Which Signals Attract Venture Capital? A Firm-Level Analysis of Cleantech Financing in India

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Abstract

Clean technology (cleantech) companies are essential to India's net-zero goals, but most struggle to secure the funding they need. A small group of firms attract most of the available capital, while many others are left out. This study applies signalling theory to examine which observable signals of a company matter most to venture capital investors. We analyse a dataset of 1,726 private Indian cleantech firms, using information from Crunchbase and promoter-ownership data from CMIE Prowess. Because only a small share of firms is funded, we use Firth-penalised logistic regression to ensure robust results. Our findings show that having more media coverage, a larger founding team, and being based in a major city are the most important signals for attracting investment. By contrast, companies with higher promoter ownership are somewhat less likely, but not certainly so, to receive funding. Each of these signals works independently. The study contributes to understanding the decision-making process of venture capital investors in India's cleantech sector and provides practical insights for entrepreneurs and investors. This also provides direction for future research in other emerging markets with similar challenges.

Keywords: Venture capital; cleantech; signalling theory; emerging markets; India; penalised logistic regression

1. Introduction

Clean-technology ventures have become central to the global effort to reduce carbon emissions, moving from a niche investment category (Cumming et al., 2016). The Paris Agreement and the proliferation of net-zero targets are driving economic transformation through cleantech entrepreneurship in renewable energy, electric vehicles, waste management, water efficiency, and sustainable manufacturing (Doblinger et al., 2019; Gaddy et al., 2017). However, the financial resources available for this transition are not enough. There is not enough private funding for early-stage cleantech start-ups to meet climate objectives, despite increased policy attention and growing interest in environmental, social and governance investing (Nanda & Rhodes-Kropf, 2013). This suggests a fundamental mismatch: Venture capital is geared toward companies with high growth and high returns because cleantech companies require high capitalisation and their returns are highly sensitive to political and regulatory stability (Gaddy et al., 2017).

India faces this challenge, as the world's third-largest energy consumer (IEA, 2021)[1] and has committed to reaching net zero emissions by 2070 (Government of India, 2022)[2]. However, India is still suffering from a significant gap in green financing as current tracked investments account for only about one-third of the annual funding needed to achieve its 2030 climate targets (Climate Policy Initiative, 2024)[3]. While public funds and public programs are more likely to support mature and late-stage initiatives like utility-scale renewables and electric mobility, many early-stage ventures are left to private financing, e.g. obtained by venture capital, to survive and expand (Owen et al., 2018; Polzin et al., 2019). However, private capital only reaches a small fraction of firms. Of the 1,726 cleantech startups in India in the sample investigated, only 14.7 per cent have received VC funding, and just 40 per cent of the funded companies were established since 2015, when green entrepreneurship has surged in India since the Paris Agreement.

The Capital distribution is highly skewed, with the top ten funded ventures taking up around 84 per cent of all capital invested. This level of concentration limits the scope of innovation that can be supported in the sector but also poses risks to market resilience when a few firms dictate resource allocation. Addressing this imbalance is a big challenge for the growth and sustainability of India's cleantech ecosystem. Although investor capital exists within the system, most Indian cleantech startups remain unfunded because they are unable to convincingly demonstrate their quality to investors, who cannot directly observe it (Akerlof, 1970; Chen et al., 2010; Spence,

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[1] International Energy Agency (2021). *India Energy Outlook 2021*. Paris: IEA. Available at: https://www.iea.org/reports/india-energy-outlook-2021
[2] Ministry of Environment, Forest and Climate Change (2022). *India's Long-Term Low-Carbon Development Strategy*. Government of India. UNFCCC, COP27.
[3] Climate Policy Initiative (2024). *Landscape of Green Finance in India 2024*. Available at: https://www.climatepolicyinitiative.org/publication/landscape-of-green-finance-in-india-2024/

1973). Investment in early-stage ventures includes judgment under uncertainty as the investor has to infer the potential of the business, technology or management team from observable signals (Spence, 1973). The cleantech sector faces the challenge of limited history, few exit precedents and returns uncertainty that is extremely sensitive to policy changes. So, the question is not whether capital is available, but which firms get funded, and what differentiates the few funded ventures from the unfunded many ventures.

