

ORIGINAL RESEARCH ARTICLE

Interplay of Human and Structural Capital Signals for New Technology Ventures in Early-Stage Venture Capital Funding

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Abstract

By drawing on the socio-cognitive perspective of signalling theory, this study examines how the interplay of human and structural capital signals may be associated with early-stage venture capital (VC) funding for new technology ventures. Using a dataset of 453 French new technology ventures operating in the digital industry, the findings reveal that strong signals such as patents or trademarks enhance firm legitimacy, while weaker signals such as education level or degrees from elite institutions reinforce team credibility. Both types of signals are positively correlated with early-stage VC funding. However, the results indicate that combining signals of the same dimension and strength yields diminishing returns because additional within-dimension signals are informationally redundant, add little new information about legitimacy or credibility, and lower the likelihood of funding. In noisy, information-saturated contexts, overlapping signals create redundancy and investor cognitive overload rather than facilitating decision-making. This study advances signalling theory by framing signal interactions as a strategic portfolio choice, and outlines implications for entrepreneurial research, investor decision-making, and future work on signalling strategies.

Keywords: *Fundraising; New technology venture; Signal interactions; Signal portfolio dynamics; Venture signalling strategies*

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Which new technology ventures are funded, and why, is a recurring theme in signalling theory and entrepreneurial finance. (Bafera & Kleinert, 2023; Cavallo et al., 2019; Colombo, 2021; Connelly et al., 2011; Ghassemi et al., 2015). In particular, signalling theory offers a strategic lens for understanding how ventures deliberately design and combine signals to attract external resources (Plummer et al., 2016; Vanacker et al., 2020). Acquiring financial resources is crucial for new ventures' survival and expansion (Hor et al., 2021; Subramanian et al., 2022), making the determinants of attracting such resources of interest to researchers, practitioners, and policymakers (Autio, 2016).

Addressing funding gaps is critical for new technology ventures (Gompers et al., 2020) and venture capitalists (VCs) play a central role in the entrepreneurial process (Cavallo et al., 2019; Hor et al., 2021; Silchenko, 2020). To gain investors' confidence and secure early-stage VC funding, without a performance track record (Ko & McKelvie, 2018; Subramanian et al., 2022), new ventures rely on alternative quality signals to signal their growth potential (Spence,

2002). These signals can reduce uncertainty, mitigate information asymmetry and highlight prospects for future growth. Founders' characteristics and ventures' initial innovation strategies are significant signals for reducing information asymmetry and establishing team credibility and venture legitimacy. To attract funding, founders highlight their human capital (education, professional experience, and social capital), as well as degrees from elite institutions (Ko & McKelvie, 2018; Nigam et al., 2020; Shane & Cable, 2002). Similarly, initial innovation strategies can be signalled through patents and trademarks, indicating technological and market legitimacy (Block et al., 2014; Islam et al., 2018; Nigam et al., 2020).

However, recent findings demonstrate that analysing signals independently is becoming less relevant for understanding funding outcomes. In the noisy context of early-stage financing (Huang et al., 2022; Silchenko, 2020), top-down systematic processing mechanism investor decisions do not rely on the analysis of one particular signal but on the complete signal portfolio with varying strengths (Bafera & Kleinert, 2023;

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Vanacker et al., 2020; Yang et al., 2023). It is also recognized that signals can interact, sometimes being complementary or in competition, which can affect their effectiveness (Courtney et al., 2017; Drover et al., 2018; Plummer et al., 2016; Rooks et al., 2009; Santarelli & Tran, 2013; Steigenberger & Wilhelm, 2018; Svetek, 2022). Furthermore, in complex environments, signals may carry incongruent valences (positive and negative), shaping investors' perceptions (Vergne et al., 2018) and because signal incongruence may lead to negative attitudes towards issuers (whether signals are of the same dimension or not) (Paruchuri et al., 2021; Zhang et al., 2022), contradictory signals regarding firm innovation strategy or team characteristics can erode investor trust (Fischer & Reuber, 2007). However, signals' interaction and association with early-stage venture financing remains underexplored. This gap is identified by Connelly et al. (2011), who note combinations of signals with varied effects, highlighting the need to explore how firms manage and combine them.

Motivated by the need to better understand how the interplay of human and structural capital signals for new technology ventures may be associated with early-stage VC financing, this study investigates the French early-stage VC environment. This context offers a valuable empirical setting for theory development for two reasons. Firstly, France has a mature startup scene concentrated in the Paris region, with record VC financing in recent years (France Digitale, 2024), providing relevant variance in the focal phenomena. Secondly, France offers a distinctive environment that challenges US-centric VC research assumptions by combining regulatory-driven innovation policies (Hall, 2002), shaping investments (Taupin et al., 2024) that underscore structural capital and close ties between private and public sectors, with most entrepreneurs emerging from elite institutions (Maclean et al., 2007; Milosevic, 2018; O'Brien, 2023).

This study extends the understanding of signal interactions and examines how the coexistence of multiple costly, objective information signals of similar dimensions and strength may be associated with new technology ventures' ability to secure early-stage VC funding. In doing so, the findings emphasize the strategic dimension of signalling in which ventures make deliberate, strategic choices not only about which signals to send, but also about how to configure their portfolios across human and structural capital. By treating signals as part of a portfolio strategy rather than isolated cues, this study answers recent calls to examine the strategic use of signals in resource acquisition (Connelly et al., 2011; Zahera & Bansal, 2018). By drawing on signalling theory applied to entrepreneurship (Bafera & Kleinert, 2023) and human capital theory (Becker, 1975), and applying cognitive-science principles to signalling theory (Drover et al., 2018), we propose that the interaction of signals of similar dimensions and strength can create informational redundancy, which may

have a negative effect on fundraising outcomes. To test our hypotheses, we use data from 453 new technology ventures located in the Paris region (France). We collect data on weak human capital signals and strong structural capital signals as independent variables, and examine their interactions by dimension and strength to assess their impact on early-stage VC fundraising.

The results reveal that ventures combining signals of similar dimensions and strength may experience diminishing returns, reducing the likelihood of securing funding. We interpret these results as evidence of informational redundancy, where overlapping signals of the same dimension and strength fail to provide incremental value, as each additional signal adds limited new insights and generates cognitive overload for investors (Betsch & Glöckner, 2010; Courtney et al., 2017; Vanacker et al., 2020; Zahera & Bansal, 2018). In information-saturated contexts, investors rely on heuristic shortcuts to assess ventures efficiently. When signals are too similar, they may overwhelm investors' evaluative capacity, particularly in noisy environments where multiple ventures compete for attention.

This study enriches entrepreneurship and signalling literature in several ways. Firstly, it extends traditional signalling theory studies (Banerji & Reimer, 2019; Marvel et al., 2016) by emphasizing the limitations of evaluating signals in isolation under rational decision-making. In contrast, the results highlight the importance of considering informational redundancy in noisy, information-saturated contexts (Drover et al., 2018; Steigenberger & Wilhelm, 2018). This contribution aligns with recent calls to refine signalling theory by incorporating socio-cognitive dynamics, signalling interactions and investor heuristics to better understand decision-making in complex environments (Connelly et al., 2011; Zahera & Bansal, 2018). Secondly, this study presents an empirical setting to explore how institutional and cultural factors shape signal interpretation. In France, regulatory incentives such as intellectual property (IP) protection amplify the salience of structural capital signals such as patents and trademarks, whereas cultural emphasis on elite education prioritizes human capital signals such as degrees from prestigious institutions (Bourdieu, 1979; Hall, 2002; Maclean et al., 2007). In other words, this article is a strong candidate for understanding how the interplay between competitive pressure, regulatory incentives and cultural expectations shapes the way investors interpret, prioritize and validate signals.

The article is structured as follows. The next part reviews the literature on signalling theory for early-stage ventures' resource acquisition and signal dimensions and interactions in the French VC context. We then describe the data and methods, followed by a presentation of key findings. The final part concludes by discussing implications for entrepreneurship, signalling and venture financing literature and analysing this study's limitations.

Theoretical framework and hypothesis

Signalling in new technology ventures' early-stage financing in a noisy environment

While the entrepreneurship literature acknowledges the role of financial resources for new technology ventures' survival and growth (Cooper et al., 1994; Klein et al., 2020), securing funding from external investors remains a challenge, with investors encountering difficulty in predicting which teams will succeed (Ghassemi et al., 2015), notably due to the lack of past financial results (Ko & McKelvie, 2018; Subramanian et al., 2022) and inherent information asymmetries with the founding team. Therefore, investors rely on quality signals to mitigate these asymmetries, with signalling theory particularly relevant in uncertain entrepreneurial processes (Bafera & Kleinert, 2023).

