristics across both groups (including firm size, age, sectoral distribution, financial slack and SME-I evaluation outcomes. Results are reported in **Table A.1** in the Appendix.

Fig. 1 summarizes the multi-step procedure for the construction of the final analytical sample.

For these firms, each proposal is then classified into one of the three official SME-I evaluation categories: *Main List*, *Below Available Budget*, and *Below Threshold*. Proposals deemed inadmissible, ineligible, or withdrawn are excluded from the analysis, as they did not undergo a proper evaluation process and therefore did not receive an official score. **Table 2** reports descriptive statistics by evaluation outcome, while Table 3 presents summary statistics on the regional location of SMEs' applicants, grouped into four major European macro-regions[2] and their classification according to the European Innovation Scoreboard (RIS) 2024 framework.[3] For completeness, Appendix **Tables A.2** and **A.3** present analogous statistics for non-patenting SME-I applicants.

[2] The regional grouping adopted is as follows:

1. **Northern Europe**: Denmark (DK), Estonia (EE), Finland (FI), Ireland (IE), Latvia (LV), Lithuania (LT), Sweden (SE), United Kingdom (GB);
2. **Southern Europe**: Cyprus (CY), Greece (GR), Italy (IT), Malta (MT), Portugal (PT), Spain (ES), Croatia (HR), Slovenia (SI);
3. **Western Europe**: Austria (AT), Belgium (BE), France (FR), Germany (DE), Luxembourg (LU), Netherlands (NL);
4. **Central and Eastern Europe**: Bulgaria (BG), Czech Republic (CZ), Hungary (HU), Poland (PL), Romania (RO), Slovakia (SK).

[3] https://research-and-innovation.ec.europa.eu/statistics/performance-indicators/european-innovation-scoreboard_en

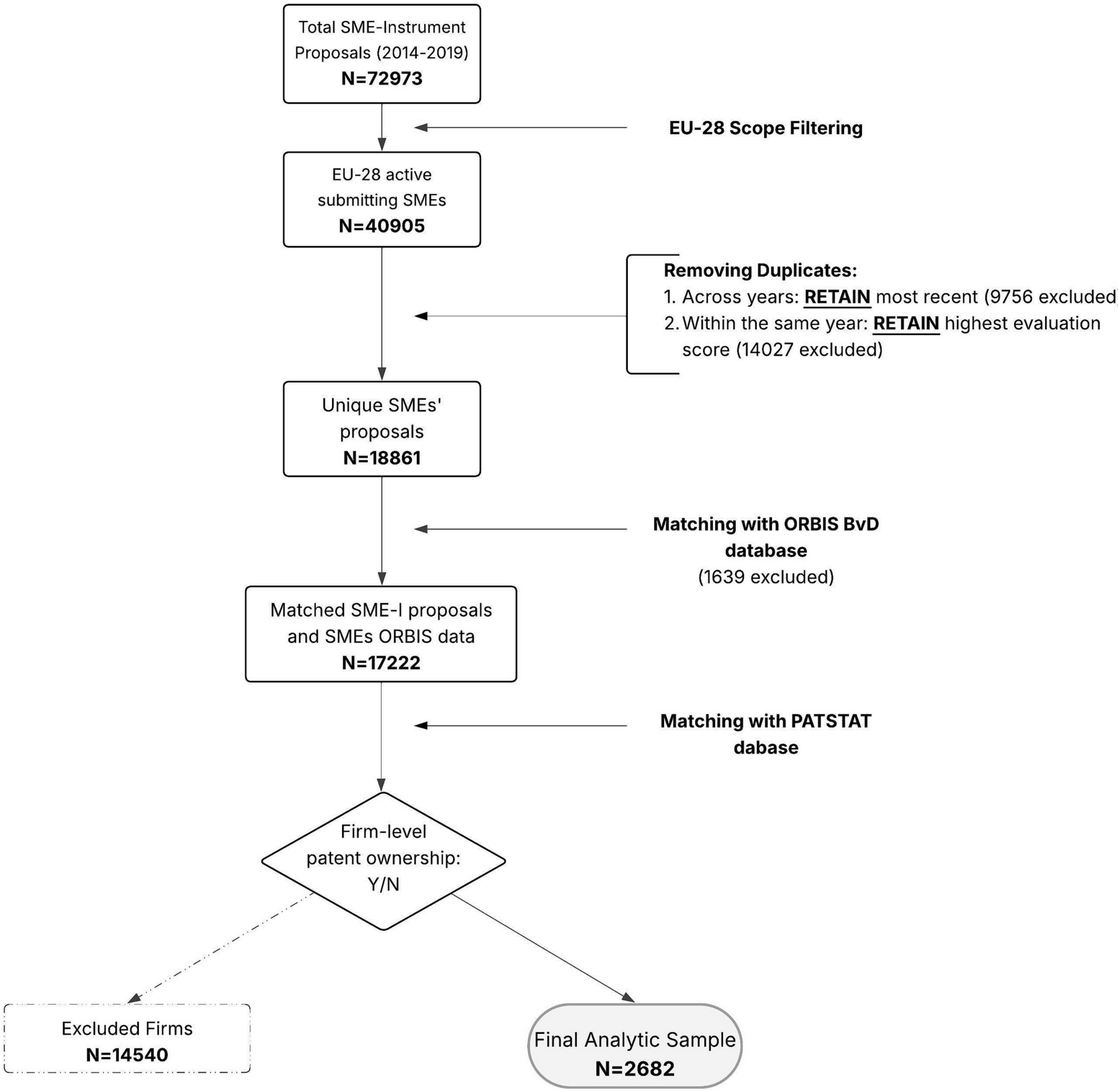

Fig. 1. Sample Construction Flowchart.

3.3. *Control group*

Starting from the population of all SME-I applicants, in order to address self-selection bias, we selected the non-applicants control group from ORBIS, by implementing a structured matching algorithm that allows to reduce both imbalance and model dependence (Rosenbaum, 2020). We first restricted the ORBIS population to firms that meet EU SME criteria,[4] thus ensuring that non-applicants are drawn from the

[4] According to the Annex of the Regulation 3003/361/EC, article 2-comma 1 "*The category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million*". Comma 2 specifies "*Within the SME category, a small enterprise is defined as an enterprise which employs fewer than 50 persons and whose annual turnover and/or annual balance sheet total does not exceed EUR 10 million.*", while comma 3 reports "*Within the SME category, a microenterprise is defined as an enterprise which employs fewer than 10 persons and whose annual turnover and/or annual balance sheet total does not exceed EUR 2 million*".

Table 2
SME Instrument Patenting Applicants (n = 2682)' Groups Definition, Acronym, Sample Size, and Evaluation Score.

SME-Instrument Firms Group	Definition	Acronym	Number	Average Evaluation Score
Main List	SMEs that received the award.	Win	337	13.62
Below Available Budget	SMEs whose proposals met the quality threshold but were not funded due to budget constraints.	SoE	647	13.04
Below Threshold	SMEs whose proposals did not meet the minimum evaluation criteria and were not funded.	Bel_Thr	1698	10.73

Note: Evaluation scores range from 0 to 15. To be considered eligible for funding (Main List and Below Available Budget), proposals must achieve an overall score of at least 13. Proposals with an evaluation score less than 13 are classified as Below Threshold.

Table 3
Distribution of Patenting SME-I Applicants (n = 2682) by European Region and Innovation Performance (RIS) 2024.

Panel a) Regional distribution by Macro-Region

European Macro-Region	Number of firms	Share (%)
Central and Eastern Europe	187	7.0
Northern Europe	1183	44.1
Southern Europe	938	35.0
Western Europe	374	13.9

Panel a) Regional distribution by RIS 2024 Category

RIS Category	Number of firms	Share (%)
Emerging Innovator	136	5.1
Moderate Innovator	998	37.2
Strong Innovator	1003	37.4
Innovation Leader	545	20.3

same policy-relevant population. Matching was performed using a 1:1 nearest neighbor algorithm by country, because of the large cross-country variations in the number of applications. Specifically, we matched treated (applicant) and control (non-applicant) forms based on the following dimensions: sector (NACE Rev.2 primary code at the 2-digit level), firm size (log of total assets) and age (number of years since incorporation). The distance choice allows to retain all treated firms and select the best-matching control firms while ensuring balance across key dimensions of structural firm characteristics and avoiding excessive reuse of the same control unit across multiple matches. While we acknowledge the limitations of matching for casual inference (King and Nielsen, 2019), our goal here is not to estimate the effect of treatment, but rather to model self-selection biases (Henningsen et al., 2015) and focus on within-applicants heterogeneity, ensuring the internal validity and robustness of our estimates through the Heckman correction. After the exclusion of duplicate units in the matched control group, the resulting sample contains 2682 applicants and 2218 non-applicant SMEs.

3.4. Variable definition and measurement

3.4.1. Dependent variables

The first dependent variable (*Pr_status*) is a categorial variable that captures the official evaluation outcomes of each SME-I proposal. The variable was coded as 1 = *Below Available Budget*, for those SMEs whose proposals successfully passed the quality threshold but were not funded due to budgetary constraints. These proposals received the "Seal of Excellence" (SoE), indicating recognized quality despite non-funding. SMEs' proposals that met or exceeded the evaluation threshold and were awarded funding were coded as 2 = *Main List*. Finally, the variable was coded as 0 = *Below Threshold* for proposals that failed to meet the minimum quality threshold and were therefore excluded from funding. This ordered categorical variable is used as the main outcome in our multinomial logit estimations, with *Below Threshold* serving as the reference category. The second dependent variable, namely *Score*, is a continuous variable that quantifies the overall evaluation score assigned to each SME-I proposal. It offers a more granular assessment of proposal quality, thereby complementing the categorical outcome variable and allowing for additional robustness tests.