Preliminary evidence from the dataset indicates that these signals distinguish funded from unfunded firms. In terms of visibility and external endorsement, funded firms have a median of seven media articles (interquartile range: five to ten), compared to two articles for unfunded firms (interquartile range: one to three). Further, in terms of ecosystems, metropolitan cities such as Bengaluru, Mumbai, Delhi-NCR, Hyderabad, and Chennai exhibit a funding rate of 19.2 per cent, while other locations have a rate of 10.0 per cent, supporting the notion that ecosystem membership influences funding outcomes (Sorenson & Stuart, 2001a). Bengaluru confirms the pattern. Of the 204 cleantech firms based there, 53 (26.0 per cent) secured venture capital, against 14.7 per cent across the full sample, nearly double the rate, consistent with the idea that ecosystem membership shapes funding outcomes. These patterns are only descriptive, but they point to the question at the heart of this study: how do firm-level signals, innovation, media attention, location, number of founders, and promoters' ownership work *together* to shape a venture's chances of being funded, over and above what any single signal explains?

There is surprisingly little guidance from existing research. While there is much research discussing a single signal, it has focused on patents (Conti et al., 2013; Hsu & Ziedonis, 2013), media visibility (Petkova et al., 2012), geographic proximity (Sorenson & Stuart, 2001a), and founding-team human capital (Colombo & Grilli, 2005; Hsu, 2007), but typically on just one variable, with developed-country samples, and rarely includes political and regulatory uncertainty. The result says little about how signals perform when they compete inside a single decision. The gap is big for India, where the cleantech venture environment differs from developed economies. India has weak corporate governance institutions (Khanna & Palepu, 2000), a young venture-capital market, and extreme concentration of investment. Recent work has studied Indian cleantech venture capital at the country level (Rehman, 2026), but firm-level evidence on which venture characteristics attract investment is missing.

This study fills that gap. Its central question is: when several firm-level signals are considered together, which are most strongly linked to an Indian cleantech venture securing venture capital? We break this into three sub-questions.

> **RQ1.** Which observable firm-level signals are linked to an Indian cleantech venture securing venture-capital funding?
>
> **RQ2.** Do the signal effects found in developed-economy research also hold in an emerging-market cleantech setting marked by weak institutions?
>
> **RQ3.** Do these signals work independently (additively), or does the effect of one depend on the level of another?

This study makes three primary contributions. Theoretically, it is grounded in signalling theory, supplemented by concepts from agency and institutional theories, and, unlike prior research, it tests multiple signals simultaneously rather than individually, as recommended by (Connelly et al., 2011a). Empirically, this study fills a gap between two existing studies: (Bhattacharyya & Subrahmanya, 2024), which examined how signalling affects venture-capital access for 124 Indian digital startups using a two-stage model based on founder surveys, and (Rehman, 2026), which studied cleantech venture capital at the national level. Neither, however, looked at individual Indian cleantech firms, and that is the gap this study addresses, drawing on Crunchbase data for 1,726 ventures together with promoter-shareholding data from CMIE Prowess. The two data sources complement each other.

Surveys capture what databases miss, such as how founders value the mentoring, networks and credibility that investors provide beyond money, whereas database records cover the entire population at a scale survey cannot reach. Methodologically, the study employs an estimation technique that addresses the bias inherent in ordinary estimation when the proportion of funded firms is small (14.7 per cent), the models include numerous variables, and some categories are sparsely populated.

The rest of the paper is organised as follows. The theory and hypotheses are developed in Section 2. Design, data and estimation are discussed in Section 3. The results are reported in Section 4. Section 5 discusses what they mean. Limitations and directions for future work are outlined in Section 6, and Section 7 concludes.

2. Theoretical Background and Hypotheses

The study is based on two related concepts: information asymmetry and signalling. In markets dealing with quality uncertainty, (Akerlof, 1970) found that the markets can fail unless the seller can credibly demonstrate quality. This is central to the entrepreneurial finance literature, in which startups have no history, and investors' uncertainty is heightened regarding the team, the technology, and the market(P. Gompers & Lerner, 2001).