Signalling theory posits that two parties consciously take steps to reduce asymmetric information and perceived uncertainty, primarily through the signals they emit (Spence, 1974, 2002). This theory is applied across disciplines to address social selection issues where perfect information is lacking (Colombo, 2021; Connelly et al., 2011). In entrepreneurship, certain signals have a significant influence on reducing potential investors' uncertainty. These signals address the quality of a venture's economic activities (activity-related uncertainty, i.e., what the business does) and its ability to execute these activities effectively (firm-related uncertainty, i.e., the team and organization) (Bafera & Kleinert, 2023). Firm-related attributes refer to characteristics that demonstrate project quality. This includes assessing the firm's legitimacy through structural capital such as patents (Zhou et al., 2016) or trademarks (Block et al., 2014; Llerena & Millot, 2020) and team credibility through human capital¹ (Huang et al., 2022). These attributes are known as objective and indirect firm-related quality signals that influence early-stage financing (Gompers et al., 2020; Svetek, 2022).

However, in information-saturated early-stage financing contexts, where many ventures compete for funding and few will survive (Plummer et al., 2016), the assumption of the traditional signalling theory that rational investors process signals in isolation to evaluate ventures potential (Bergh et al., 2014), is increasingly challenged (Steigenberger & Wilhelm, 2018; Tumasjan et al., 2021; Vanacker et al., 2020). In reality, ventures bundle multiple signals into portfolios (Plummer et al., 2016), while investors with limited capacity to process

them all face cognitive overload (Betsch & Glöckner, 2010). This is particularly true for the digital industry, where ventures endeavor to build investor trust by sending alternative signals that highlight startup potential (Bafera & Kleinert, 2023). These dynamics raise questions about how investors interpret such signal portfolios and whether existing signalling theory can adequately capture their decision-making. Understanding the contrasting effects of focal signals in specific settings is key for signalling research (Connelly et al., 2011; Paruchuri et al., 2021), as neglecting signal interactions or overlooking the institutional or regulatory environments that shape signal interpretation can lead to overstated signal effectiveness or even misinterpretation. From a practical perspective, investors who solely rely on traditional signal typologies may miss subtle but critical cues that distinguish high-potential ventures (Gompers et al., 2020).

To better account for these challenges, the socio-cognitive perspective of signalling theory provides a more realistic alternative to the rational actor assumption, acknowledging that rationally bounded investors (Simon, 1991) simplify decision-making through heuristic shortcuts when confronted with complex information (Zahera & Bansal, 2018). Specifically, Drover et al. (2018) argue that in information-saturated environments, portfolios of overlapping signals (i.e., those signalling the same hidden attribute) increase cognitive overload (Betsch & Glöckner, 2010). Therefore, each additional signal of similar intensity and dimension may add limited new insight, potentially introducing cognitive dissonance when an excess of similar signals creates informational redundancy rather than strengthening the evaluation process. For example, in this emerging area of signalling research, Steigenberger and Wilhelm (2018) find that investors perceive multiple signals from the same domain as redundant rather than complementary in high-noise crowdfunding contexts, reducing investment attractiveness perceptions. Similarly, Courtney et al. (2017) demonstrate that overlapping signals can either enhance or diminish one another.

Despite these advances, debates persist regarding how redundant signals interplay with investors' decision-making in early-stage venture contexts. To the best of our knowledge, no study has empirically examined how costly indirect firm-related signals of similar dimension and strength interact in noisy early-stage financing contexts. We argue that refining this understanding requires accounting for institutional, regulatory, and cultural contingencies. Furthermore, as this study focuses on early-stage funding, it is important to acknowledge that the nature and salience of signals may evolve as ventures progress through different development stages (Cavallo et al., 2019; Ko & McKelvie, 2018). For instance, in later stages, new technology ventures are more likely to display advanced performance metrics such as efficient user base growth (Bessagnet & Abreu, 2025) or structural capital

¹ Research demonstrates that founding team characteristics affect VC access strongly (Gompers et al., 2020; Roure & Keeley, 1990). Scholars investigate demographic attributes (Eisenhardt & Schoonhoven, 1990) and human capital traits such as functional backgrounds (Ratzinger et al., 2018), educational backgrounds (Nigam et al., 2020) and previous experience (Ko & McKelvie, 2018). Since most ventures are driven by groups rather than individuals (Klotz et al., 2014), the focus is generally on teams that are responsible for formulating and executing strategies.

(Zhou et al., 2016) reducing reliance on indirect quality signals to attract VC funding. Conversely, reliance on human capital signals might be more pronounced in early-stage contexts due to the absence of such metrics (Subramanian et al., 2022). Therefore, stage-based heterogeneity in VC demand is an important contextual factor in this study, as it can shape signal portfolio effectiveness. The next section presents the context of this study and its implications for signalling theory in early-stage VC financing.

Hypotheses development

This section introduces a framework for categorizing new technology ventures based on signalling configurations and expected funding outcomes. We then establish a baseline by examining how individual legitimacy and credibility signals influence early-stage financing (Hypotheses 1a–1d). Finally, we investigate interaction effects and potential redundancies that arise when signals of similar strength and dimension co-occur, particularly in noisy decision-making environments (Hypotheses 2a and 2b).

This framework classifies new technology ventures into three groups based on the presence and configuration of signals covering (1) *no signal*, (2) *distinct signals*, where ventures possess at least one signal in each dimension but avoid redundancy and (3) *redundant signals*, where multiple signals accumulate within the same dimension. While this approach organizes ventures into clear categories, it involves transforming continuous variables into binary forms, potentially reducing statistical granularity. The classification and expected funding outcomes are summarized in Table 1.

Baseline evidence of signalling quality through founding team credibility and firm legitimacy for early-stage financing

In entrepreneurship literature, founders' human capital characteristics such as education levels or prestigious institutional affiliations are considered to be indirect and weak firm-related quality attributes that signal team credibility to investors (Packalen, 2007), reducing uncertainty about firm's quality (Beckman et al., 2007; Colombo & Grilli, 2005).

The human capital literature in entrepreneurship suggests that more educated founding teams can attract financial support more effectively as education enhances perceived credibility (Esen et al., 2023). Higher education signals traits such as risk-taking, proactive behavior, resilience, adaptability and the ability to capitalize on opportunities (Becherer & Maurer, 1999; Shane & Venkataraman, 2000; Wu et al., 2023). It also equips founders with technical skills for innovation and provides access to non-financial resources essential to early growth (Beckman et al., 2007; Marvel & Lumpkin, 2007). Therefore, we propose the following hypothesis:

H1a: *Founding teams with higher education levels are associated with higher VC funding.*

This study also extends the focus beyond founding teams' education by considering the prestige of the institutions attended. Degrees from elite institutions serve as weak indirect firm-related signals that convey information about founding teams' capabilities, persistence, and decision-making (Bourdieu, 1979; Hong & Page, 2001). Such degrees also enable access to networks that can facilitate financing, as investors may view founders from elite institutions as more likely to lead successful ventures (Huang & Knight, 2017; Plummer et al., 2016; Semrau & Werner, 2014; Shane & Cable, 2002). Therefore, we propose the following hypothesis:

H1b: *Founding teams with degrees from prestigious institutional networks are associated with higher VC funding.*

Research in entrepreneurship shows that firms' initial innovation strategy, particularly involving IP outcomes of innovation processes (Rosenbusch et al., 2011), impacts revenue growth (Helmers & Rogers, 2011; Power & Reid, 2021; Suh & Hwang, 2010) and sends a strong, indirect firm-related legitimacy signal to investors in emerging industries within developed countries (Islam et al., 2018) and in developed industries within emerging markets (Xiao et al., 2024).

Entrepreneurial studies find that patents increase firms' fundraising chances and improve market valuation (Audretsch et al., 2012; Block et al., 2014). For example, Baum and Silverman (2004) and Hsu and Ziedonis (2013), respectively, find that biotechnology and semiconductor startups with

Table 1. Signal configurations and expected outcomes for new technology ventures

Category	Configuration	Hypothesis	Expected funding
(1) No signal	(0-0)	Absence of signals	Low
(2) Distinct signals	(1-0; 0-1; 1-1)	Balanced dynamics with moderate signaling (HC = 1 or SC = 1)	High
(3) Redundant signals	(2-0; 0-2; 2-1; 1-2; 2-2)	Potential diminishing returns due to excess signal accumulation of similar intensity and strength	Moderate

Source: own elaboration.

patent filings attract more VC funding, as patents protect IP and signal quality to investors. As observed by Hall (2002), even with tax incentives, external research and development (R&D) financing is costly, particularly for small, innovative firms. These barriers emphasize the importance of strong signals such as patents to reduce perceived risks and attract funding in highly uncertain environments. Based on this understanding, we propose the following hypothesis:

H1c: *Founding teams with patents are associated with higher VC funding.*

In addition, trademarks are a strong and indirect firm-related legitimacy signal that indicates growth potential (Helmers & Rogers, 2011; Suh & Hwang, 2010). Trademark registration enhances performance by protecting original innovations, particularly in tech sectors where copyrights can improve efficiency and success (Suh & Hwang, 2010). Trademarks also secure exclusive rights that strengthen brand image and economic returns (Sandner & Block, 2011), influencing investors' decisions. For instance, VCs often encourage startups to register trademarks (De Vries et al., 2017). However, the number and diversity of trademark applications exhibit an inverted U-shaped effect on valuation, with diminishing returns in later rounds (Block et al., 2014). Overall, like patents, trademarks provide strong signalling and protective value, helping startups secure early-stage funding. Therefore, we propose the following hypothesis:

H1d: *Founding teams with trademarks are associated with higher VC funding.*

Signal interactions in new technology ventures' early-stage financing

This section examines how costly and indirect signals of similar dimensions and strength interact in noisy environments. The socio-cognitive perspective of signalling theory (Drover et al., 2018) argues that investors have limited capacity to process multiple signals simultaneously, leaving them vulnerable to cognitive overload in noisy environments—a cognitive cost that is associated with interpreting abundant information (Betsch & Glöckner, 2010; Fischer & Reuber, 2007). Given the information-saturated nature of early-stage financing (Plummer et al., 2016; Tumasjan et al., 2021) in which junior partners often manage deal sourcing and evaluation (Gompers et al., 2020), cognitive overload is intensified as scouts who are typically less specialized than senior professionals process high volumes of signals and investment opportunities. In this context, we argue that ventures' portfolios of overlapping signals (i.e., where each signal addresses the same hidden attribute) increase cognitive costs as each additional signal adds minimal new

information. Rather than reinforcing confidence, redundant signals can create confusion and complicate evaluations, diminishing the impact on funding decisions (Bafera & Kleinert, 2023; Plummer et al., 2016). Consistent with the principle of marginal utility applied to signalling theory wherein, as more signals of the same type and strength are added, each contributes less to decision-making clarity. Rather than enhancing the evaluation, an overload of similar signals can yield diminishing returns, decreasing the likelihood of investment (Betsch & Glöckner, 2010).

In the case of costly and strong indirect signals that legitimize firm quality, patents and trademarks are candidates for informational redundancy, as both convey the firms' innovation strategy. Patents and trademarks represent exclusive IP rights that secure competitive advantage and market position (Block et al., 2014). When held individually, each signal value by protecting startups' IP rights related to product exploitation and reflecting innovation capacity. However, while patents already provide robust information about IP protection, once a strong signal is established, the incremental benefit of another from the same dimension decreases, offering little new value. This redundancy may even introduce cognitive dissonance wherein scouts-investors faced with patents and trademarks may interpret this combination as an excessive emphasis on IP without meaningful differentiation. This can create an impression of overemphasis on IP rather than enhancing credibility, potentially at the expense of other critical aspects of early-stage success in digital industry such as product-market fit or user base growth (Bessagnet & Abreu, 2025). Consequently, this redundancy can complicate rather than clarify VC decision-making, as potential investors may perceive overlapping signals as cognitively taxing. Therefore, we propose the following hypothesis:

H2a: *Founding teams with both patents and trademarks are associated with lower VC funding.*

Costly and weak indirect signals such as high education and degrees from elite institutions are often used to validate the credibility of a startup's founding team (Bourdieu, 1979; Fischer & Reuber, 2007; Hsu, 2007). While rhetorical in nature (Steigenberger & Wilhelm, 2018; Tumasjan et al., 2021), such signals can shape investor perceptions of managerial capabilities (Spence, 2002). Indeed, high educational attainment and prestigious institutional affiliations tap into the same human capital dimension—namely the team's quality—reinforcing the team's credentials. However, following the principle of marginal utility, once a certain high educational level is established, additional similar signals such as a degree from a prestigious institution may yield diminishing returns. This aligns with Pinelli et al. (2020), who demonstrate that adding more human capital to a team does not necessarily lead to greater

success. Rather than enhancing differentiation, excess education—rhetorical credentials may signal conformity, potentially diminishing perceived adaptability to address early-stage uncertainties.

Again, this redundancy may introduce cognitive dissonance among scouts/investors who could interpret abundant academic qualifications as an over-reliance on pedigree rather than practical entrepreneurial skills. This can facilitate the perception that a team emphasizes formal education over qualities that are crucial for early-stage success such as resilience or risk tolerance (Becherer & Maurer, 1999; Esen et al., 2023). This perception may subsequently generate cognitive friction, leading investors to consider overlapping human capital signals as superficial or counterproductive. Therefore, we propose the following hypothesis:

H2b: *Founding teams with both high educational levels and degrees from prestigious institutional networks are associated with lower VC funding.*

Methods

We construct a dataset including organizational and individual-level data for new technology ventures in the digital industry, differentiating between those backed by VCs and those without funding to test our hypotheses. Access to the datasets for replicability is available from the corresponding author upon request. Table 2 lists the variables, definitions, and sources. The data collection procedure is described below prior to presenting the French VC context and its implications for signalling theory.

Table 2. Variable definitions and sources

Variable name	Description	Data source
<i>Dependent variable</i>		
Capital raised (log)	Natural logarithm of the amount of investment provided by VC investors in the first round (€).	Crunchbase, BPI
<i>Independent variables</i>		
High education level	Dummy variable. A value of 1 if at least one founder of the new technology venture possesses a PhD or an MBA, and 0 otherwise.	LinkedIn
Prestigious institutional network	Dummy variable. A value of 1 if at least one founder of the new technology venture possesses a degree from a prestigious institutional network, and 0 otherwise.	LinkedIn
Trademark	Dummy variable. A value of 1 if the new technology venture reported at least a trademark, and 0 otherwise.	INPI
Patent	Dummy variable. A value of 1 if the technology digital venture reported at least a patent, and 0 otherwise.	INPI
<i>Control variables</i>		
<i>Team level</i>		
Previous STEM	Dummy variable. A value of 1 if at least one start-up team member holds a master's degree or a doctorate in a STEM field, to control for technical expertise, and 0 otherwise.	LinkedIn
Previous manager	Dummy variable. A value of 1 if at least one start-up team member has previously worked in a managerial capacity, to control for managerial expertise, and 0 otherwise.	LinkedIn
Previous founder	Dummy variable. A value of 1 if at least one start-up team member has prior founding experience, to control for entrepreneurial expertise, and 0 otherwise.	LinkedIn
Previous working experience	Maximum number of years of work experience of a start-up team member. Each new technology venture in our sample is assigned the highest score associated with any of its start-up team member.	LinkedIn
Network size	Logarithm sum of start-up team LinkedIn digital networks.	LinkedIn
Gender	Dummy variable. A value of 1 if the founder is male, 0 for female.	LinkedIn
<i>Firm level</i>		
Accelerator	Dummy variable. A value of 1 if the new technology venture has participated in an accelerator programme and 0 otherwise.	Crunchbase, BPI
Firms' assets	Number of total assets of the firms.	INPI
Size	Number of start-up team members.	LinkedIn
Founding Years	Dummy variables for each year from 2010 to 2018. Each variable takes the value 1 if the firm was created in the corresponding year, and 0 otherwise. This control for time-specific effects across the nine-year period.	Crunchbase, BPI
Industry	Nine industry dummies that take value 1 if the firm is operating in (1) business intelligence analytics, (2) customer relationship management, (3) developers software infrastructure, (4) education human resources, (5) finance legal insurance, (6) logistics supply chain, (7) marketing and media, (8) productivity collaboration, and (9) retail ecommerce.	Crunchbase, BPI

Source: own elaboration.

Data collection procedure and sample construction

Firstly, this study uses Crunchbase and Bpifrance databases for organization-level data collection. Crunchbase tracks innovative firms globally, capturing financing activities, business models, and organizational details such as founding dates and headquarters. Bpifrance is a national investment bank that provides records of innovative French-based firms through its portal.² This database includes headquarters' locations, founders' names, fundraising stage (if any), business models and founding dates. While BPI France tracks various financing instruments, including public subsidies, our analysis focuses on VC fundraising activities that impact equity structures. Accordingly, the main dependent variable (*capital raised*) captures equity-based VC investments. Data were collected in March 2020.

We followed a multistep approach to construct the sample. Firstly, we extracted all firms listed in the BPI France portal that matched our definition of a new technology venture (i.e., an early-stage technology-based firm operating within the digital industry with a digital business model). A digital business model is a firm's core logic and strategic choices for creating, delivering, and capturing value (Shafer et al., 2005) using digital technologies (Nambisan, 2017), including digital-centric businesses such as software-as-a-service (SaaS), digital marketplaces and cloud-based services. This yielded an initial list of firms headquartered in France. Secondly, we cross-referenced the Bpifrance data with Crunchbase to enrich the dataset with additional organizational details, including funding histories, business models and founder information, merging firms that appeared in both databases to avoid duplicates and ensure consistency across variables. When encountering discrepancies (e.g., founding dates or funding amounts), we prioritized Crunchbase data. Thirdly, we applied several inclusion criteria to refine the sample. Each venture in our sample is (1) founded between 2010 and 2018, ensuring ventures were operational for at least two years to capture signalling dynamics consistently; (2) headquartered in the Greater Paris Metropolis, a setting with unique features for exploring the link between geography, signal quality, and fundraising (France Digitale, 2024; Milosevic, 2018); (3) independent; and (4) using a digital business model for innovations. This process yielded a sample of 516 new technology ventures. For criteria (3) and (4), we manually reviewed each firm for hardware-based business models and parent firm dependency. This excluded 59 ventures (48 hardware-based, of which 29% fundraised, and 11 subsidiaries, of which 18% fundraised).