3.4.2. Exploratory variables

3.4.2.1. Innovation coherence. Our main explanatory variable, Innovation coherence (*Inn_Coherence*) quantifies the semantic alignment between each firm's SME-I proposals and its prior technological base, as reflected in its patent portfolio. Grounded in the theoretical concept of corporate coherence (Teece et al., 1994) and drawn on Pugliese et al. (2019), innovation coherence operationalizes the extent to which the proposal builds upon the firm's existing technological competencies and knowledge assets.

Rather than relying on hierarchical patent classifications such as the International Patent Classification (IPC) - which suffer from issues of technological overlap (McNamee, 2013) and inconsistent reclassification over time (Kay, 2014) – we adopt a data-driven, text-based grounded in the recombinant perspective of innovation (Arthur, 2007). Specifically, following prior studies on this topic (e.g., Ghaffari et al., 2023; Xu and Zuo, 2016) we apply Latent Dirichlet Allocation (LDA- Blei et al., 2003) to extract latent topics from the abstract of SME-I proposals and the firm's patents filings up to the application year. The abstract of SME-I proposals serves as a valuable source for identifying the domains where firms operate and the technology trajectories they pursue, while the focus on patents' abstracts is due to their superior ability to "*communicate the technical description in a concise and straightforward manner, avoiding unnecessary words that may increase noise in the extraction process*" (Tshitoyan et al., 2019), thereby ensuring a clear and comparable semantic representation across textual corpora. Following recent advances (e.g., Zaccaria et al., 2014), this method enables a scalable and valid representation of firm's technological and project-level knowledge domains.

The textual data (proposals and patents) were cleaned and tokenized, through a normalization process encompassing lowercasing, removing blanks and extra whitespaces, followed by lemmatization, and word frequency filtering to remove most common (appearing in more than 20 % of documents) and less common words (appearing in fewer than 200 documents) (Feldman and Sanger, 2007; Hassler and Fliedl, 2006). Further, since abstract's SME-I proposals and patent do not have any keyword information, with the aim to enhance the semantic quality of the analysis, we applied part-of-speech (POS) tagging (Wang et al., 2014). Significant domain-relevant noun phrases were automatically extracted using the Stanford POS Tagger ("noun", "noun, adj" and "noun, adj, verb, adv"), with the spaCy Phython's library (Honnibal, 2017). Additionally, we constructed bigrams and trigrams using the Gensim library,[5] to capture multi-word technical concepts. Separate multiple LDA models were trained on the corpora of SME-I proposals and patents to extract significant latent topics. Hyperparameters optimization was conducted via grid search on a validation set (30 % of complete dataset) with optimal coherence scores for K = 9, α = 0.41,

[5] Řehůřek, R., & Sojka, P. (2010). Software framework for topic modeling with large corpora.

and β = 0.8 (proposals) and K = 6, α = "asymmetric", and β = 0.9 for patents. The search grid for the hyperparameters is given in Table 4.

The resulting LDA models produced 9 coherent topics for SME-I proposals and 6 technological domains for patents. Each topic contains the most relevant keywords identified at varying levels of λ relevance, allowing a multidimensional understanding of the semantic structure underpinning each latent class. Topic interpretability was further validated through manual inspection and labeling by two independent coders, following the approach of Sievert and Shirley (2014).

Table 5 represents the labels associated with each topic for both SME-I proposals and patents, along with their brief description. The full list of keywords associated at varying levels of λ is available upon request.

Building on the extracted latent structures, we operationalized Innovation Coherence using Latent Semantic Indexing (LSI; Dumais, 2004), which projects both the proposals and patents' abstract corpora in a lower dimensional shared latent vector space. Each SME-I proposal was represented as a vector $v_{SME-I\ proposal}$, and the centroid of a firm's patent portfolio as $v_{SME\_patent\ portfolio}$. Coherence was then defined as the cosine similarity between the two, and computed as follows:

$$Inn\_Coherence = Cosine\ similarity\left(v_{SME-I\ proposal}, v_{SME\_patent\ portfolio}\right) = \frac{v_{SME-I\ proposal} {}^{*} v_{SME\_patent\ portfolio}}{\| v_{SME-I\ proposal} \| \| v_{SME\_patent\ portfolio} \|}$$

The higher the value of cosine similarity the stronger the semantic alignment between the proposal and the firm's technological portfolio, signaling more path-dependent innovation strategies.

Fig. 2 is a simple illustration of how LDA models allowed us to obtain a cosine similarity measure, reflecting the alignment between a firm's SME-I proposal and its technological portfolio. For completeness and better readability, the same illustrative example is reported in tabular form in Table A.4 of the Appendix.

This measure is applied only to the subset of 2862 patenting SMEs, as coherence requires non-empty patent corpus. This design choice, combined with the control group introduced in Section 3.2, enables us to implement a selection-corrected framework while focusing our main estimations on technology-active firms.

To assess the validity of our measure of innovation coherence, we randomly drawn a subsample of 50 SME-I patenting applicants, for which we retrieve 2538 patents from PATSTAT. We restricted the set of patents by controlling for patent families, and we further filtered the data by retaining patents with at least one English abstract to ensure comparability with text proposal.

This yielded 754 unique patents. For feasibility and to balance firms' contributions, we then sampled up to five patents per firm (including all patents for firms with fewer than five), to avoid over-representation of large portfolios while preserving cross-firm comparability. This procedure resulted in 79 proposal–patent pairs across the 30 firms (firms contributed between 1 and 5 patents). The evaluators - blind both to the algorithmic scores and the evaluation outcomes - followed a standardized protocol and rated the alignment of each patent with the SME-I proposal on a 7-point Likert scale (1 = not coherent at all, 7 = highly coherent). For each proposal–patent pair, we computed the average score across the three raters and then aggregate to the firm-level by averaging across the sample patents to obtain a human-coded coherence. Inter-coder reliability was high (ICC = 0.87, C.I. 0.811–0.913), indicating a good agreement among evaluators. Finally, we compare the human-coded scores with the LSI-based Innovation coherence measure through Spearman's rank correlation ($\rho = 0.3839$, $p = 0.077$). While only moderately significant, the positive and moderate correlation provides support for the construct validity of the LSI innovation coherence measure.

3.4.2.2. Available financial slack. The second main explanatory variable represents available financial slack (namely *av_FinSlack*), capturing a firm's liquidity buffer and risk-absorbing capacity. It was computed as log ratio between working capital and total assets, a standard proxy in the literature (George, 2005; Nohria and Gulati, 1996). This ratio reflects the firm's ability to reallocate flexible resources to fund innovation activities without external financing, serving also as a key indicator of organizational resilience and strategic autonomy under uncertainty.

3.4.2.3. Control variables. In line with previous studies, our empirical strategy incorporates a set of firm- and proposal-level control variables that are known to influence the probability of obtaining public R&D funding.

First, we include firm size (*F_Size*), measured as the natural logarithm of total assets. Firm size has a well acknowledged yet nuanced relationship with both innovation behavior and public funding outcomes (Dai and Cheng, 2015; Herrera and Sánchez-González, 2013; Herrera and Ibarra, 2010). On the one hand, larger firms are more likely to be subsidized due to superior organizational capabilities and visibility (Mina et al., 2021; Blanes and Busom, 2004), even if exhibiting more "free rider" behavior (Heijs, 2003). On the other hand, smaller firms often have higher R&D intensity and responsiveness to subsidies, thereby enhancing policy effectiveness (González and Pazó, 2008). Including firm size allows us to control for this structural heterogeneity across firm classes. We also control for firm age (*F_Age*), computed as the number of years since incorporation. Empirical findings on the role of firm age are mixed: some studies report no significant effect (e.g., Huergo and Trenado, 2010; Almus and Czarnitzki, 2003), while others suggest that older firms may benefit from better-established organizational routines and legitimacy (e.g., Clausen, 2009), or alternatively, that younger firms are more likely to secure funding due to their dynamic and growth-oriented profiles (Srhoj et al., 2021; Segarra-Blasco and Teruel, 2016). Furthermore, to account for firms' financial structure and potential constraints (Mina et al., 2021; Czarnitzki and Hottenrott, 2011), we include long-term debts over total assets (*Lt_Debts_TotAss*) as a proxy for leverage. Leverage can influence funding outcomes in multiple ways: highly leveraged firms may be perceived as riskier, thereby reducing their funding chances (e.g., Meuleman and De Maeseneire, 2012). On the other hand, public funding itself may mitigate such constraints by acting as a signal of technological quality to external investors and lenders (Demeulemeester and Hottenrott, 2015), ultimately reinforcing policy strength.

We further include a variable capturing firms' past experience with the SME-I scheme (*Prev_attempts*), defined as the cumulative number of SME-I proposals submitted by each firm prior to the last successful application. This variable accounts for potential learning-by-doing

Table 4
Summary of the hyperparameter search grid/set values' range used for LDA models (SME-I proposals and SMEs' patents).

Panel a) SME-I proposals	
Hyperparameter	Search grid/set values' range
K	[1,2,3,4,5,6,7,8,9,10,11,12,13,14]
α	[0.01, 0.21, 0.41, 0.6, 0.8, 1.0,"asymmetric","symmetric"]
β	[0.01, 0.21, 0.41, 0.6, 0.8, 1.0]
Dataset	["Noun","Noun,Adj"," Noun,Adj,Verb,Adv"]

Panel b) SMEs' patents topics	
Hyperparameter	Search grid/set values' range
K	[2,3,4,5,6,7,8,9,10,11,12,13,14,15]
α	[0.01, 0.21, 0.41, 0.6, 0.8, 1.0,"asymmetric","symmetric"]
β	[0.01, 0.21, 0.41, 0.6, 0.8, 0.9,1.0]
Dataset	

Note: Hyperparameter variation ranges used for LDA training. Optimal values, indicated in bold, correspond to the highest coherent score achieved.

Table 5
Topics' labels and brief description for SME-I proposals and SMEs' patents.