A possible solution to the dilemma is (Spence, 1973) signalling model, in which high-quality ventures do something that not only they are willing to do, but that is also costly enough that less capable ventures could not easily pretend to do. In the VC field, founders demonstrate qualities through their visible actions (filing patents, attracting media, structuring the firm) (Conti et al., 2013; Hsu & Ziedonis, 2013). The investor revises their perception of quality and changes their chances of investing accordingly. To function, a signal must be observable, credible and costly; patents are strong signals as they represent a legal commitment and sunk cost, and when the media reports it, it is a reputational cue of market momentum (Block et al., 2014a; Petkova et al., 2012). In cleantech, which has long development cycles and high capital requirements, these signals are even more important, leading to a greater information gap (Gaddy et al., 2017).

Signalling theory describes information dynamics at the micro-level, while institutional theory situates investors' choices in the broader context of formal and informal rules (North, 1990). Weak institutions and unstable regulation are other uncertainties that affect how signals are read in emerging economies (Khanna & Palepu, 2000; Li & Zahra, 2012). Existing models of VC decision-making, e.g., Kaplan et al. (2004), examine how contracts deal with information problems but make little mention of the non-financial signals that investors use before taking investment action. However, Connelly et al. (2011b) argue that problems are better considered in combination rather than in isolation. The present study is similar, except that it estimates multiple signals in the same model and evaluates each signal net of the others. The hypotheses are outlined in the next few subsections.

2.1 Innovation Signals

Patents and trademarks signal to investors the information that is not otherwise verifiable. Whether a venture's technology is real and defensible. A filing is costly and public, and it has already survived an external examination, so it helps investors separate stronger ventures from weaker ones. Existing studies show that patents lift both the odds of funding and the valuation a venture receives, most of all when it has few other endorsements, the situation most early-stage cleantech firms are in (Hsu & Ziedonis, 2013). Further, findings suggest that even patent applications carry signalling value, though it depends on the context, and show that filing a patent speeds up VC financing because the examination trail gives investors information they use to judge quality(Conti et al., 2013; Haeussler et al., 2014). Trademarks send a different message, about readiness to commercialise; findings suggest their number and breadth relate to VC valuations in an inverted-U shape (Block et al., 2014b). We stress the cleantech context here, because these ventures run long, research-heavy development paths where investors cannot easily tell what technology will become (Gaddy et al., 2017). Since patents and trademarks capture different facets of innovation and both are scarce among early-stage firms, we combine them into a single innovation measure and expect it to raise the chance of funding.

H1 (Innovation). Cleantech firms with more innovation output are more likely to receive venture-capital funding.

2.2 Media Visibility Signals

Media coverage may be the strongest signal an early stage cleantech venture has, because it works in two ways at once. First, it cuts the effort a venture capitalist spends screening opaque, technology-heavy firms: coverage in a credible outlet means a journalist has already judged the venture worth noticing. Findings suggest that media attention shapes how even expert investors value new ventures, and that coverage in specialised industry media, specifically, predicts VC funding (Petkova et al., 2012). Ventures' financial information media coverage by credible sources moves investor valuations, while non-credible sources' coverage drags them down (Guldiken et al., 2017). Second, coverage builds legitimacy that a venture cannot manufacture for itself. Simply being known earns a price premium independent of underlying quality (Rindova et al., 2005). In India, where audited records are not available for early-stage businesses and formal quality checks are weak, the probability of investors leaning harder on visible cues is higher. This suggests cleantech media coverage matters as much as legal and governance factors in explaining cleantech VC (Cumming et al., 2016). Therefore, we expect greater media visibility to raise the chance of funding.

H2 (Media visibility). Cleantech firms with more media coverage are more likely to receive venture-capital funding.

2.3 Ownership Concentration Signals

The ownership structure of a venture tells VC investors how well founders' and outside investors' incentives line up. When promoters' shareholding is high, it can signal genuine commitment because the owner's fortunes are tied to the venture's, which is hard to falsify (Brealey et al., 1977). The equity a promoter or founder's team retains is one of the clearest commitment signals that VCs consider for funding (Busenitz et al., 2005). In India, promoter shareholding is a clean signal to read, because ownership disclosures are formalised through SEBI (Stock Exchange Board of India) rules, MCA (Ministry of Corporate Affairs) and reported by CMIE. But the direction is not obvious in advance. High promoter ownership can mean commitment, yet very high control can also mean entrenchment, i.e. a reluctance to give up equity or cede governance that puts investors off (Jensen C. Michael, 1979). Because these two forces pull opposite ways, we do not predict a direction; we treat the net effect as an empirical question and test whether promoter ownership concentration is associated with the chance of funding.