Ultimately, 63 of the initial 516 firms (48 developing hardware devices, 11 dependent on a parent company, and 4 lacking fundraising data) were excluded. Regarding the

four excluded ventures (<1% of the population), a qualitative review revealed no significant differences with the ventures included, indicating that their inclusion would not alter results. This process yielded a sample of 453 new technology ventures, each evaluated for early-stage VC investments, excluding government subsidies and non-dilutive funding. Table 3 presents the ventures' general statistics and sector distribution.

Secondly, this study used LinkedIn and the French public INPI database to obtain data on (individual level) human capital and (organizational level) structural capital for the 453 ventures in our sample. LinkedIn was used to collect founders' backgrounds, including education, work experience, biodata, and roles within ventures. We chose LinkedIn because it provides granular information on professional trajectories, which is valuable for entrepreneurial studies (Gasiorowski & Lee, 2022; Reese et al., 2020). While we acknowledge potential biases arising from the public nature of LinkedIn data and performativity and self-presentation tendencies, we assume that these limitations do not undermine overall data reliability, given its widespread adoption and validation in professional and academic contexts. Finally, we used INPI to manually collect information on the number of trademarks and patents held by each venture, identified through their unique SIREN number. Notably, we only considered trademarks or patents acquired before any funding dates.

French VC context and its implications for signalling theory

The French VC environment offers an interesting setting to explore early-stage financing signalling dynamics. Firstly, it is among the most dynamic VC markets in Europe (Milosevic & Fendt, 2016; Testa et al., 2024) and concentrated in a few

Table 3. Distribution of sample: new technology ventures by industry classification

Industry	Number of firms	Percentage
Business intelligence analytics	40	8.8
Customer relationship management	51	11.3
Developers software infrastructure	53	11.7
Education human resources	55	12.1
Finance legal insurance	49	10.8
Logistics supply chain	45	9.9
Marketing and media	70	15.5
Productivity collaboration	52	11.5
Retail ecommerce	38	8.4
Total	453	100

Source: own elaboration.

² <https://lehub.web.bpifrance.fr/search>

industries and geographies, with Paris accounting for most activity. Between 2016 and 2020, the digital industry, SaaS- and marketplace-based firms accounted for 55% of total capital raised in France, 75% of fundraising rounds in Paris and over 85% of total investment value (France Digitale, 2024). Another characteristic is the deep intertwining of (business) French VC activities with the (state) public funding mechanisms (Maclean et al., 2007). Public agencies such as BPI France play a significant role in financing innovation, contrasting with countries like the United States (US) and the United Kingdom, where private institutional investors dominate (Köhn, 2018). Between 2007 and 2021, the French government invested €17.1 billion in innovation through the BPI, making it the largest public investor in Europe (Testa et al., 2024). This dynamic facilitates signalling incentives that may require ventures to appeal to private investors as well as governmental priorities (Shane, 2009).

Secondly, France's regulatory framework significantly shapes IP signalling dynamics. Strong protections for IP rights and targeted incentives, such as the French Patent Box regime (Hall, 2002) or French Tech Mission 'deep-tech programmes' (Taupin et al., 2024), encourage ventures to acquire patents and trademarks as core elements of growth and differentiation. This regulatory context establishes an environment in which structural capital signals influence investor decision-making strongly, offering insight into how this context modulates the relative weight of these signals (Meuleman & De Maeseneire, 2012; Santoleri et al., 2024).

Thirdly, elite educational credentials (e.g., *grandes écoles*) have deep cultural and economic significance in France (Bourdieu, 1979). According to O'Brien (2023), based on Schradie's analysis of the VC-backed French Tech Next40 companies, more than 93% of these firms have at least one founder who graduated from a *grande école*. As a result, investors may overweight educational credentials as proxies for founder quality and reliability. This emphasis risks crowding out the perceived value of other quality indicators and highlights how cultural expectations shape human capital signals in investor decision-making.

Finally, unlike the US market, which is dominated by private institutional investors, the French context is marked by significant public sector participation and a regulatory framework that imposes additional layers of accountability and strategic signalling (Hall, 2002; Testa et al., 2024). Therefore, ventures must optimize human and structural capital signals to rise above the noise. Regulatory incentives impose pressure to formalize structural capital signals, amplifying their relevance to investor perceptions. At the same time, the cultural weight of founder credentials may cause investors to prioritize educational signals over performance-based indicators. These interactions imply that signal salience and redundancy may be contextually

driven phenomena, where competitive pressures, regulatory incentives, and cultural expectations shape how signals are interpreted, prioritized, and validated. This offers a fertile context for refining and expanding signalling theory by considering how institutional differences influence the design, interpretation, and efficacy of signalling mechanisms in venture financing and the potential detrimental effects of informational redundancy when signals of incongruent valences overlap.

Measures

Dependent variable

The dependent variable is the total amount of funding acquired by a new technology venture in its first round, measured in euros (€). We apply logarithmic transformation and ventures without funding during the observation period that are assigned a nominal value of zero. To avoid censoring the fundraising variable, we introduce a small constant to all entries. This adjustment enables us to maintain information continuity for all new technology ventures, regardless of their fundraising success. Consequently, the adjusted *logFundraising* variable spans from 0 to 16.524.

Independent variables

This study operationalizes four key independent variables encompassing *high education level*, *prestigious institutional network*, *trademark* and *patent*, to examine their influence on new technology ventures' success.

High education level is the academic education level within the startup team, specifically identifying founders that hold a PhD or MBA. This metric assumes that higher educational achievements, particularly PhDs or MBAs, signify superior capabilities that are correlated with a higher likelihood of securing funding and valuations (Hsu, 2007; Jin et al., 2017). A value of 1 is assigned to the firm if at least one founder possesses such qualifications and 0 otherwise.

Prestigious institutional network is a human capital characteristic embedded within venture team members' elite network affiliations, as conceptualized by Bourdieu (1979). Degrees from prestigious institutions are weak indirect quality signals that reduce information asymmetry for VCs by conveying competence, persistence, and access to influential networks (Ferrary, 1999; Nigam et al., 2021). These institutions are valued by VCs for reputation, selectivity, and alumni influence, which enhance the perceived credibility and potential success of ventures led by their graduates. In France, prestigious institutions are *grandes écoles*,

recognized for selective admission, high academic standards, and strong alumni networks that often lead to decision-making roles in corporate and public sectors (Maclean et al., 2007; O'Brien, 2023). This institutional prestige aligns with the halo effect observed in decision-making, where elite education extends to expectations of superior performance and trustworthiness (Stern et al., 2014). This variable combines the top 10 universities worldwide (Academic Ranking of World Universities [ARWU] 2022 ranking) and the best French business and engineering schools (Figaro Étudiant Ranking 2023). The ARWU ranking is less suited to capturing French entrepreneurial elite due to the weight and attractiveness of *grandes écoles*, which are poorly represented in ARWU-type international rankings based on Clarivate bibliometric data. The Figaro Étudiant ranking integrates the quality of faculty recruitment, industry ties, and graduate salaries. A value of 1 is assigned if at least one founder holds a degree from a prestigious institutional network and 0 otherwise.

Finally, *trademark* and *patent* are proxies for ventures' commitment to IP protection, reflecting initial innovation strategy and subsequent market and technological legitimacy, respectively. IP protection denotes voluntary, observable, strong, and cost-intensive efforts to secure unique market positions. These variables underscore the strategic use of IP to attract VC by signalling innovation and market potential (Audretsch et al., 2012; Block et al., 2014). Each venture is assessed for trademark and patent filings as indicators of innovative capacity and intent. A value of 1 is assigned if the venture reported at least one trademark (0 otherwise) and 1 if it reported at least a patent (0 otherwise).

Control variables

This study introduces several firm- and team-level control variables into the analytical framework that may influence new technology ventures' success.

Gender quantifies the proportion of male and female founders within the team, offering insights into gender diversity and funding likelihood (Dai et al., 2019). A binary coding is used, assigning 1 for male, 0 for female.

Previous STEM, *previous manager*, and *previous founder* are operationalized using a binary indicator that assigns 1 if at least one team member has the specified background. We differentiate entrepreneurial, managerial, and technical competencies referencing Chandler and Jansen (1992). *Previous STEM* is defined as holding a master's degree or a doctorate in a STEM field to control for technical expertise. *Previous manager* applies if a team member worked in a managerial role. *Previous founder* applies if a team member has prior founding experience, indicating entrepreneurial expertise (Hsu, 2007).

Previous working experience is defined as the maximum years of professional experience among team members, reflecting industry and functional knowledge, a factor for attracting investments and navigating early-stage challenges (Subramanian et al., 2022).

Network size represents social capital, measured through the cumulative size of founders' LinkedIn networks (Smith et al., 2017). To normalize the distribution and reduce the outlier impact, we use the logarithm of this aggregate measure, following Nigam et al. (2020).

Accelerator is a binary variable coded 1 if the venture participated in an accelerator programme and 0 otherwise; we use participation as an indicator of access to resources and mentorship linked to venture performance (Hallen et al., 2020).