Panel a) SME-I proposals' topics

Topic	Name	Description
1	Water Management	Innovations for digitalized irrigation systems and smart public water management to optimize usage, avoid leakage, manage wastewater, and prevent floods and contaminations.
2	Health, Diagnosis and Treatments	Innovations for cancer diagnosis and treatment, through process and product innovations.
3	Health, Rehabilitation and Medical Devices	Smart medical devices and rehabilitation technologies for patient care and healthcare data management.
4	Digital solutions for cyber security and surveillance	Development of digital platforms, apps and tools to enhance data protection and enable remote surveillance.
5	Recycling and Circular economy	Industrial solutions to enhance waste management and recycling processes, thus reducing environmental footprint.
6	Digital solutions for transportation and mobility	Development of digital tool and platform-based solutions for urban mobility, traffic monitoring, smart cities and transportation safety.
7	Food production, agriculture, fishing and livestock	Industrial innovations in food production, agricultural techniques, food production systems and smart application for value chain management.
8	Energy production, storage and distribution	Industrial and digital innovation for optimizing energy production, distribution and consumption, with a strong focus on environmental impacts' reduction, mainly through the integration of smart grids into value chains.
9	Digital solutions for e-commerce, business platforms and content sharing	Platforms for e-commerce, digital marketing, and data and content sharing.

Panel b) SMEs' patents topics

Topic	Name	Description
1	Advanced processing materials and semiconductor devices	Industrial applications in the fields of radiation, lasers, and semiconductors, primarily for electronic sensors, imaging systems, and advanced material processing techniques.
2	Cancer diagnostic and treatment	Patents related to pharmaceutical compositions, formulae, detention kits, and therapeutic innovations specifically for cancer diagnosis and treatment.
3	Information and data collection, management, and storage	Innovations in data handling systems, storage solutions, graphical interfaces and data analysis processes for information management.
4	Energy, fluids, and gases containment, control and distribution	Devices and inventions for controlling and distributing energy, fluids and gases, often related to supply chain industrial systems.
5	Chemicals applications in waste and production processes	Chemical applications for food production and preservation, waste management, and surface treatment technologies.
6	Housing construction materials and tools	Innovations in construction materials and tools for housing and infrastructure building.

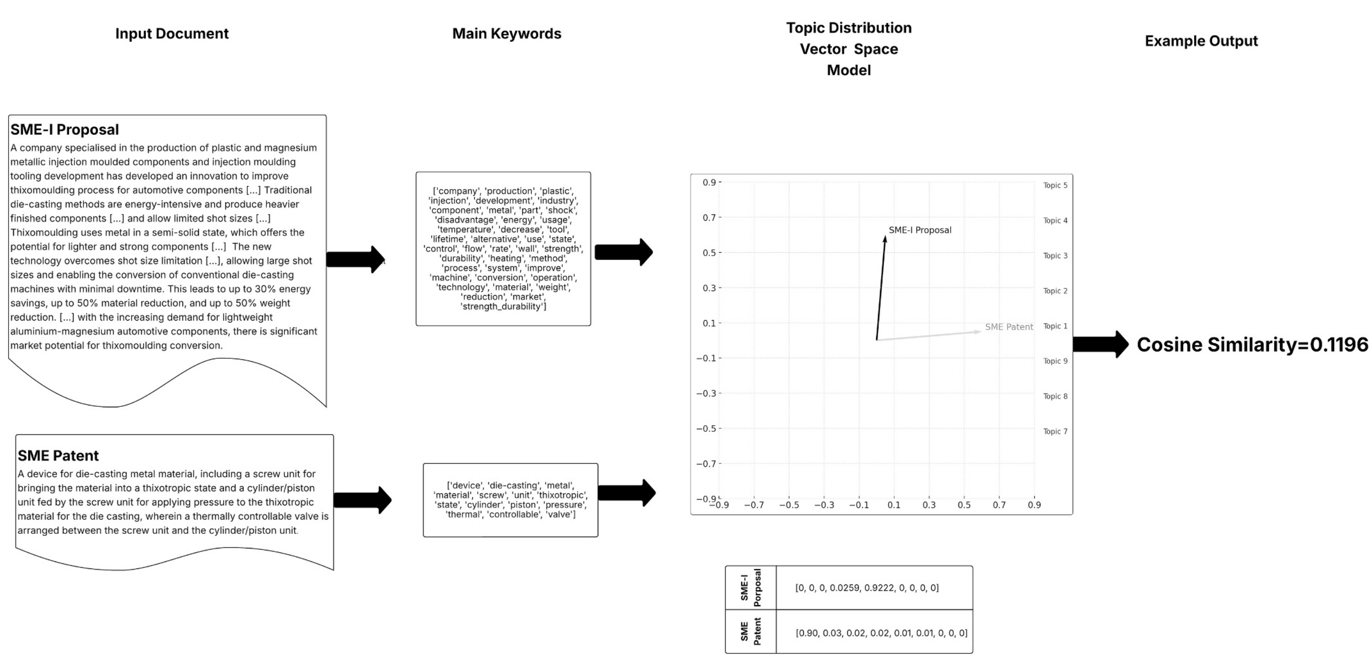

Fig. 2. Illustrative example of the semantic proximity assessment between an SME-I proposal and its patent portfolio through LDA topic modeling and cosine similarity measurement
Note: In this illustrative case, the SME submitting the SME-I proposal held only a single active patent at the time of the submission. Therefore, the centroid vector representing the firm's patent portfolio coincides with the vector of the individual patent.

effects and growing familiarity with the application process, that may increase firms' ability and efficiency to navigate evaluation criteria effectively (De Rose and Malavenda, 2024; Sakhartov, 2017). We also included a binary variable *Phase*, indicating whether the application pertains to Phase I or Phase II of the SME-I program, as they differ in their scope and competitiveness, potentially affecting success rates (Di Minin et al., 2016).

At the sectoral level, we include a dummy variable (*D_Man*), indicating whether the firm operates in manufacturing sectors. This control accounts for potential policy prioritization toward manufacturing sectors, which are often favored due to their role in promoting growth and technological development (Czarnitzki and Lopes-Bento, 2014; D'Este et al., 2012). Finally, to control for temporal variation and technological heterogeneity across proposals (European Court of Auditors, 2020), we included year fixed effects (*D_Year SME—I) and topic fixed effects* (*Topic_Cluster*).

A detailed overview of dependent and exploratory variables - including their full name, the acronyms used in our econometric results tables, and their precise construction methods - is provided in Table 6.

3.5. Estimation method

For the first dependent variable, *Proj_Status*, we use a multinomial logit regression (MLR) model to assess the likelihood of a firm being classified in one of the three evaluation outcomes (Main List, Below Available Budget, or Below Threshold). For the second dependent variable, *Score*, we estimate a linear regression model using ordinary least square (OLS). In both cases, assuming that firms are aware of the existence of the SME Instrument, the evaluation outcome is observed only for applicant SMEs. This results in a censored sample, as the dependent variables are not observed only for a subsample of eligible SMEs. Such censoring raises the concern of sample selection bias, since the application decision may be non-random and influenced by some unobservable firms' characteristics that also possibly affect the evaluation outcome. To address this issue, we implement a Heckman sample selection correction, estimated through two different equations: one for the sample selection and one for the evaluation outcome, conditional on selection. Formally:

$$\textit{sample selection equation}: S_i = Z_i\delta + u_i$$

Table 6
Variables name, definition and construction, and acronyms.

	Definition and Construction	Acronym
a) Dependent Variables		
Project Status	SME-I firms' group: 1 = Below Available Budget (SoE), 2 = Main List; 0 = Below Threshold	*Pr_Status*
Evaluation Score	Overall evaluation score for each proposal, assigned by EASME.	*Score*
b) Main Exploratory Variables		
Innovation Coherence	LSI- based similarity index	*Inn_Coherence*
Available Financial Slack	Log (Working Capital/Sales)	*av_FinSlack*
c) Control Variables		
Long term debts over total assets	Log (Long Term Debts/Total Assets)	*Lt_Debts_TotAss*
Firm Size	Log of total assets	*F_Size*
Firm Age	Year of application to the SMEi minus year of incorporation	*F_Age*
Profit Margin	Earning as % of total revenues	*Profit_Margin*
Previous Attempts	Number of the previous attempts each firm made before the most recent attempt.	*Prev_Attempts*
Dummy Phase	1 = if the firms apply to Phase 2 and 0 = otherwise	*D_Phase*
Dummy Manufacturing	1 = the firm operates in a manufacturing sector (according to NACE Rev.2 classification); 0 = otherwise	*D_Man*
Topic cluster	A multinomial variable, with values ranged between 1 and 9, deriving from NPL analysis.	*Topic_cluster*
Year of SME-I application	The year in which the SME-I proposal was submitted.	*D_Year SME-I*

Note: the table reports variables information for the variables contained in our baseline specifications.

$$\textit{outcome response equation}: y_i^* = X_i\beta + p\lambda_i + \varepsilon_i, \text{observed only if } S_i = 1$$

where S_i is the latent propensity of the firm to apply and y_i^* is the evaluation outcome variable – either the continuous *Score* or the categorical outcome *Proj_Status* - for firm *i*; Z_i and X_i are the vectors of explanatory variable for the selection indicator and response variable, respectively; δ and β are the vectors of coefficients for the selection indicator and response variable, respectively; and u_i and ε_i are the error terms. Importantly, λ_i is the inverse Mill Ratio (IMR) compound from the sample selection equation and defined as $\frac{\phi(Z_i\widehat{\delta})}{\Phi(Z_i\widehat{\delta})}$, where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and cumulative distribution functions, respectively. Finally, p captures the correlation between the unobserved components of the selection and outcome equations. In the case of *Proj_Status*, given each *k* group and by including the IMR as an additional covariate, the MLR is the following:

$$log\frac{Pr(y_i = k|X_i)}{Pr(y_i = 0|X_i)} = X_i\beta^{(k)} + p^{(k)}\lambda_i$$

for $k = 1, \ldots, K-1$. For the *Score* variable, which is continuous, we estimate an OLS regression, with IMR as additional regressor:

$$y_i = X_i\beta + p\lambda_i + \varepsilon_i$$

In both specifications, the inclusion of the IMR allows to correct for potential sample-selection bias. or potential selection bias stemming from non-random application behavior. To ensure identification of Heckman selection, we include Profit Margin as exclusion restriction: while profitability may influence the decision to apply for public funding (e.g., Mina et al., 2021), it is unlikely to directly affect the evaluation outcome, which is based on quality and feasibility of the proposal. Tables A.5, A.6, A.7 and A.8 in the Appendix show the estimation of independent equations, supporting the validity of our instrument.