H3 (Ownership concentration). Promoter ownership concentration is associated with the chance of venture-capital funding.

2.4 Sector and Location Signals

Where a venture is based is itself informative, because location is bound up with quality through the way investors find and monitor deals. Sorenson & Stuart (2001) show that VC money is geographically concentrated because information about good opportunities travels through local, network-bound channels, and that proximity lowers the cost of due diligence and monitoring. (P. A. Gompers et al., 2020) confirm that geographic proximity remains a real screening criterion because it allows the relationship-based due diligence VCs rely on, and both investors and the firms they back cluster in a few metros, with location predicting how investments turn out (Chen et al., 2010). The more VC presence in an area brings more startups, which then draws in more VC, so a hub address provides information about a venture's prospects to some extent (Samila & Sorenson, 2011). This matters even more in emerging markets, where formal institutions are uneven, and metropolitan hubs provide quality assurance through networks and peer monitoring.

Funding needs also differ across cleantech sub-sectors by capital intensity, maturity, and policy exposure. Reading sector and location together as structural cues of ecosystem legitimacy and sector opportunity, we expect the chance of funding to vary systematically across sub-sectors and metropolitan locations.

H4 (Sector and location). The chance of venture-capital funding varies systematically across cleantech sub-sectors and metropolitan locations.

2.5 Founding-Team Signals

Investors who reach a funding decision with little financial history to go on tend to fall back on the founding team, and human capital is hard to fake. Assembling several capable co-founders takes credibility and effort. A team with more founders broadens the venture's skill capacity, network, and ability to adapt quickly to new areas, and the founders' experience reassures investors that the firm can execute and does not depend on one person (Beckman et al., 2007; Colombo & Grilli, 2005). Existing work ties team characteristics to funding outcomes and finds early-stage investors respond strongly to information about the founding team, but not to a firm's traction or existing backers, i.e., the team causes funding, rather than merely correlating with it (Baum & Silverman, 2004; Bernstein et al., 2017; Hsu, 2007). In India specifically, findings suggest that the breadth of the founding team raises access to VC (Nigam et al., 2020). Because cleantech demands technical, regulatory, and commercial skills together, we expect a larger team to matter here especially and predict that a greater number of founders raises the chance of funding.

H5 (Founding-team size). Cleantech ventures with a greater number of founders are more likely to receive venture-capital funding.

These five hypotheses add up to a single picture, which we set out in **Figure 1.** The idea comes from signalling theory (Connelly et al., 2011b; Spence, 1973). A venture knows things about its own quality that an investor cannot see, so it sends signals the investor can see, ones that are hard to fake, and the investor reads these when deciding whether to fund it. We group the five signals into five dimensions taken from a systematic review of cleantech venture-capital investment (Manethiya et al., under review). Innovation is placed under Technological Paradigms, media, sector and location under Contextual Environments, and founders’ team size under Cognitive Drivers. To this we add a fifth signal that was not covered by the review, i.e., promoter ownership, which we treat as a governance signal grounded in agency theory (Jensen C. Michael, 1979). Institutional Frameworks sit around the whole process as a backdrop rather than a signal, because India's regulatory and market conditions shape how every signal is read but barely differ from one firm to the next in a single-country sample (Li & Zahra, 2012; North, 1990). The end point is a simple yes-or-no funding decision, which then feeds back to the venture as a kind of endorsement. Because we see only the deals that closed, not a venture's decision to go looking for money, we treat this as one visible stage rather than the two stages used when survey data capture both sides (Bhattacharyya & Subrahmanya, 2024).

Figure 1. A signalling model of firm-level venture-capital funding in Indian cleantech.

The venture (signaller) sends five firm-level signals, each tied to a hypothesis. Under information asymmetry, the venture capitalist (receiver) reads these signals and reaches a yes-or-no funding decision that feeds back to the venture. Institutional frameworks form the boundary condition rather than a firm-level signal.