Firms' assets is the cumulative number of firms' intellectual resources, including patents and trademarks. Referencing Bertoni et al. (2011), who use the cumulative number of patents granted to the focal firm, we adopt a quantitative approach consistent with the signalling logic to capture visible resource endowment as perceived by investors, rather than its accounting valuation.³

Size is the number of founders in the team as a proxy. This variable addresses the potential advantages of larger teams, which may be perceived as more capable of delivering business plans (Harrison & Klein, 2007).

Industry dummies. To account for industry-specific dynamics, we introduce dummy variables for nine sectors relevant to our context. Each venture is classified into one sector, with the dummy taking a value of 1 if the venture operates in that sector, 0 otherwise. The sectors are (1) business intelligence analytics, (2) customer relationship management, (3) developers software infrastructure, (4) education human resources, (5) finance legal insurance, (6) logistics supply chain, (7) marketing and media, (8) productivity collaboration, and (9) retail ecommerce, providing a comprehensive overview of the industry effects on venture success.

Founding years. We control for year fixed effects (FEs) by creating nine dummies (2010–2018).

Table 4 presents descriptive statistics of all variables (means, standard deviation [SD], minimum, maximum). To assess the economic significance of our findings, note that *logFundraising* ranges from 0 to 16.5, with a mean of 9.21 and a SD of 6.60. For example, a coefficient of 1 for any independent variable corresponds to an approximate 15% SD increase in *logFundraising*.

³ While we apply a quantitative measure to reduce valuation ambiguity and enhance comparability across heterogeneous ventures, future research could explore monetary valuations where reliable data are available. We thank an anonymous reviewer for highlighting this point.

Table 4. Descriptive statistics

Variables	Obs	Mean	SD	Min	Max
<i>Dependent variable</i>					
Capital raised (log)	453	9.210	6.599	0	16.524
<i>Independent variables</i>					
High education level	453	0.272	0.445	0	1
Prestigious institutional network	453	0.528	0.500	0	1
Trademark	453	0.486	0.500	0	1
Patent	453	0.097	0.296	0	1
<i>Control variables</i>					
<i>Team level</i>					
Previous STEM	453	0.603	0.490	0	1
Previous manager	453	0.892	0.311	0	1
Previous founder	453	0.333	0.472	0	1
Previous working experience	453	17.210	8.897	1	47
Network size (log)	453	8.474	0.902	4.369	10.819
Gender	453	0.938	0.184	0	1
<i>Firm level</i>					
Accelerator	453	0.064	0.245	0	1
Firms' assets	453	0.909	1.270	0	8
Size	453	2.333	0.873	1	5
2010	453	0.049	0.215	0	1
2011	453	0.062	0.241	0	1
2012	453	0.084	0.278	0	1
2013	453	0.113	0.316	0	1
2014	453	0.126	0.332	0	1
2015	453	0.152	0.360	0	1
2016	453	0.183	0.387	0	1
2017	453	0.152	0.360	0	1
2018	453	0.079	0.271	0	1
Business intelligence analytics	453	0.088	0.284	0	1
Customer relationship management	453	0.113	0.316	0	1
Developers software infrastructure	453	0.117	0.322	0	1
Education human resources	453	0.121	0.327	0	1
Finance legal insurance	453	0.108	0.311	0	1
Logistics supply chain	453	0.099	0.299	0	1
Marketing media	453	0.155	0.362	0	1
Productivity collaboration	453	0.115	0.319	0	1
Retail ecommerce	453	0.084	0.278	0	1

Source: own elaboration.
SD, standard deviation.

Econometric approach

To analyze the factors influencing fundraising, our primary model is an ordinary least squares (OLS) regression on the log-transformed dependent variable *logFundraising*,

facilitating straightforward interpretation. The baseline econometric model is as follows:

$$\begin{aligned}
 \text{LogFundraising}_i = & \alpha + \beta_1 \cdot \text{HighEducation}_i \\
 & + \beta_2 \cdot \text{PrestigiousInstitutionalNetwork}_i \\
 & + \beta_3 \cdot \text{Trademark}_i + \beta_4 \cdot \text{Patent}_i \\
 & + \delta_1 \cdot (\text{HighEducation}_i \cdot \\
 & \text{PrestigiousInstitutionalNetwork}_i) \\
 & + \delta_2 (\text{Trademark}_i \cdot \text{Patent}_i) \\
 & + \gamma \cdot X_i + \varphi \cdot Z_i + \varepsilon_i,
 \end{aligned} \tag{1}$$

where the dependent variable, *LogFundraising_i* is the natural logarithm of the total funding acquired by a venture. The model includes the independent variables *HighEducation_i*, *Prestigious InstitutionalNetwork_i*, *Trademark_i* and *Patent_i*, with interaction terms. *X_i* represents control variables capturing the previously described team and firm characteristics. The model also includes sector FEs, *Z_i* includes time FEs to account for temporal variations (2010–2018) and ε_i is the error term. To address stage-based differences across ventures, we control for venture age and firm assets as proxies for venture maturity and resource endowments. However, ventures with patents and trademarks may not only signal greater legitimacy but also reflect a more advanced stage of development (Zhou et al., 2016), which is discussed as a limitation.

Results

Descriptive results

Table 5 presents the bivariate correlations between the key variables. All correlations are well below the 0.7 threshold, and the variance inflation factors for all independent variables are below 3, indicating that multicollinearity is not a concern.

Baseline findings

Table 6 presents the outcomes of the stepwise approach used in this study. Initially, control variables are added to Model 1. Subsequently, the two weak signals (*high education level* and *prestigious institutional network*) and two strong signals (*patent* and *trademark*) are added, followed by the four signals and their interaction terms. The OLS with time FEs (years) and sector FEs (sector categories) is employed where the dependent variable in each model is *logFundraising*.

The results reveal that *previous founder* (1.932, $p < 0.05$), *network size* (1.684, $p < 0.001$) and *accelerator* (2.753, $p < 0.05$) have a significant positive association with VC funding (Model 1).

Table 5. Correlation table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Capital raised log	1													
2 High education level	0.32**	1												
3 Prestigious institutional network	0.27***	0.21***	1											
4 Trademark	0.23***	0.14**	0.11*	1										
5 Patent	0.16***	0.13**	0.06	0.05	1									
6 Previous STEM	0.10*	0.01	0.15**	0.06	0.02	1								
7 Previous manager	0.02	-0.01	0.05	0.05	0.04	0.02	1							
8 Previous founder	0.19***	0.14**	0.08	0.02	0.02	0.05	0.08	1						
9 Previous working experience	0.07	0.05	-0.02	-0.03	0.07	-0.01	0.14**	0.15**	1					
10 Network size (log)	0.30***	0.12**	0.20***	0.11*	0.05	0.10*	0.16***	0.17***	0.03	1				
11 Gender	0.05	0.04	0.03	-0.06	0.06	0.06	-0.05	0.04	0.04	0.04	1			
12 Accelerator	0.19***	0.14**	0.06	-0.05	0.06	0.11*	0.06	0.04	-0.02	0.12**	-0.01	1		
13 Size	0.19***	0.17***	0.27***	0.12*	0.05	0.33***	0.25***	0.25***	0.08	0.45***	-0.12**	0.14**	1	
14 Firms' assets	0.20***	0.17***	0.11*	0.57***	0.28***	-0.02	0.06	0.01	0.06	0.06	-0.07	-0.05	0.07	1

Notes: $N = 453$; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; determinant of the correlation matrix: 0.187. Source: own elaboration.

According to the anticipated outcomes, *high education level* (3.206, $p < 0.001$) and *prestigious institutional network* (2.174, $p < 0.001$) have positive effects on VC funding (Model 2). Additionally, *patent* (2.324, $p < 0.05$) and *trademark* (2.266, $p < 0.05$) have a positive impact on the VC funding secured by new technology ventures (Model 3). In Model 4, *high education level* (3.035, $p < 0.001$), *prestigious institutional network* (2.115, $p < 0.001$), *patent* (1.927, $p < 0.1$) and *trademark* (1.977, $p < 0.05$) have positive and significant effects on VC funding. These findings align with our predictions and support hypotheses H1a–H1d, increasing our confidence in subsequent hypotheses testing.

To understand how costly indirect firm-related signals of varying intensities and similar valence interact in the noisy environment of early-stage financing, Table 6 also encompasses the interactions between weak (*high education level* and *prestigious institutional network*) and strong (*patent* and *trademark*) signals. In terms of the moderating impacts, H2a posits that when new technology ventures hold both patents and trademarks, it could reduce the financing obtained from investors, which is confirmed (-4.543 , $p < 0.05$) in

Model 5. This adverse moderating influence is illustrated in Figures 1 and 3.

Hypothesis H2b suggests that when new technology ventures have both *high education level* and *prestigious institutional network*, it may decrease the funding received from investors. This hypothesis is corroborated (-4.173 , $p < 0.05$) in Model 5. We illustrate this negative moderating effect in Figures 2 and 4.

Robustness tests

Endogeneity and selection bias are concerns in our study, particularly due to the non-random nature of VC funding and potential sorting effects. To address these, we implement robustness tests to confirm the stability of our results and credibility of interpretations.