4. Results

Descriptive statistics for the main dependent and exploratory variables are reported in Table 7. Bivariate correlations among the baseline variables are reported in Table 8. Variance inflation factors (VIF, available in the Appendix- Table A.9) show that multicollinearity is not a concern in our estimations, as both the mean and individual VIF values are well below the commonly accepted threshold of 10.

Estimation results from the multinomial logit regression models for Model 1 and Model 2 are reported in **Tables 9 and 10**, respectively. All

Table 7
Sample ($n = 4900$*) Descriptive Statistics.

	Mean	Min	Max
a) Dependent Variables			
Pr_Status	1.4927	0	2
Score	11.644	1.053	15
b) Main Exploratory Variables			
Inn_coherence	0.1165	−0.198	0.541
av_FinSlack	−0.3789	−6.717	16.317
c) Control Variables			
Lt_Debts_TotAss	0.0933	−0.079	7.271
F_Size	8.8111	3.583	11.981
F_Age	2.4355	0	4.859
Profit_Margin	−0.1063	−129.571	14.4
Prev_Attempts	1.0205	1	3
D_Phase	1.5095	1	2
D_Man	0.4174	0	1

Note: the table reports descriptive statistics only for the variables contained in our baseline specifications. The final sample of 4900 firms includes 2862 SME-I applicants and 2218 non-applicant SMEs (control group).

Table 8
Pairwise correlation table.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1]	*Inn_Coherence*	1.000								
[2]	*av_FinSlack*	0.0217	1.000							
[3]	*Lt_Debts_TotAss*	−0.0330	−0.2574	1.000						
[4]	*F_Size*	0.0829	−0.0714	0.0277	1.000					
[5]	*F_Age*	0.0191	−0.1486	−0.0091	0.3108	1.000				
[6]	*Profit_Margin*	−0.0244	−0.0691	0.0142	0.0071	−0.022	1.000			
[7]	*Prev_Attempts*	−0.0281	-0.0079	0.0244	0.0170	−0.0046	−0.0059	1.000		
[8]	*D_Phase*	0.0398	0.1224	−0.0038	0.1678	0.0063	0.0185	−0.0001	1.000	
[9]	*D_Man*	0.0456	−0.1325	−0.0039	0.1338	0.2555	0.0031	−0.0107	−0.0112	1.000

Note: the table pairwise correlations only for the variables contained in our baseline specifications.

Table 9
Multinomial logit model regression- Model 1.

Multinomial Logit									
Model 1									
	Parametrization (1–0)			*Parametrization (2–0)*			*Parametrization (2–1)*		
	Below Available Budget/Below Threshold			*Main List/Below Threshold*			*Main List/ Below Available Budget*		
Inn_coherence	1.2663	*	(0.7674)	2.0964	**	(0.9566)	0.8301		(1.0912)
Lt_Debts_TotAss	0.7623		(0.6271)	1.5281	**	(0.6517)	0.7658		(0.7733)
F_Size	0.1645	**	(0.0844)	0.3011	**	(0.1066)	0.1367		(0.1206)
F_Age	−0.2107	**	(0.0846)	−0.3106	**	(0.1065)	−0.0999		(0.1207)
D_Prev_attempts	1.0345	**	(0.4066)	0.7575		(0.4952)	−0.2769		(0.5295)
D_Phase	1.3292	***	(0.1394)	−0.1634		(0.1666)	−1.4927	***	(0.1970)
D_Man	0.0459		(0.1389)	−0.8869		(0.1781)	−0.1384		(0.2033)
Lambda (IMR)	−2.4113	**	(0.8658)	−2.5676	**	(1.1009)	−0.1562		(1.2491)
Constant	−4.0833		(0.5512)	−3.7047		(0.6604)	0.3786		(0.4977)
Topic_cluster	Yes			Yes			Yes		
D_Year SMEi	Yes			Yes			Yes		
Tot. Obs	4900			4900			4900		
Censored Obs	2218			2218			2218		
Uncensored Obs	2682			2682			2682		
Robust Stand.Errors	Yes			Yes			Yes		
Log PseudoLikelihood	−1374.79			−1374.79			−1374.779		
Pseudo R2	0.0841			0.0841			0.0841		
Marginal Effects									
Inn_coherence	0.1497		(0.1193)	0.1757	*	(0.0919)	0.1801	*	(0.0923)
Lt_Debts_TotAss	0.0836		(0.0906)	0.1320	**	(0.0625)	0.1348	**	(0.0626)
F_Size	0.0187		(0.0126)	0.0260	**	(0.0103)	0.0262	**	(0.0102)
F_Age	−0.0258	**	(0.0127)	−0.0254	**	(0.0102)	−0.0262	**	(0.0102)
D_Prev_attempts	0.1601	**	(0.0780)	0.0477		(0.0597)	0.0491		(0.0562)
D_Phase	0.2164	***	(0.0204)	−0.0494	**	(0.0159)	−0.0452	**	(0.0156)
D_Man	0.0101		(0.0218)	−0.0099		(0.0171)	−0.0098		(0.0171)

Notes: The table reports results obtained from multinomial logit regression- Model 1. The dependent variable is Project status. Robust standard errors reported in parentheses. Model (2–1) changes the base outcome to "Below Available Budget" to enable pairwise comparison with the "Main List" group.
[*] $p < 0.1$.
[**] $p < 0.05$.
[***] $p < 0.001$.

specifications include the computation of marginal effects.

Model 1 estimates the effect of innovation coherence, together with standard firm-level controls, while Model 2 adds available financial slack and its interactive effect with the innovation coherence index to test for the moderating effect in Hypothesis 2.

The results reveal significant differences between the three SME-I firms' outcome groups- *Below Available Budget*, *Main List* and *Below Threshold*. Notably, innovation coherence emerges as a key driver of evaluation success. In Model 1, it is positively and significantly associated with an increased likelihood of falling into the Main List relative to the below threshold SME-I group ($\beta = 2.0964, p < 0.05$), by 17.57 % ($p < 0.10$). When introducing the moderating role of financial slack (Model 2), the coefficient remains positive and significant ($\beta = 2.1951$, $p < 0.1$), although the corresponding marginal effect loses significance, suggesting the effect may be moderated by other factors. Interestingly in Model 2, the coefficient for innovation coherence relative to the Below Available Budget vs Below Threshold (parametrization 1–0) becomes significant ($\beta = 1.9596, p < 0.1$), with a corresponding marginal effect of 24.98 %, highlighting the importance of technological alignment in surpassing evaluation threshold even when funding is not awarded.

The interaction between innovation coherence and financial slack, in Model 2, confirms this interpretation. Indeed, this effect is positive for all SME-I groups but statistically significant only for Main List SME-I group vs Below Threshold ($\beta = 1.3332, p < 0.05$), with a marginal effect of 11.3 %, further reinforcing the idea that available internal resources enhance the positive impact of innovation coherence on funding success.

Among financial variables, the ratio of long-term debts over total assets shows non-linear and somehow context-sensitive relationships with founding outcomes, even if the coefficient is positive across SME-I groups and all specifications. In particular, in Model 1 the coefficient is significant only for the Main List vs Below Threshold ($\beta = 1.5281, p < 0.05$), with an associated increase in the probability of successful funding of the 13.20 %. In Model 2, when introducing the

Table 10
Multinomial logit model regression- Model 2.

Multinomial Logit									
Model 2									
	Parametrization (1–0)			*Parametrization* (2–0)			*Parametrization* (2–1)		
	Below Available Budget/Below Threshold			*Main List/Below Threshold*			*Main List/ Below Available Budget*		
Inn_coherence	1.9596	**	(0.9728)	2.1951	*	(1.2821)	0.2355		(1.2745)
Lt_Debts_TotAss	0.3775		(1.0550)	4.0388	***	(1.1523)	3.6612	**	(1.3212)
F_Size	0.0692		(0.1032)	0.3197	**	(0.1395)	0.2505		(0.1621)
F_Age	−0.1060		(0.1035)	−0.2826	**	(0.1389)	−0.1766		(0.1608)
D_Prev_attempts	1.2621	**	(0.5106)	0.6261		(0.6876)	−0.6360		(0.6249)
D_Phase	1.3093	***	(0.1692)	−0.4028	*	(0.2086)	−1.7121	***	(0.2415)
D_Man	0.0742		(0.1718)	−0.1503		(0.2245)	−0.1578		(0.2549)
av_FinSlack	0.0658		(0.0674)	−0.0239		(0.0919)	−0.0898		(0.0876)
Inn_coherence##av_FinSlack	0.3933		(0.4588)	1.3332	**	(0.6068)	0.9399	*	(0.5314)
Lamda (IMR)	−1.8305	*	(1.0696)	−2.2323	*	(1.3719)	−0.4018		(1.5385)
Constant	−3.7033		(0.6660)	−4.4902		(0.9448)	−0.7869		(1.0471)
Topic_cluster	Yes			Yes			Yes		
D_Year SMEi	Yes			Yes			Yes		
Tot.Obs	4900			4900			4900		
Censored Obs	2218			2218			2218		
Uncensored Obs	2682			2682			2682		
Robust Stand.Errors	Yes			Yes			Yes		
Log PseudoLikelihood	−943.0080			−943.0080			−943.0080		
Pseudo R2	0.1031			0.1031			0.1031		
Marginal Effects									
Inn_coherence	0.2498	*	(0.1454)	0.1587		(0.1078)	0.0895		(0.1078)
Lt_Debts_TotAss	−0.0278		(0.1491)	0.3598	***	(0.0975)	0.3505	***	(0.0984)
F_Size	0.0037		(0.0150)	0.0276	**	(0.0134)	0.0270	**	(0.0119)
F_Age	−0.0101		(0.0148)	−0.0235	*	(0.0133)	−0.0230	*	(0.0112)
D_Prev_attempts	0.2073	**	(0.0829)	0.0217		(0.0612)	0.0204		(0.0676)
D_Phase	0.2086	***	(0.0244)	−0.0655	***	(0.0179)	−0.0589	***	(0.0174)
D_Man	0.0043		(0.0252)	−0.0138		(0.0201)	−0.0134		(0.0194)
av_FinSlack	0.0145		(0.0096)	−0.0036		(0.0075)	0.0098	**	(0.0047)
Inn_coherence##av_FinSlack	0.0314		(0.0698)	0.1131	**	(0.0494)	0.1126	**	(0.0518)