<table>
<tr><td colspan="5">A Signalling Model of Venture-Capital Funding in Indian Cleantech</td></tr>
<tr><td colspan="5">Institutional Frameworks (boundary condition: India's regulatory & market context in which all signalling occurs)</td></tr>
<tr><td>Signaller
The Indian cleantech venture holds private information about its unobservable quality</td><td>→
emits signals</td><td>Signal set (firm-level)
Innovation patents/trademarks (H1)
Media visibility (H2)
Promoter ownership (H3)
Sector (EV) & metro location (H4)
Founding-team size (H5)</td><td>→
interprets</td><td>Receiver
The venture capitalist screens & interprets the observed signals</td></tr>
<tr><td colspan="5">Signalling environment: under information asymmetry, investors weigh each signal by its cost, observability, and fit, and they weigh the signals additively, not in required bundles.</td></tr>
<tr><td></td><td></td><td>↓
Outcome
VC-funded vs. not funded
254 of 1,726 firms (14.7%) funded</td><td></td><td></td></tr>
</table>

Feedback: *the funding decision acts as a feedback signal to the venture. The entrepreneur's prior decision to* ***seek*** *VC (Bhattacharyya & Subrahmanya's Stage I) is unobserved and is folded into the signaller, collapsing their two-stage process into one observed stage.*

Determinant dimensions (from the review framework): Technological Paradigms (H1), Contextual Environments (H2, H4), Cognitive Drivers (H5). Promoter ownership (H3) is added as a governance signal beyond the review. Institutional Frameworks form the boundary condition.

Source: *Author's own construction, developed from signalling theory (Connelly et al., 2011; Spence, 1973)*

3. Research Methodology

3.1 Research Framework

We use a cross-sectional design to test the five hypotheses. Each cleantech firm is treated as a single case, and the outcome is whether it has received venture-capital funding. This design fits the question because it captures the observable firm characteristics investors use to select ventures for funding, rather than relying on survey responses (Baum & Silverman, 2004; Islam et al., 2018). Each signal is tested in a model that holds two controls, i.e., firm age and industry breadth, constant, so we can isolate its contribution from these other variable influences. Holding firm-level controls constant reflects how investors judge a signal not on its own, but against a venture's broader profile. Because the signals are recorded for different numbers of firms, we estimate each hypothesis on its own sample rather than forcing them into one combined model, which would restrict every test to the small set of firms where all signals are observed and discard most of the data, a structure we set out in full in Section 3.6.

3.2 Data Sources, Cleaning and Sample Construction

We combined two independent databases, Crunchbase and Prowess. Funding history, media counts, innovation records, web-technology data, sector tags, and location all come from Crunchbase, a widely used startup database (van den Heuvel & Popp, 2023). Promoter-shareholding data for a matched sub-sample comes from CMIE Prowess, the standard source for Indian corporate ownership (Allen et al., 2012).

We built the sample in five steps. First, we took two Crunchbase exports of Indian cleantech companies (1,000 and 862 records, sharing 105 common fields) and removed duplicates by organisation name, leaving 1,833 unique companies. Second, we screened for eligibility, dropping 83 publicly listed firms (post-IPO, no longer venture candidates), 2 delisted firms, and 22 non-profits, which left 1,726 private, for-profit cleantech firms. Third, we coded the outcome from each firm's last equity funding type: it equals 1 when that type is a venture type (Seed, Pre-Seed, Angel, Series A–G, or Venture–Series Unknown) and 0 otherwise, giving 254 venture-funded firms (14.7 per cent). We used the last equity funding type rather than the last funding event of any kind, because it isolates equity financing and is not overwritten by a later debt or grant event; we treat private equity as distinct from venture capital and exclude it. Fourth, we transformed continuous count signals as the natural log of one plus the count, which reduces skew while keeping the zeros (Cameron & Trivedi, 2005). Fifth, we added promoter-shareholding data from CMIE Prowess for 177 firms. Because Prowess records companies under the legal name filed with the Ministry of Corporate Affairs, we matched firms to Crunchbase on their registered legal-entity name and kept only those with an identifiable Prowess record. Ownership is therefore observed for these firms and missing for the rest, and we test the ownership hypothesis (H3) on that sub-sample. We analysed each model on complete cases, reported the number of cases explicitly, and made no imputations.