Firstly, we conduct a two-stage residual inclusion (2SRI) analysis as a primary robustness test (Terza et al., 2008). Presented in Table 7, this approach addresses endogeneity in non-linear models without requiring a traditional instrumental variable. The second-stage results (Model 6) demonstrate that the residual term is not statistically

Table 6. Results of OLS with time fixed effects (years) and sector fixed effects (categories of sectors)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Theoretical					
High education level (E)		3.206*** (0.669)		3.035*** (0.664)	5.744*** (1.074)
Prestigious institutional network (N)		2.174*** (0.598)		2.115*** (0.592)	3.025*** (0.659)
Trademark (T)			2.266** (0.714)	1.977** (0.686)	2.468*** (0.700)
Patent (P)			2.324** (1.024)	1.927* (0.984)	4.666** (1.429)
E*N					-4.173** (1.313)
T*P					-4.543** (1.853)
Controls					
Previous STEM	0.726 (0.641)	0.804 (0.616)	0.584 (0.634)	0.672 (0.611)	0.731 (0.602)
Previous manager	-1.118 (0.977)	-0.817 (0.936)	-1.201 (0.965)	-0.905 (0.927)	-0.891 (0.912)
Previous founder	1.932** (0.641)	1.644** (0.614)	1.957** (0.632)	1.680** (0.608)	1.435** (0.602)
Previous working experience	-0.001 (0.035)	0.007 (0.033)	0.005 (0.034)	0.012 (0.033)	0.009 (0.033)
Network size (log)	1.684*** (0.371)	1.491*** (0.356)	1.614*** (0.366)	1.439*** (0.352)	1.502*** (0.347)
Gender	2.474 (1.606)	1.964 (1.536)	2.150 (1.587)	1.713 (1.522)	1.887 (1.498)
Accelerator	2.753** (1.203)	1.772 (1.160)	2.752** (1.188)	1.822 (1.149)	1.757 (1.130)
Size	0.144 (0.418)	-0.338 (0.407)	0.092 (0.413)	-0.364 (0.403)	-0.373 (0.398)
Firm assets	0.864** (0.247)	0.656** (0.239)	0.192 (0.307)	0.085 (0.295)	0.059 (0.290)
Industry dummy	Yes	Yes	Yes	Yes	Yes
Years dummy	Yes	Yes	Yes	Yes	Yes
Intercept	-11.54** (3.525)	-10.41** (3.373)	-11.18** (3.479)	-10.15** (3.339)	-11.25** (3.295)
Adj. R-squared	0.152	0.227	0.175	0.243	0.268
Observations	453	453	453	453	453
AIC	2,945	2,906	2,935	2,898	2,885
2 × log-likelihood	-2,893	-2,849	-2,878	-2,838	-2,820

Notes: log of funds received is the dependent variable; SEs are in parentheses; *** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$.
Source: own elaboration.

significant ($p = 0.39$), indicating that endogeneity is not a major concern in our baseline model.

Secondly, we apply a Heckman two-stage selection model to assess potential selection bias among ventures without VC funding (Certo et al., 2016; Ko & McKelvie, 2018; Wolfolds & Siegel, 2019). A recent meta-analysis from Bendig and Hoke (2022) suggests that when selection bias is plausible but valid instruments are unavailable, the significance of the inverse Mills ratio (IMR) and its effect on coefficient stability can offer insights when used with caution to assess potential selection effects rather than correct for them. In our case, with no valid instrument, the IMR is statistically insignificant, and its inclusion does not alter the sign or significance of our core coefficients (see Table 8). Therefore, in line with this literature, we interpret the IMR as an additional indicator rather than a definitive correction for causal interpretation.

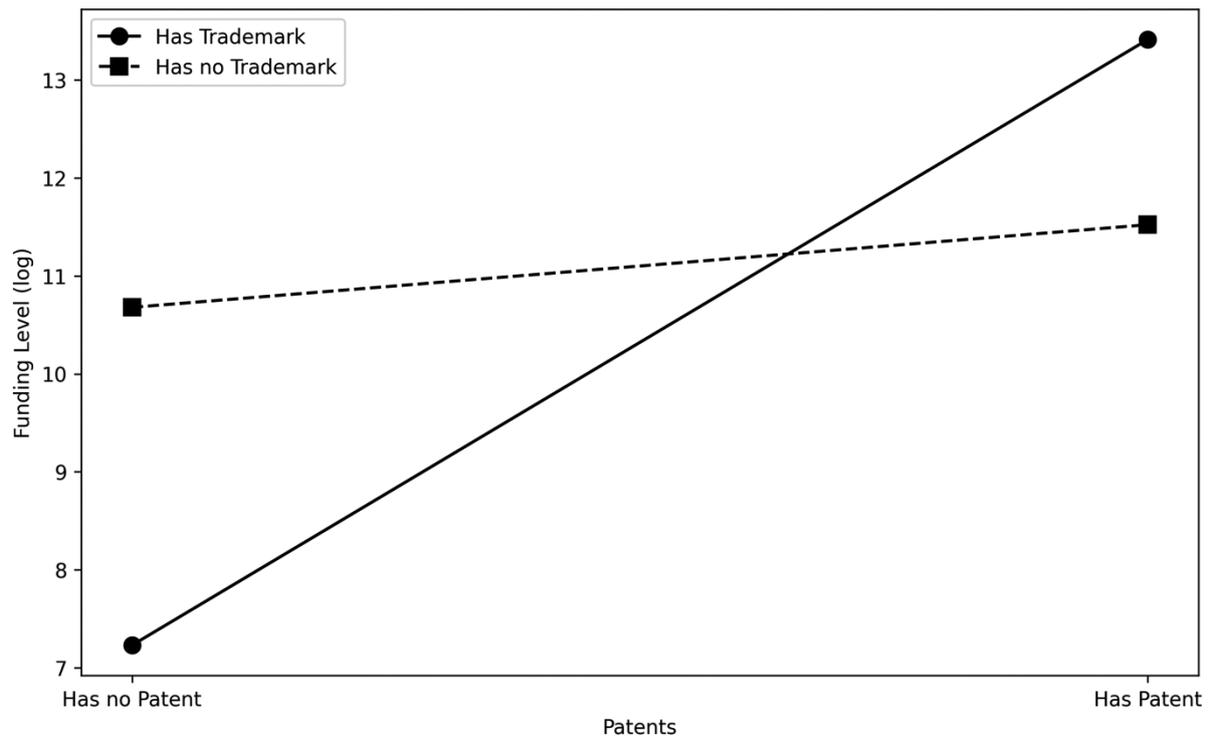
Thirdly, to address selection bias related to ventures in the zero dependent variable category, we conduct additional analyses to isolate sorting effects and re-estimate the OLS model under different conditions. Firstly, we exclude ventures with patents or trademarks to test the influence of human capital

predictors. Results reveal that coefficients for human capital variables and their interactions remain consistent in magnitude, direction, and significance. We then exclude ventures with high human capital (*high education level* and *prestigious institutional network*), which also yields consistent results. Finally, we remove ventures with both high human and structural capital. While this reduces the sample size, the key variables' effect sizes and directions remain consistent, although with lower statistical significance due to limited data.

Overall, findings across 2SRI, the Heckman model and subsample tests follow best practices in applied research (Bendig & Hoke, 2022; Certo et al., 2016; Wolfolds & Siegel, 2019) and confirm the likelihood that results are not driven by unobserved selection or endogeneity.

Discussion and conclusion

This study contributes to the signalling theory by highlighting its strategic dimensions concerning how ventures configure and manage portfolios of signals at organizational (patents, trademarks) and individual (education, elite degrees) levels to



Source: own elaboration.

Figure 1. Interaction effect of patents and trademark on log of funds received in VC early-stage funding.

attract early-stage VC funding. By focusing on the interactions of costly, indirect signals of similar dimension and strength, the results demonstrate that signalling is not merely a set of isolated actions but a set of strategic portfolio choices with potential benefits and costs. Using a dataset of 453 French new technology ventures operating in the digital industry, we provide empirical evidence on the interplay between portfolios of human and structural capital signals and their influence on investor decision-making. Drawing on the socio-cognitive perspective of signalling theory and the concept of informational redundancy, we explain why additional signals within the same dimension offer limited new insight and may ultimately be associated with a reduced likelihood of securing funding.

This analysis confirms that structural capital, such as patents and trademarks, significantly enhances ventures' legitimacy by signalling technological and market capabilities. However, when both are present simultaneously, the odds of securing funding decreases. Similarly, while human capital signals such as high education levels (e.g., MBA, PhD) and prestigious institutional affiliations can indicate team credibility, funding likelihood declines when both attributes appear. Results suggest that investors constrained by bounded rationality (Simon, 1991) may struggle to process portfolios with overlapping signals, resulting in negative valence (Betsch & Glöckner, 2010). Therefore, new technology ventures operating in noisy environments are

encouraged to optimize the diversity and complementarity of their signals rather than relying on cumulative informational redundancy. This aligns with the socio-cognitive perspective of signalling theory (Drover et al., 2018), which emphasizes the cognitive overload investors experience when evaluating many similar signals (Betsch & Glöckner, 2010; Courtney et al., 2017; Steigenberger & Wilhelm, 2018).