Notes: The table reports results obtained from multinomial logit regression- Model 1. The dependent variable is Project status. Robust standard errors reported in parentheses. Model (2–1) changes the base outcome to “Below Available Budget” to enable pairwise comparison with the “Main List” group.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.001$.

moderating effect of financial slack, the effect of long-term debt on evaluation outcomes becomes much stronger. The coefficient for Main List vs Below Threshold sharply increases ($\beta = 4.0388, p < 0.001$) and the associated marginal effect rises to 35.98 % ($p < 0.001$), implying that in presence of available internal resources, leverage plays a decisive signaling role of project feasibility and financial commitment. This confirms that long-term debt, especially if combined with financial slack is not detrimental per se, rather it appears to differentiate the highest-ranked SMEs from those with weaker funding outcomes, effectively acting as a strategic firm buffer.

Being larger significantly increases the likelihood of falling in the Main List relative to the Below Threshold (parametrization 2–0) in both specifications. In Model 1, size has a significant effect ($\beta = 0.3011, p < 0.05$) with a marginal effect of 2.610 % for Main vs Below Threshold. In Model 2 the size effect remains statistically significant, with $\beta = 0.3197, p < 0.05$, and a marginal effect of 2.76 %. In contrast firm age consistently shows a negative and statistically significant relationship with the probability of funding success in most cases. In Model 1, the marginal effect of age on the probability of being in the Below Available Budget relative to the Below Threshold (parametrization 1–0) is statistical significant ($-2.58\%, p < 0.05$) although the coefficient itself is not statistically significant ($\beta = -0.2107$).Even more interestingly, in both Model 1 and Model 2, firm age is significantly negatively associated with the probability of being in the Main List relative to the Below Threshold group (parametrization 2–0): $\beta = 0.3106, p < 0.05$ in Model 1, with a resulting lowered probability of successful funding of 2.54 %, and $\beta = 0.2826, p < 0.05$ in Model 2, when introducing moderation effect, with a marginal effect of −2.35 %.

Taken together, these findings suggest that younger firms may be viewed more favorably by evaluators, potentially due to their innovative potential or closer alignment with the innovation-driven goal of the SME-I of fostering innovation ready for commercialization.

Previous participation in SME-I program is consistently associated with a higher probability of meeting the evaluation threshold compared to firms without such experience. In Model 1, previous attempts significantly increase the probability of being in the Below Available Budget rather than in the Below Threshold group, with a marginal increase of 16.01 % ($\beta = 1.0345, p < 0.05$). This effect remains significant and even slightly stronger in Model 2, where having prior experience with the SME-I scheme – combined with a higher availability of internal financial resources- is associated with an increased probability of being awarded a Seal of Excellence rather than being in the Below Threshold of 20.73 % ($\beta = 1.261, p < 0.05$). The dummy variable Phase plays a central role in shaping evaluation outcomes, even if not uniformly across groups. In both Model 1 and Model 2, the coefficients are positive and statistically significant for the Below Available Budget vs Below Threshold (parametrization 1–0) comparison: $\beta = 1.3292$ *and* $\beta = 1.3093$ (both $p < 0.0010$) with associated statistically significant marginal effects of 21.64 % and 20.86 %, respectively. This suggests that Phase 2 proposals are technically sound, making them more likely to meet the minimum evaluation threshold. In contrast, when comparing Main List vs Below Threshold (parametrization 2–0), we observe a negative effect. Phase 2 applicants are less likely to be awarded funding, even when the moderating role of financial slack is introduced: $\beta = -0.1634$ and $\beta = -0.4028$, respectively, with corresponding statistically significant reduced probabilities of being funded of −4.94 % ($p < 0.05$)

and of −6.55 % ($p < 0.001$). These results reveal a dual dynamic: if Phase 2 applicants are more capable of drafting a high-quality proposal, they are less likely to rank among the top, also reflecting the higher competitiveness of the granting scheme for innovations closer to market demonstration and replication. Finally, the manufacturing sector dummy, on the other hand, does not have statistically significant effect across all model specifications and parametrization, with coefficients often small in magnitude.

Beyond these comparison with the base outcome category (Below Threshold), to better understand the differences between SMEs' proposals that scored highly but where not funded and those that were, Table 9 and Table 10 report the third Model parametrization (2–1), which change the base category to Below Available Budget, thus enabling a direct comparison with the Main List group. This allows us to better understand drivers that move a SME's proposal from "excellent" to "funded".

Innovation coherence maintains a positive, though not statistically significant, effect in Model 1 ($\beta = 0.8301$), while the corresponding marginal effect is significant ($+18\%, p < 0.1$), signaling a relevant increase in predicted probability even in the absence of a significant structural coefficient.

In Model 2, although the coefficient remains positive and non-statistically significant ($\beta = 0.2355$), the effect of the interaction with financial slack become statistically significant ($\beta = 0.9399, p < 0.1$), with an increase in the probability of being in the Main List SME-I group by 11.26 %. Long-term debts become highly predictive. In particular, in Model 3, it statistically increases the list of being in the Main List relative to the Below Available Budget group of 13.48 % ($\beta = 0.7658, p < 0.05$). This effect is even higher in Model 2, with $\beta = 3.6612$ ($p < 0.05$) and a marginal effect of 35.05 %.

Firm size also distinguishes funding firms. Larger firms experience an increase in probability of being awarded with funding of +2.62 % in Model 1 and of 2.70 % in Model 2 (both with $p < 0.05$), despite non statistically significant coefficients ($\beta = 0.1367$ *and* $\beta = 0.2505$, respectively). Firm age, while still negatively signed, does not have a significant impact in both Model 1 and 2, suggesting that maturity does not sufficiently differentiate among high-quality proposals in the final selection.

Previous SME-I participation, although relevant in crossing the evaluation threshold, loses its significance in both specifications, indicating that experience alone is not sufficient to secure funding. Finally, the Phase 2 dummy continue to exhibit a negative and significant effect: in Model 1 the probability of Phase 2 applicants of being funded rather than being award a Seal of Excellence lower of 4.52 % $\beta = -1.4927$, $p < 0.05$), while in Model 2 this effect intensifies $\beta = -1.7121$, $p < 0.001$), with a marginal effect of −5.89 %.

To complement the marginal effect estimates, Figs. 3, 4 and 5 offer a three-dimensional representation of the estimated probability of being assigned to each of the three evaluation outcome SME-I groups, as a function of innovation coherence and available financial slack. Fig. 3 clearly shows a monotonic increase in the likelihood of being included in the Main List as both innovation coherence and financial slack rise, with a more pronounced effect at higher level of available financial slack. This pattern supports the idea that financial slack plays a moderating role in converting highly innovation coherent proposals into successful funding outcomes. In contrast, the probability of being assigned to the Below Available Budget group (Fig. 4**)** shows a more complex pattern.

It shows a non-linear relationship whereby the probability of being assigned to the Below Available Budget SME-I initially increases with increasing level of innovation coherence-particularly when financial slack is low- but then declines at high levels of coherence. This suggests that SMEs with moderately coherent projects and limited financial