Cleantech sub-sectors. Crunchbase often tags a company with several overlapping industries, so we used a priority rule to place each firm in a single sub-sector. The rule checks tags in a set order and assigns the firm to the first that matches: Electric Vehicle, then Energy Storage, then Solar, then Other Renewables (wind, biofuel, biomass, geothermal, hydrogen), then Waste & Recycling, and finally Other Cleantech for firms that fit nowhere else. Ordering the tags this way assigns the most specific deep-technology segment first when several overlap. Our sub-sectors reflect the low-carbon energy-technology startup landscape mapped for India by Krishna et al. (2023). We group firms into six categories: Electric Vehicle, Energy Storage, Solar, Other Renewables, Waste & Recycling, and Other Cleantech, assigning each firm to a single category by a priority rule. We keep Electric Vehicle and Energy Storage as separate deep-technology segments, following the Crunchbase-based classification of van den Heuvel & Popp (2023) and the hardware-versus-software distinction of Gaddy et al. (2017). Solar is the reference category.

Metropolitan hubs. India's cleantech firms cluster in a few key cities. Three main hubs: Bengaluru, Delhi-NCR, and Mumbai stand out, while Hyderabad, Chennai, Pune, and Ahmedabad act as important secondary centres. We use this grouping to classify company headquarters (Korreck, 2019). Following earlier work, we treat Delhi-NCR as a single cluster covering Delhi, Gurugram, Noida, Faridabad, and Ghaziabad. This also matches the government's definition of a metropolitan area (a population of at least one million) and the Ministry of Finance's 'X-class' city list.[4] The economic logic for grouping cities comes from agglomeration theory, which holds that a hub location brings benefits through networks, shared resources, and local expertise (Chen et al., 2010) . "Other cities" is the reference category. Because every classification rule involves some judgment, we have applied ours clearly and consistently, and the main findings hold under reasonable alternative ways of grouping cities.

3.3 Variable operationalisation

The five hypotheses are measured as follows. Innovation (H1) is the log of one plus the sum of patents and trademarks. Media (H2) is the log of one plus the number of articles. Promoter ownership (H3) is mean-centred promoter shareholding, in per cent. Sector (six mutually exclusive categories, with Solar as the reference) and city (eight categories, with Other cities as the reference) enter as categorical variables (H4), so the model returns an odds ratio and adjusted probability for each sub-sector and hub; their construction is detailed in Section 3.2. Founding-team size (H5) is the number of founders. Two controls are included. Firm age (standardised) captures the liability of newness (Bruderl & Schussler, 1990; Stinchcombe, 1965). Industry breadth is the standardised number of industry groups a firm spans, a rough measure of how diversified rather than focused it is: focused ventures may be more fundable, since investors tend to favour propositions, they can readily evaluate, whereas a wide spread of activities can signal strategic ambiguity (Berger & Ofek, 1995; Rajan et al., 2000; Zuckerman, 1999). This control shows no problematic overlap with the sector classification; no pairwise correlation among the predictors exceeds 0.32 **(Table 3).**

3.4 Model Specification

The outcome we want to predict is a simple yes-or-no question whether a firm received venture capital, so logistic regression is the natural choice. But its usual maximum-likelihood version does not suit this study's data. Maximum likelihood works best in large samples; when the sample is small, the variables many, and the funded firms few, it can push estimates away from zero and

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[4] Government of India, Ministry of Finance, Department of Expenditure, *Classification of cities for the purpose of House Rent Allowance*, O.M. No. 2/5/2014-E.II(B), dated 21 July 2015.

bias them (Firth, 1993). We face exactly that problem, for three reasons. First, only 254 of 1,726 firms (14.7 per cent) are funded. Second, several models estimate many variables relative to the number of funded firms: the models testing H4 carry twelve category dummies (five for sector, seven for city) on top of the focal signal and two controls, so the sample's composition is not credited to the focal signal. Third, some categories are thin in the full sample, Energy Storage holds forty firms with one funded, and Other Cleantech twenty-eight with five funded.