This study makes several contributions. Firstly, while traditional signalling theory assumes that investors evaluate signals in isolation under conditions of rational decision-making, this study highlights the potential diminishing returns of cumulative signals in noisy, information-saturated contexts. By using the concept of informational redundancy, we expand the theoretical lens to include negative interactions between signals, an underexplored area in the literature. This contribution aligns with recent calls to refine signalling theory by incorporating socio-cognitive dynamics (Courtney et al., 2017; Drover et al., 2018; Steigenberger & Wilhelm, 2018). More broadly, we position signalling as a strategic activity in which entrepreneurs deliberately design and balance signal portfolios to maximize effectiveness and minimize redundancy. This perspective positions signalling not only as a theoretical mechanism to reduce asymmetry but also as a venture strategy for resource acquisition. Secondly, the French VC context

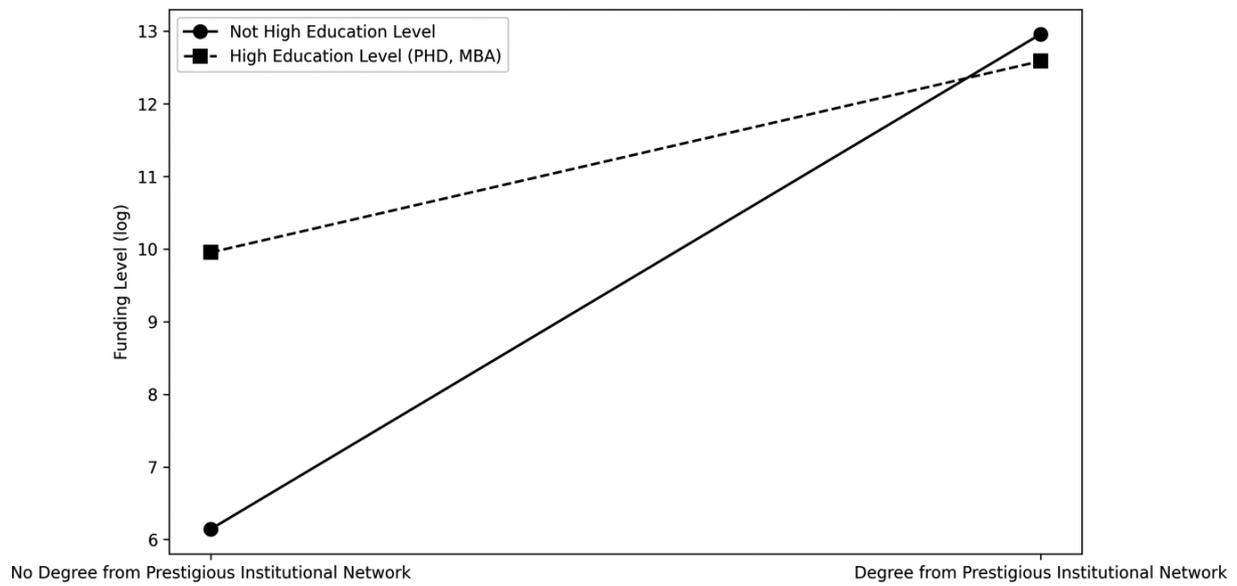


Figure 2. Interaction effect of prestigious institutional network and education level on log of funds received in VC early-stage funding. Source: own elaboration.

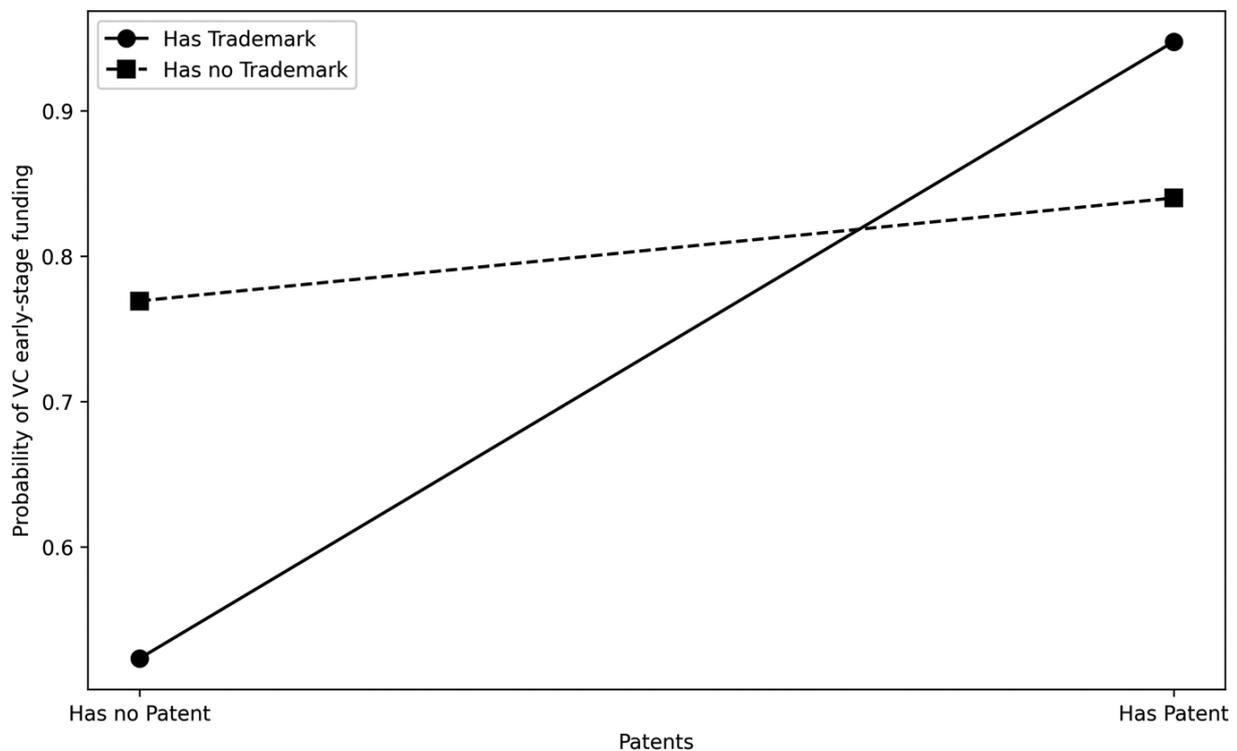


Figure 3. Interaction effect of patents and trademark on probability to receive VC early-stage funding. Source: own elaboration.

provides an interesting empirical setting to examine how institutional and cultural factors influence signal interpretation as France's innovation context is shaped by a

strong interplay between public funding mechanisms (e.g., Bpifrance) and private investment (Taupin et al., 2024). Regulatory incentives such as IP protections amplify the

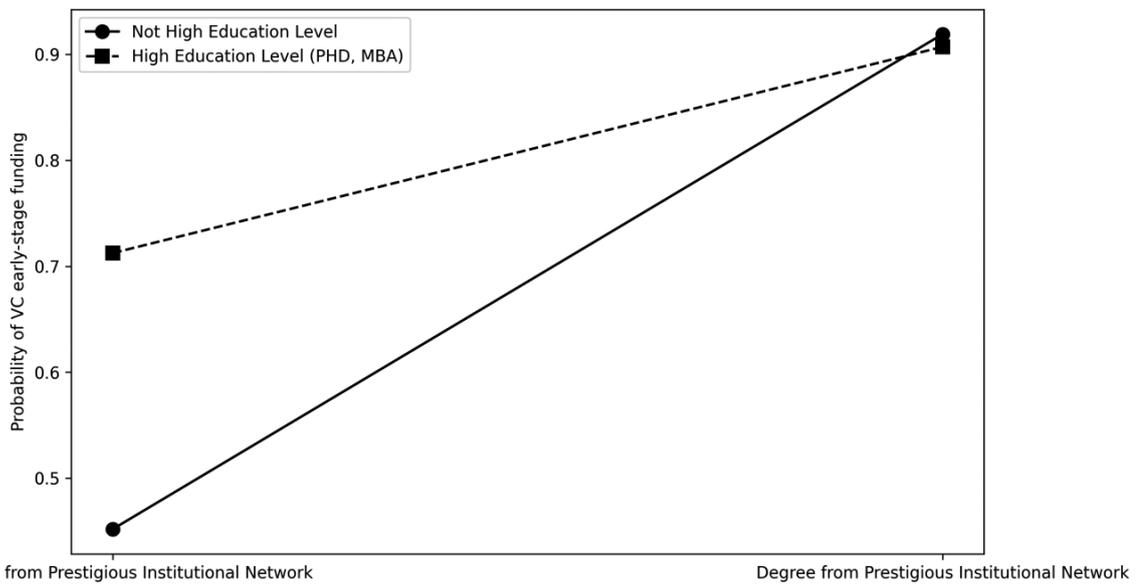


Figure 4. Interaction effect of prestigious institutional network and education level on probability to receive VC early-stage funding. Source: own elaboration.