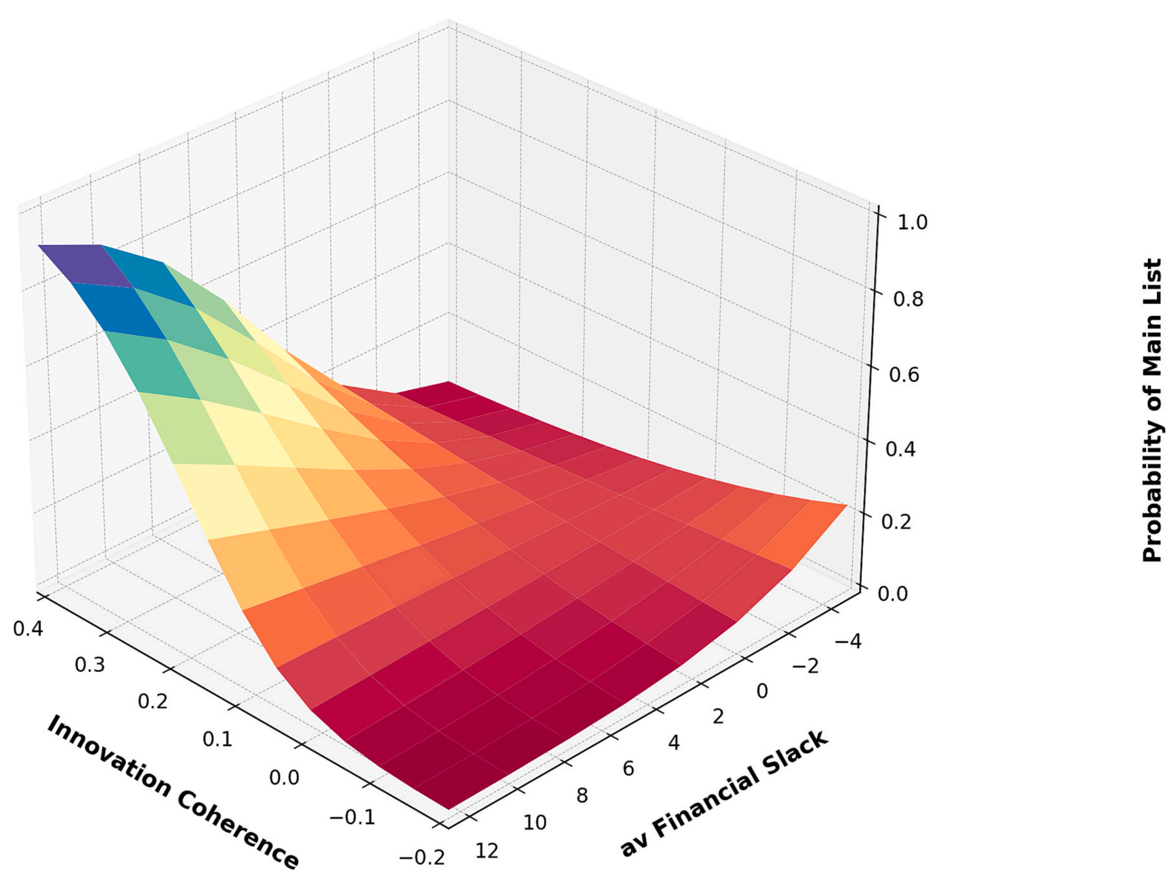

Fig. 3. The moderating effect of available financial slack on the relationship between Innovation coherence and the likelihood of being awarded (Main list SME-I group).

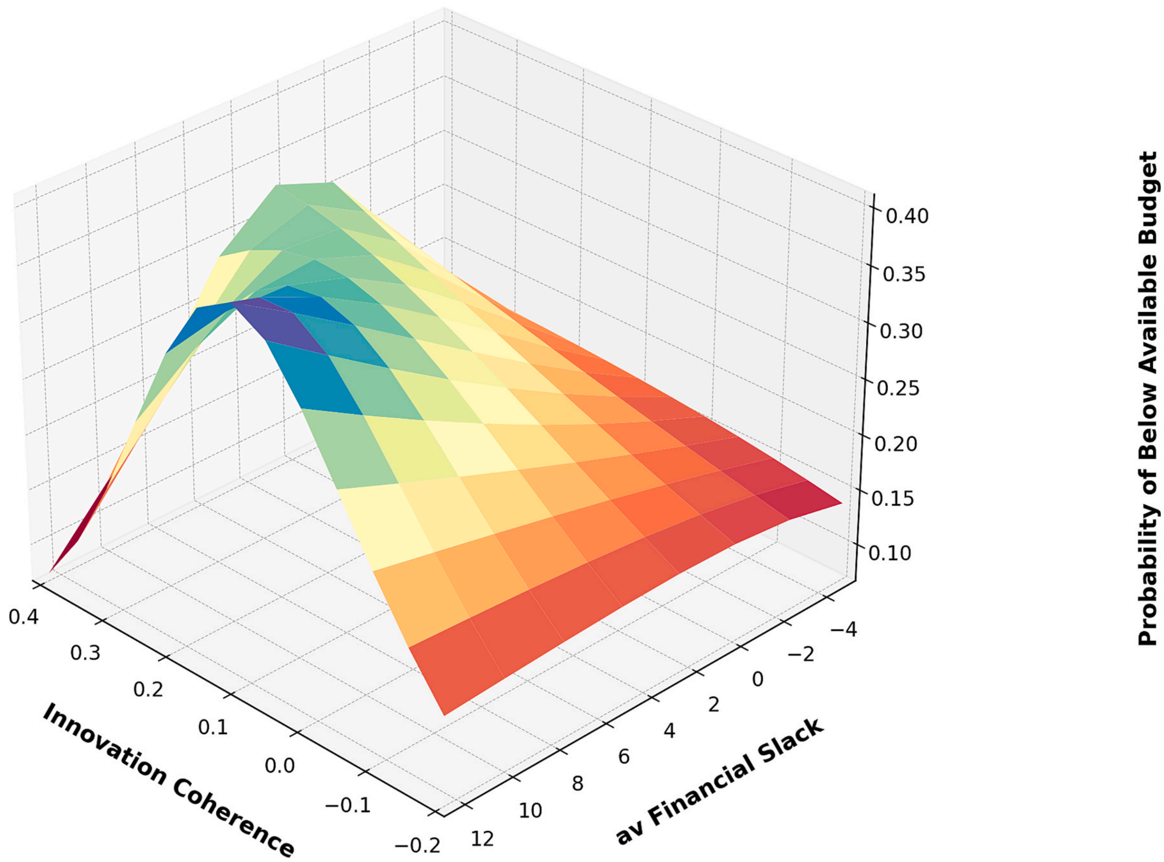

Fig. 4. The moderating effect of available financial slack on the relationship between Innovation coherence and the likelihood of belonging to the Below Available Budget SME-I group.

resources are most likely to receive a Seal of Excellence. Conversely, highly coherent projects tend to either be funded (Main List) or, if unsupported by slack, fall short of funding. This inverted-U pattern ultimately highlights the competitive threshold effect that discriminates intermediate and top-performing proposals. Finally, **Fig. 5** illustrates that the likelihood of being assigned to the Below Threshold group is higher when both innovation coherence and financial slack are low, thereby highlighting the importance of resource complementarity in competitive public innovation scheme like the SME—I.

Taken together, these Figures reinforce the interpretation that both technological alignment and availability of financial resources reduce the risk of being classified as Below Threshold, even if their interaction alone may not be sufficient to discriminate between inclusion in the Main List and Below Available Budget groups.

To gain a more nuanced understanding of the SME Instrument's functioning, we estimate a multivariate ordinary least square (OLS) regression model, using the overall evaluation score by the experts as the dependent variable (Table 11).

The results confirm the central role of innovation coherence in shaping expert evaluations under the SME—I. In both model specifications, the coefficient is positive and statistically significant, confirming the picture emerging from MLR models and emphasizing that proposals better aligned with the firms' technological bases are perceived more favorably by evaluators. Notably, this effect become stronger in Model 2, with available financial slack as moderator: the β coefficient increases from 1.0122 ($p < 0.10$) in Model 1 to 1.6115 ($p < 0.001$) in Model 2.

Although the long-term debt over total assets maintain is not statistically significant in both model specifications, its coefficient increases notably when financial slack is introduced (from $\beta = 0.5840$ *to* $\beta = 1.1577$).Firm size is still positively and statistical significantly associated with higher evaluation scores in both models: a unit increase in firm size leads to a 2.21 % increase in the evaluation score in Model 1 and of 2.22 % in Model 2, thus suggesting that larger SMEs are better equipped to design compelling SME-I proposals. In contrast, firm age maintains its negative impact on the evaluation score, with a similar magnitude in both specifications: $\beta = -0.2190$ and $\beta = -0.2081$, both with $p < 0.001$. In line with previous results, having prior experience with the SME-I scheme significantly increases evaluation scores across both model specifications ($\beta = 0.9868$ and $\beta = 1.0064$, respectively) thus confirming the existence of some learning effects. Similarly, the Phase dummy variable shows a positive and sizeable effect on the outcome score: $\beta = 0.3984, p < 0.001$ in Model 1 and $\beta = 0.3408, p < 0.05$ in Model 2. Conversely, the manufacturing dummy variable is negative and marginally significant only in Model 2 ($\beta = -0.2093, p < 0.1$). Importantly, available financial slack does not have a statistically significant direct effect on the evaluation score, nor does its interaction with innovation coherence lead to significant differences in expert assessments.

To further strengthen the robustness and internal validity of our analysis, we introduce an alternative model specification for both multinomial and OLS regression models, by incorporating two additional proposal-level controls. These variables- R&D project intensity (*R&D_proj_int*) and proposal duration (*Prop_Duration)* may be potentially endogenous if correlated with the SME-I phase and firms' "innovation history" factors. Recognizing that public agencies often pursue multiple and sometimes competing goals when designing subsidy programs, and acknowledging a degree of discretion in the selection of R&D project (Antonelli and Crespi, 2013), it becomes crucial to account for these proposal-specific characteristics to better isolate the effects of firm-level variables. *R&D_proj_int*, defined as the proportion of total budget required in the application process, serves a proxy for the applicant SME's commitment to the project's objectives. A higher R&D intensity