The strain shows up in the events-per-variable ratio the number of funded firms divided by the *total* parameters estimated (the focal signal, the two controls, and, where included, the twelve sector and city dummies) and it falls in two ways. When the category dummies sit on a modest sample, the ratio drops: Model B estimates fifteen parameters on 137 funded firms (EPV 9.1) and Model E fifteen on 176 (EPV 11.7). When the sub-sample itself is small, it drops even without category dummies: Model A estimates three parameters on 23 funded firms (EPV 7.7). Against the usual guideline of at least ten funded firms per parameter (Peduzzi et al., 1996), Models A and B fall below the line and Model E sits just above it; only the full-sample Model D is comfortable, at 18.1. Thin categories make matters worse wherever they appear, because a category with few funded firms yields an unstable coefficient with a wide confidence interval even when the model runs cleanly.

Table 1. Events per variable (EPV), by model.

Model	**Events (funded firms)**	**Parameters**	**EPV**	**Focal signal**
A	23	3	7.7	Innovation
B	137	15	9.1	Media
C	44	3	14.7	Promoter ownership
D	254	14	18.1	Sector & city
E	176	15	11.7	Number of founders

Notes*. EPV is the number of funded firms (events) divided by the number of estimated parameters. Parameters comprise the focal signal, two controls (firm age, industry breadth),* *and, in Models B, D and E, five sector and seven city indicators. The conventional guideline is at least ten events per variable (Peduzzi et al., 1996); Models A and B fall below this threshold and Model E sits close to it, which motivates the use of Firth penalisation.*

We therefore estimate all five models with Firth penalised logistic regression (Firth, 1993). Firth's method adds a small correction to the standard estimator that removes most of the small-sample bias, and the correction shrinks as the sample grows, so where ordinary estimation would already have been reliable, Firth returns almost the same answer. It also keeps producing usable estimates when a category perfectly predicts the outcome, a problem that can strike very small groups (though it did not arise in our models). Because the correction never makes things worse and only helps when data are thin, we apply it to all five models rather than switching methods between them. Use of one estimator throughout also keeps the models directly comparable. Recent management research recommends Firth as the default for outcomes that are not evenly split (Woo & Sohn, 2022). We report odds ratios with profile-penalised-likelihood confidence intervals, which are more reliable than standard intervals for data of this kind (Heinze & Schemper, 2002). We ran all estimation in R using the logistf package.

The direct comparison between Ordinary Maximum Likelihood and Firth confirms that Firth changes only what it should. When we re-run the full-sample model with ordinary maximum likelihood, the well-populated estimates barely move: the odds ratios for Electric Vehicle, Bengaluru, and industry breadth each shift by less than one per cent (0.2, 0.7, and 0.5 per cent). Only the thinnest category moves materially: Energy Storage, with a single funded firm, shifts from 0.298 under Firth to 0.202 under ordinary estimation, a 47.5 per cent difference. Firth therefore leaves the solid estimates untouched and stabilises only the sparse ones, exactly as expected.

Let π_i be the probability that firm i has received venture capital. The specification is:

$$\boldsymbol{logit(\pi_i) = \beta_0 + \beta_1 \cdot Innovation_i + \beta_2 \cdot Media_i + \beta_3 \cdot Ownership_i + \beta_4 \cdot Founders_i}$$

$$\boldsymbol{+ \Sigma_s\ \gamma_s \cdot Sector_{si} + \Sigma c\ \delta c \cdot Cityc_i + \theta_1 \cdot FirmAge_i + \theta_2 \cdot IndustryBreadth_i} \qquad \textbf{(1)}$$

where logit(π_i) is the log-odds of funding, ln [π_i / (1 − π_i)]; β_0 is the intercept; Innovation is ln (1 + patents + trademarks); Media is ln (1 + articles); Ownership is mean-centred promoter shareholding; and Founders is the number of founders. $Sector_s$ and Cityc are the sub-sector and metropolitan category sets from Section 3.5, each expressed relative to its reference (Solar; Other cities). FirmAge and IndustryBreadth are the standardised controls. Coefficients are reported as odds ratios, $\exp(\beta)$: a value above 1 raises the odds of funding, below 1 lowers them.