Table 7. 2SRI (two-stage residual inclusion) model

Variables	Stage 1 (Probit)				Stage 2 (OLS)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Theoretical						
High education level (E)		0.482** (0.148)		0.906*** (0.366)	1.503*** (0.360)	0.670** (0.338)
Prestigious institutional network (N)		0.907*** (0.195)		0.487** (0.150)	0.606*** (0.165)	0.488** (0.200)
Trademark (T)			0.552** (0.178)	0.537** (0.184)	0.668** (0.193)	0.151 (0.193)
Patent (P)			0.746** (0.295)	0.768** (0.323)	1.773 ** (0.629)	0.556* (0.347)
E*N					-0.912** (0.436)	-0.662** (0.301)
T*P					-1.596** (0.740)	-0.812** (0.388)
Controls						
Previous STEM	0.173 (0.148)	0.239 (0.155)	0.142 (0.151)	0.199 (0.159)	0.215 (0.161)	-0.062 (0.126)
Previous manager	-0.241 (0.228)	-0.170 (0.240)	-0.251 (0.231)	-0.186 (0.243)	-0.206 (0.247)	-0.276 (0.189)
Previous founder	0.419** (0.152)	0.375** (0.160)	0.444** (0.155)	0.407** (0.163)	0.371 ** (0.167)	0.344*** (0.130)
Previous working experience	0.003 (0.008)	0.001 (0.009)	-0.001 (0.008)	0.001 (0.009)	0.001 (0.009)	0.023** (0.007)
Network size (log)	0.379*** (0.089)	0.368*** (0.093)	0.366*** (0.090)	0.349*** (0.094)	0.379*** (0.095)	0.252** (0.103)
Gender	0.470 (0.368)	0.400 (0.381)	0.371 (0.374)	0.308 (0.387)	0.390 (0.396)	0.899** (0.352)
Accelerator	0.651* (0.335)	1.114* (0.335)	0.816** (0.340)	0.685* (0.356)	0.591* (0.354)	0.104 (0.215)
Size	0.053 (0.098)	-0.083 (0.104)	0.054 (0.100)	-0.080 (0.106)	-0.085 (0.108)	-0.180** (0.079)
Firm assets	0.251** (0.072)	0.199** (0.075)	0.043 (0.087)	0.003 (0.090)	-0.021 (0.090)	0.078 (0.052)
Residuals						0.730 (0.785)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Years dummy	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	-4.192*** (0.854)	-4.319*** (0.894)	-4.197*** (0.865)	-4.256*** (0.905)	-4.627*** (0.934)	10.51** (1.411)
Observations	453	453	453	453	453	301

Notes: SEs are in parentheses; *** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$.

Source: own elaboration.

Table 8. Heckman two-stage selection model with inverse Mills ratio (IMR)

Variables	Stage 1 (Probit)					Stage 2 (OLS)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Theoretical						
High education level (E)		0.907*** (0.195)		0.906*** (0.199)	1.502*** (0.360)	0.743*** (0.339)
Prestigious institutional network (N)		0.482** (0.148)		0.487** (0.150)	0.606*** (0.165)	0.523*** (0.195)
Trademark (T)			0.552** (0.178)	0.537** (0.250)	0.668** (0.193)	0.184 (0.193)
Patent (P)			0.746** (0.295)	0.768*** (0.323)	1.773** (0.629)	0.622* (0.349)
E * N					-0.911** (0.436)	-0.713** (0.303)
T * P					-1.596*** (0.740)	-0.871** (0.390)
Controls						
Previous STEM	0.173 (0.148)	0.239 (0.155)	0.142 (0.151)	0.199 (0.159)	0.215 (0.161)	-0.050 (0.126)
Previous manager	-0.241 (0.228)	-0.170 (0.240)	-0.251 (0.231)	-0.186 (0.243)	-0.206 (0.247)	-0.282 (0.189)
Previous founder	0.418** (0.152)	0.375** (0.160)	0.444** (0.155)	0.407** (0.163)	0.370** (0.167)	0.360** (0.131)
Previous working experience	-0.003 (0.008)	0.001 (0.009)	-0.001 (0.008)	0.001 (0.009)	-0.001 (0.009)	0.023*** (0.007)
Network size (log)	0.379*** (0.089)	0.368*** (0.093)	0.366*** (0.090)	0.349*** (0.094)	0.379*** (0.095)	0.271** (0.104)
Gender	0.470 (0.368)	0.400 (0.381)	0.371 (0.374)	0.308 (0.387)	0.391 (0.396)	0.908** (0.351)
Accelerator	0.789** (0.335)	0.651* (0.335)	0.816** (0.340)	0.685* (0.356)	0.591* (0.354)	0.125 (0.215)
Size	0.053 (0.098)	-0.083 (0.104)	0.054 (0.100)	-0.080 (0.106)	-0.085 (0.108)	-0.182** (0.079)
Firm assets	0.251** (0.072)	0.199** (0.075)	0.043 (0.087)	0.002 (0.090)	-0.022 (0.090)	0.077 (0.052)
IMR						0.582 (0.490)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Years dummy	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	-4.191*** (0.854)	-4.320*** (0.894)	-4.198*** (0.865)	-4.255*** (0.905)	-4.627*** (0.934)	10.17*** (1.431)
Observations	453	453	453	453	453	301

Notes: SEs are in parentheses; *** $p < 0.001$; ** $p < 0.05$; * $p < 0.1$.
Source: own elaboration.

salience of structural capital signals (Hall, 2002), while cultural emphasis on elite education prioritizes human capital signals (Bourdieu, 1979; O'Brien, 2023). This dual dynamic offers new insights into how national contexts modulate signals' relative importance and interactions. Thirdly, by categorizing ventures into signal configurations (no signal, distinct signals and redundant signals) this study provides a structured framework for analyzing signal portfolio dynamics. We conceptualize these portfolios as the outcome of deliberate signalling strategies in which ventures must balance signal intensity and diversity to mitigate potential investor cognitive overload and optimize investor perceptions (Betsch & Glöckner, 2010). This portfolio perspective shifts signalling theory's focus from individual signals to their combined effects, enriching the understanding of venture signalling strategies. Furthermore, results reveal that effect sizes for key predictors and interactions are large relative to fundraising variance. For example, negative interaction effects reduce funding by more than two thirds of a SD, indicating that overlapping signals in the same domain may

be substantially associated with the likelihood and magnitude of early-stage VC investment. This highlights the importance of signal complementarity and emphasizes the strategic costs of informational redundancy.

For practitioners, our findings emphasize the significance of strategic signal management in early-stage VC fundraising (Gompers et al., 2020; Svetek, 2022). Firstly, new technology ventures should carefully evaluate the costs and benefits of accumulating overlapping signals. While patents and trademarks can independently signal innovation capacity, combining them may dilute their effectiveness. Therefore, entrepreneurs should ensure that each signal contributes distinct value to their narrative, avoiding overemphasis on formal protections at the expense of execution-oriented indicators such as market traction or user base growth (Bessagnet & Abreu, 2025). Secondly, in the French VC context, ventures must align their signalling strategies with private investor priorities and public funding incentives. Structural capital signals such as patents are particularly salient in France due to strong regulatory protections and

public support mechanisms. However, ventures should also capitalize on the cultural weight of elite education by demonstrating how these credentials translate into entrepreneurial agility and adaptability.

This study has some limitations that pave the way for future research opportunities. Firstly, a larger sample size from different geographies could augment the generalizability of the proposed framework and findings, as we only focus on the French early-stage VC environment. Collecting data on new technology ventures in various countries would offer a more nuanced understanding of the institutional dynamics that may influence new technology venture performance via the features of different national systems of innovation. Secondly, while our analysis focuses on private VC investment, the French context is influenced strongly by public funding mechanisms such as grants, subsidies, and convertible instruments, which affect VC decisions (Meuleman & De Maeseneire, 2012; Santoleri et al., 2024). Therefore, future studies could integrate public funding data to explore how public funding signals interact with private investment decisions to provide a more comprehensive view of venture financing. Thirdly, this study primarily examines the negative interactions between redundant signals of similar dimension and strength. Future research could investigate how complementary signals such as human and social capital (e.g., reputation; Stern et al., 2014) interact to enhance investor perceptions and signalling portfolios dynamics. Fourthly, we operationalize the main independent variables as binary indicators, which is a widely used methodological approach in previous research to examine the presence or absence of key signals in VC decision-making. For example, Hsu (2007) employs binary variables to capture educational signals (PhD, MBA), and Audretsch et al. (2012) use similar measures for patents. This binary approach simplifies the interpretation of results and ensures consistency and comparability with previous studies, aligning with previous empirical studies that use binary indicators to focus on the presence or absence of traits rather than their magnitude, potentially resulting in a loss of statistical granularity. Future studies can use more granular measures (e.g., nature of patents or trademarks) to provide a richer understanding of the interplay of signals for new technology ventures in early-stage VC funding. Fifthly, our sample may exhibit stage-based heterogeneity in VC demand. Ventures with patents and trademarks may represent more mature ventures with differing capital requirements and investor evaluation frameworks than earlier-stage ventures (Zhou et al., 2016). Although we control for founding year and firm assets, these proxies may not fully capture lifecycle differences. Future research could employ longitudinal designs to distinguish signalling effects from developmental effects and clarify investor decision-making at different stages.

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