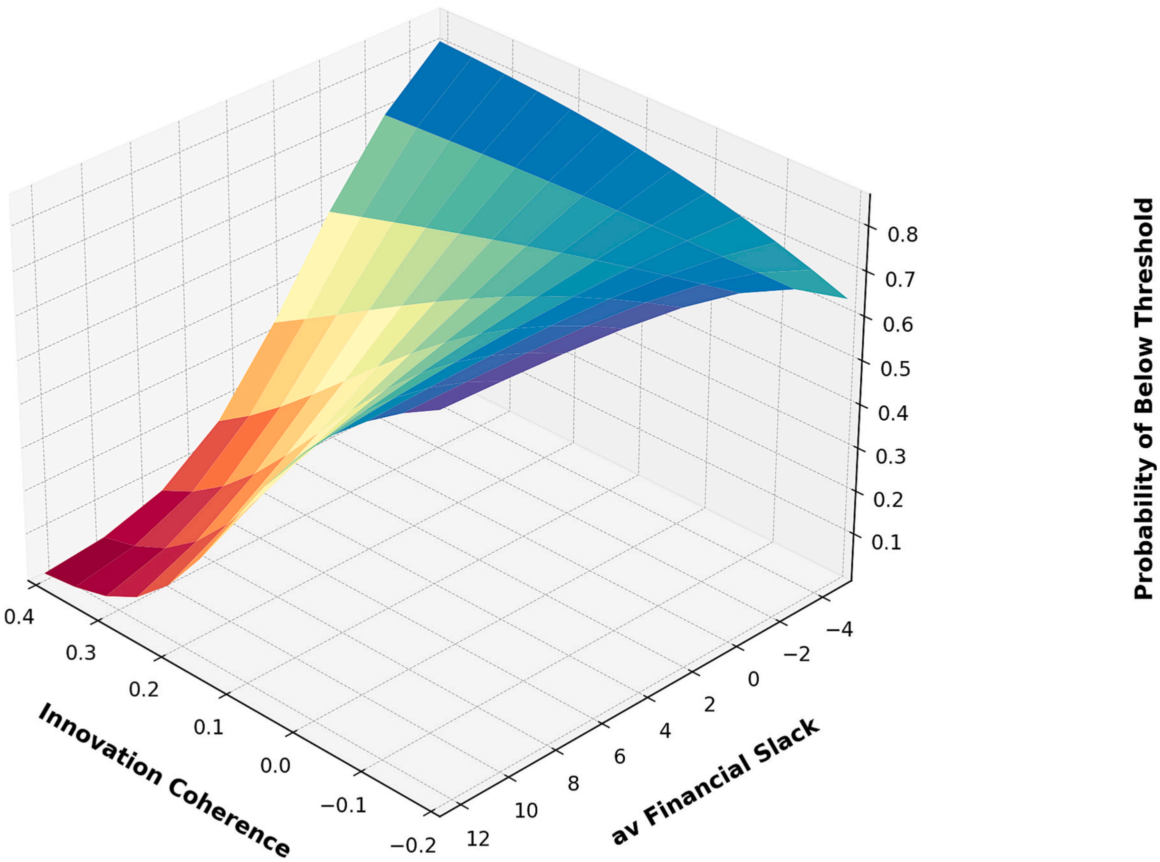

Fig. 5. The moderating effect of available financial slack on the relationship between Innovation coherence and the likelihood of belonging to the Below Threshold SME-I group.

Table 11
Ordinary least square regression.

OLS regression						
	Model 1			Model 2		
Inn_coherence	1.0122	*	(0.5698)	1.6115	***	(0.7577)
Lt_Debts_TotAss	0.5840		(0.4219)	1.1577		(0.7289)
F_Size	0.2121	**	(0.0652)	0.2222	**	(0.0881)
F_Age	−0.2190	***	(0.0652)	−0.2081	**	(0.0863)
D_Prev_attempts	0.9868	***	(0.2119)	1.0064	***	(0.2555)
D_Phase	0.3984	***	(0.0991)	0.3408	**	(0.1173)
D_Man	−0.1073		(0.1048)	−0.2093	*	(0.1286)
av_FinSlack				0.0430		(0.0717)
Inn_coherence##av_FinSlack				0.3905		(0.4282)
Lambda (IMR)	−1.9223	***	(0.6331)	−2.0655	**	(0.8154)
Constant	9.7274		(0.3866)	9.6365		(0.5055)
Topic_cluster	Yes			Yes		
D_Year SMEi	Yes			Yes		
Tot. Obs	4900			4900		
Censored Obs.	2218			2218		
Uncensored Obs	2682			2682		
R^2	0.1012			0.1050		
Adj R^2	0.0901			0.0880		
Obs	1721			1242		

Notes: The table reports results obtained from OLS regression. The dependent variable is the overall evaluation Score of experts. Robust standard errors reported in parentheses. Model 1 specification is the baseline model. Model 2 introduces the available financial slack and its interaction effect with innovation coherence measure.
[*] $p < 0.1$.
[**] $p < 0.05$.
[***] $p < 0.001$.

can be interpreted by evaluators as a credible signal of ambition, technical depth, and alignment with the program's innovation goals, thereby potentially increasing the likelihood of positive evaluation outcomes. *Prop_Duration*, expressed as the number of months indicated for project completion, may capture temporal expectations embedded in the proposal. From the perspective of the funding agency, shorter project durations may be perceived as better aligned with the policy imperative to stimulate innovation in the short run, while also enhancing SMEs' survival chances and preventing financial losses. Conversely, longer durations might allow for more comprehensive research but could be perceived as riskier and raise concerns about feasibility or delayed returns, thereby being evaluated less favorably (Myers and Tham, 2023). Results are reported in the Appendix- Tables A.10, A.11 and A.12.

These additional models confirm the validity of our main results. Innovation coherence is still positively associated with the likelihood of funding success, remaining statistically significant for the Main List vs Below Threshold comparison ($\beta = 2.0874, p < 0.05$), with a corresponding increase in the predicted probability of being founded of 17.6 %. Similarly, when the interaction with financial slack is introduced in Model 2, the effect persists: for the Below Available Budget vs Below Threshold comparison (parametrization 1–0), innovation coherence retains its significance ($\beta = 1.96747, p < 0.05$) with an associated marginal effect of 22.58 %. Notably, the interaction of innovation coherence and financial slack remain consistent across all specifications: for the Main List vs Below Threshold comparison, the effect is statistical significant ($\beta = 1.3599, p < 0.05$) with a marginal effect of +11.52 %, while in the Main List vs Below Available Budget (parametrization 2–1), the effect is slightly lower ($\beta = 0.9716, p < 0.05$) still yielding a + 11.33 % increase in probability. Looking at the evaluation score outcomes, results are still consistent: innovation coherence is positively associated with positive evaluations ($\beta = 1.0109$, $p < 0.1$ in Model 1 and $\beta = 1.6347, p < 0.05$ in Model 2), reinforcing its role as a signal of strategic focus and project quality. However, the interaction with financial slack, while positive, is not statistically significant in either model, suggesting that while financial slack may help in securing funding decisions (as shown in the MLR), it does not directly alter experts' scoring of project quality.

Overall, while some changes emerge, the inclusion of these two proposal-level controls does not alter the core findings of our baseline specifications, further reinforcing the consistency of our framework.

Finally, to ensure unbiased estimates and account for potential selection bias, all specifications include the Inverse Mills Ratio (IMR) derived from the first-stage regression (Table A.4 of the Appendix). Notably, the IMR correction term is statistically significant in most specifications- with the only exception being the MLR parametrization comparing the Main List vs Below Available Budget group - thereby supporting the appropriateness of the selection correction.

Taken together, these findings imply that successful SME-I proposals are more likely to benefit from a combination of strong technological alignment and adequate financial resources, both of which credibly signaling project feasibility and innovation potential.

5. Discussion

This paper explores and examines firm and proposal-level characteristics that shape the likelihood of success in highly competitive innovation funding schemes, using the Horizon 2020 SME-Instrument as empirical setting of analysis. Our analysis, grounded in the signaling theory and the resource-based view, uncover hidden mechanisms through which firms signal credibility to evaluators. Specifically, leveraging a novel measure of innovation coherence- measured as the degree of semantic alignment between firm's proposals and their existing technological bases – emerges as a strong predictor of positive evaluation outcomes. Firms that submit proposals more closely connected to their prior technological portfolios consistently receive higher scores and are more likely to be funded, as coherence credibly signal intellectual continuity in innovation efforts (Ayoubi et al., 2020). Furthermore, our results find that the effect of innovation coherence is strengthened in presence of financial slack, used to signal to evaluators high project feasibility, reduced perceived risk of execution (Hottenrott and Lopes-Bento, 2016) and organizational efficiency (Modi and Cantor, 2021). These results confirm the role of financial slack in attenuating firms' capital constraints, reshaping value creation processes (Voss et al., 2008) and supporting innovation's efforts and outcomes (Bentley and Kehoe, 2020).

In contrast, firms with coherent technological base but financially constrained are less likely to be evaluated positively, thus confirming the importance of complementarities in innovation activities (Voss et al., 2008; George, 2005). Additional findings offer further insights into evaluation dynamics. Large firms are more likely to succeed in competitive innovation contexts, due to established organizational routines, which evaluators may interpretate as a signal of the ability to scale innovation (Huergo and Trenado, 2010). Similarly, repeated participation to the SME-I also has a positive effect, thus supporting the existence of learning-by-doing in grant applications (De Rose and Malavenda, 2024; Aschhoff, 2010) and consistently signaling strategic planning capacity (Takalo et al., 2008). Conversely, older firms are less likely to succeed, that may reflect the preference for younger SMEs whose projects are expected to be more aligned with the SME-I commercialization goals (Marullo et al., 2024). Additionally, our analysis suggests that the financial structure of the firms matters: long-term debt exposure positively influences evaluation outcome, thus reinforcing its role as a disciplining mechanism that signals commitment to the pursue of value-enhancing projects. Furthermore, our results remain robust when controlling for proposal-level variables, such as project R&D intensity and proposal duration, both of which are in line with the SME-I design and its goals of funding short-to-medium term projects aimed at accelerating innovation exploitation and commercialization (European Court of Auditors, 2020).

Taken together, these results suggest that evaluators in the SME-Instrument funding scheme reward a combination of technological maturity, financial robustness and commitment to innovation, as well as organizational learning. That is, rather than assessing proposal on quality and novelty criteria alone, evaluators appear to rely on some observable signals that reduce uncertainty while also indicating innovation potential. In this perspective innovation coherence and financial slack act as complementary signals, effectively helping evaluators to identify firms most capable of drawing innovative project proposals and with higher commercialization rates.

6. Conclusions

Based on a unique dataset of both SME-I's proposals and applicants, our study sheds light on the main predictors of evaluation outcomes in innovation competitive funding schemes.

In doing so, our results contribute to the literature on innovation funding and public policy evaluation, by shedding light on implicit decision logics used by evaluators. While prior research has mostly focused on the ex-post evaluations and ex-post funding effects - such as performance differentials between funded and unfunded firms or long-term innovation outcomes - our analysis sheds light on the ex-ante evaluative criteria that could shape grant allocation. Understanding what drives evaluators' ex-ante decisions offer useful insights on how uncertainty is managed and how project merit is perceived. Despite the formal existence of evaluation criteria such as excellence, impact and implementation, evaluation is practice still has a certain degree of subjectivity. Evaluators are often called to discriminate among multiple high-quality proposals, and in such highly competitive environments, relying on observable projects and firm-level characteristics may not be enough. Conversely, they are more likely to rely on some implicit shortcuts to differentiate among proposals. In such context, innovation coherence becomes the instrument through which reducing uncertainty and subjectivity, while ensuring successful and efficient funding. In such contexts, we propose innovation coherence as a data-driven and objective metric able to capture the semantic alignment between a firm's technological base and its proposed innovation proposal, thus credibly signaling project feasibility and firm's commitment to innovation. In this perspective, our work adds to signaling theory, through the conceptualization of a new construct able to reflect an endogenous connection between firms' internal capabilities and future innovation trajectories. As our results emphasize, proposals with higher innovation coherence scores are more likely to be positively evaluated, thereby going beyond the mere evaluation of project novelty. This is particularly relevant for one-shot funding scheme, such as the SME Instrument, which aims to support rapid commercialization of innovations: if funded firms are expected to scale up quickly, evaluators are called to balance innovation potential with feasibility, while also reducing biases. That is, our construct contributes to advance resource-based theory, offering a novel operationalization of firms' innovation capabilities potential, marking a shift from the breadth of technological diversifications strategy to the depth of innovation efforts. Moreover, our results confirm that innovation coherence could mitigate effect of confounding yet controversial, firm-level characteristics. For instance, if high level of long-term debt penalize evaluation due to the perceived financial fragility of the applicants, when such firms show high innovation coherence, this may signal strategic focus, potentially offsetting concerns about financial risks. Furthermore, our findings suggest that the effect of innovation coherence may be amplified when combined with the presence of financial slack, defined as the availability of excess resources that may be easily reallocated among innovative assets (Marlin and Geiger, 2015; Voss et al., 2008). In presence of high innovation coherence, slack signals the ability to absorb external shocks and manage unexpected events, thereby increasing the execution potential of proposals (Bentley and Kehoe, 2020; Deb et al., 2017). This suggests that evaluators could assess proposals' merit by considering the interaction between innovation coherence and resource availability.

Taken together, these fundings offer a more nuanced understanding of how public evaluators assess innovation projects ex-ante, characterizing innovation coherence at the intersection between policy evaluation logics, strategic capability signaling and resource alignment.

Beyond its predictive value in highly competitive innovation funding scheme, we introduce innovation coherence as a novel construct that goes beyond technological diversification, by emphasizing directional consistency (Pugliese et al., 2019; Zaccaria et al., 2014) and can be applied in any contexts where evaluators or investors are called to discriminate among highly qualified candidates – from venture capitalist screening, corporate R&D portfolio selection, or grant programs.

6.1. Managerial implications

From a managerial perspective, our findings offer evaluable insights for SMEs seeking to enhance their competitiveness in grant-based funding schemes. First, firms should recognize that evaluators value consistency between existing capabilities and future innovation trajectories. Accordingly, innovation proposals that stress existing technological base are more likely to be rewarded, as effectively signaling firms' ability to effectively manage technological diversification and relatedness strategies (Guerrero et al., 2023). This implies that firms should carefully choose the direction of their technology diversification (Hidalgo et al., 2018) while also actively monitoring their innovation coherence, for instance through portfolio mapping tools or internal evaluation processes. Second, managers should consider financial slack as a strategic lever that enables experimentation and reduce the perceived risk of innovation (Liang et al., 2023). In this sense managers should preserve and communicate financial slack as part of their innovation narrative, framing it as a cushion to absorb risks and sustain project execution. Third, as the interaction between coherence and financial slack is positive, our results inform managers seeking for success in competitive funding schemes to adopt an integrated approach to innovation strategy and resource management, treating coherence and slack as complementary assets: high level of coherence without adequate slack my raise concerns about project execution, while slack alone without a coherent innovation portfolio may signal inefficiency.

6.2. Policy implications

Our findings carry several implications for policymakers designing and implementing competitive innovation funding schemes.

First, our results show that innovation coherence is a reliable indicator of firms' absorptive capacity and project feasibility (Hottenrott and Lopes-Bento, 2016; Cohen and Levinthal, 1990). Policymaker should therefore integrate coherence-based metrics into the evaluation process, complementing traditional evaluation criteria. By doing so, they can reduce biases and subjectivity, improving transparency and resources allocation processes. Second, recognizing the role of innovation coherence as a driver of knowledge and technology cumulability, highlights its potential to boost the speed of innovation commercialization while enhancing public returns (Yoo and Lee, 2023). Projects that build on coherent technological trajectories are more likely to scale successfully and generate spillovers, suggesting that evaluation guidelines should give explicit weight to technological consistency alongside novelty. Third, policymakers should not only reward coherent innovation trajectories but also support SMEs in developing them, through portfolio mapping tools that help firms assess and communicate their internal technological consistency. Fourth, our results suggest that coherence alone is insufficient: evaluators are called to value firms' readiness to invest and execute innovative projects. That is, to enhance policy efficacy, policymakers should combine support for capability building with instruments that enhance financial slack, so that financially constrained innovations are not excluded despite having strong technological potential. Finally, the positive role of repeated participation in funding scheme highlights the cumulative value of learning and capability-building, suggesting policymakers to design funding mechanisms that recognize this effort and innovation focus. More broadly, the introduction of a data-driven construct of innovation coherence highlights the value of integrating computational indicators into grant evaluation, to mitigate biases and enhance legitimacy of funding decisions (Li et al., 2021; Edler et al., 2012).

6.3. Limitations and future research

In addition to the evaluable insights of this work, several limitations should be acknowledged. First, our analytical sample focuses on patenting SME-I applicants as the operationalization of innovation coherence requires firm-level patent portfolio. As a consequence, the majority of the original population was rolled out, raising the likelihood of systemic selection bias and potentially limiting the external validity of our findings, which are most directly applicable to more IP-active and technological mature SMEs rather than to the broader population of early-stage innovators.

This restriction may also underrepresent the true scope of a firm's innovation activity, especially in early stages when intellectual property is frequently assigned to individual founders or inventors rather than the firm itself (Balasubramanian and Sivadasan, 2011). Additionally, even if we correct for self-selection into grant application, through a matching 1:1 neighbor algorithm and Heckman correction, we cannot rule out residual bias.

These selection and attrition constraints may cause some interpretative bias at policy level, as firms not holding patents formally registered at the corporate level may send misleading signals about their actual innovation efforts. In particular, firms without codified intellectual property may appear as "less coherent", not because they lack a strategic innovation focus, but because their innovation activities are less likely to be captured through formal intellectual records or text-based similarity measures. In this sense, part of the observed heterogeneity in innovation coherence could reflect differences in the visibility of innovation signals rather than the true differences in innovation orientation or capabilities. As a result, policy evaluations relying solely on coherence-based indicators should be interpreted with caution, as it may systematically favor SMEs that are more technologically mature and IP-active. In this perspective, future research should incorporate additional sources of technological capability (e.g., inventor-owned patents, trademarks, scientific publications, and websites), not only to broaden the computation basis of innovation coherence, but also to ensure that the signals conveyed by firms participating in funding schemes more accurately reflect their underlying innovation structure. This, in turn, would help minimize these potential biases and enhance the effectiveness of policy evaluation itself.

Second, measurement limits of the innovation coherence itself. Our measure relies on text-based topic modeling and latent semantic similarity between proposal and patent abstracts. Even if we validate the measure through human coding over a small subsample, obtaining high inter-rater reliability and a significant correlation with our measure, text methods are sensitive to preprocessing choices, hyperparameters and language coverage. This opens up potential for measurement misalignments, thereby leaving space for alternative embedding and multi-text validations. Closely related, our measure is focused on technological relatedness, thereby not accounting for other complementary dimensions of firms' coherence. Future research could develop a multi-dimensional construct of coherence beyond a purely technological focus.

Third, our study is observational and designed to explain ex-ante evaluation outcomes, not to estimate the casual effect of receiving a grant. Likewise, we limited our analysis to financial slack as the only form of slack resource. Although justified by its relevance to innovation finding and direct measurability, we acknowledge that non-financial forms of slack - like human capital and organizational routines- may influence innovation capacity (Stan et al., 2014), thereby impacting of firms' performances. Future work could model slack as multi-dimensional and time-varying, and integrate richer organizational indicators (teams, governance, partner ecosystems). Fourth, our empirical framework is tested within the SME-I context, that entails one-shot, highly competitive decisions. While providing a clear setting of our analysis, this may moderate how evaluators use coherence and read financial signals, thereby further limiting the generalizability of our results. Future research could formally account for such contextual heterogeneity to provide policymakers with clearer insights on how to design a more efficient mix of policy tools to boost SMEs' innovation outcomes. Lastly, future research could investigate how sequencing or combination of different funding schemes could shape firms' innovation strategies and success. Taken together, these limitations emphasize the descriptive and exploratory nature of our study. While we identify relevant association, our findings should not be interpreted as evidence of casual mechanisms, but rather as correlational patterns that can inform future research and policy design aimed at fostering innovation in SMEs.

CRediT authorship contribution statement

Alessandra Costa: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Antonio Crupi:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Saverio Barabuffi:** Writing – review & editing. **Alberto Di Minin:** Funding acquisition, Conceptualization.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2025.124416.

Data availability

The data that has been used is confidential.

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