The sample size differs across signals; therefore, equation (1) is not estimated as a single combined model. Every model and hypothesis is tested on its own complete-case sample:

Model A (H1), N = 45:

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{Innovation} + \beta_2 \cdot \text{FirmAge} + \beta_3 \cdot \text{IndustryBreadth}$$

Model B (H2), N = 374:

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{Media} + \beta_2 \cdot \text{FirmAge} + \beta_3 \cdot \text{IndustryBreadth} + \Sigma\gamma_s \cdot \text{Sector}_s + \Sigma\delta c \cdot \text{City}c$$

Model C (H3), N = 177:

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{Ownership} + \beta_2 \cdot \text{FirmAge} + \beta_3 \cdot \text{IndustryBreadth}$$

Model D (H4), N = 1,726:

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{FirmAge} + \beta_2 \cdot \text{IndustryBreadth} + \Sigma\gamma_s \cdot \text{Sector}_s + \Sigma\delta c \cdot \text{City}c$$

Model E (H5), N = 600:

$$\text{logit}(\pi) = \beta_0 + \beta_1 \cdot \text{Founders} + \beta_2 \cdot \text{FirmAge} + \beta_3 \cdot \text{IndustryBreadth} + \Sigma\gamma_s \cdot \text{Sector}_s + \Sigma\delta c \cdot \text{City}c$$

We include the sector and city indicators only where the sample can support them (Models B, D and E).

We considered several alternatives and set them aside. We rejected the linear probability model because it can predict probabilities below zero or above one and assumes a constant effect unlikely to hold for a screening decision. Probit reaches essentially the same conclusions but does not report odds ratios, the convention in this literature, and does not correct small-sample bias. The rare-events correction of King et al. (2001) tackles the low-funded share but not our second problem, many variables estimated on small samples. We could not fit a two-stage selection model of the kind Bhattacharyya and Subrahmanya (2024) use for Indian digital startups: its first stage needs the seeking decision to be observed, and that decision leaves no trace in transaction records a venture that approached investors and was turned down looks identical in Crunchbase to one that never approached anyone. Their design works because they surveyed founders directly, which is also why their sample runs to about a hundred firms rather than a thousand. Fitting such a model without an observed seeking decision would give us the shell of a selection correction with none of its content, so we estimate the second stage alone and describe the outcome throughout as the probability of having received venture capital, not of obtaining it conditional on seeking. We did not use penalised-selection methods, because we only have a small number of predictors and each is chosen for a specific theoretical reason—not picked from a large list of possible variables. We also avoided using machine-learning classifiers. Our main aim is to understand which signals are linked to funding, in a way that is clear and easy to interpret, with effect sizes and confidence intervals. Maximizing prediction accuracy was not our goal. Multilevel models that treat sector and city as random effects were not appropriate either, since these categories are the focus of one of our main hypotheses (H4), not just background variation. Finally, we could not use panel or time-series models, because our data is just a single snapshot, with one observation per firm.

We include two controls, firm age and Industry breadth, in every model. Control variables are added when a variable could sway the outcome and is also tied to the focal signals; leaving it out would let its effect be wrongly credited to those signals. Firm age is the clearest case,which shows how it is linked with both the signals and the funding outcome; older firms generally have had more time to build up patents, media coverage, and staff, yet venture capitalists tend to prefer younger ventures. In controlling for it, we follow established work on the difficulties new firms face the liability of newness (Bruderl & Schussler, 1990; Stinchcombe, 1965), and make sure the signals are not simply standing in for how long a firm has existed. Industry breadth is the standardised count of Crunchbase industry groups a firm span; ventures spanning many categories can be harder for investors to classify and judge, which may weaken their appeal (Zuckerman, 1999). Crunchbase assigns these groups automatically from a firm's tags rather than from firm reports, and one tag can map to several groups, so the count reflects the platform's classification as much as the venture's true scope. It is also a count-based proxy, not the sales-weighted diversification index used for public firms, for which private-venture data do not exist, so we include it as a control and read it with caution. Both controls enter all five models. We carry the sector and city variables only in Models B, D and E, where the sample can support them; they are the object of H4 and estimated there, and in Models B and E we hold them constant so the focal signal is not credited with its sample's make-up. Models A and C leave them out because their samples cannot bear twelve extra category dummies: on 23 and 44 funded firms, adding them would push the events-per-variable ratio down to roughly 1.5 and 2.9.

Table 2 states descriptive statistics. Of the 1726 firms , only 14.7 per cent are venture-funded, confirming the rarity of funding that motivates the penalised estimator. Media coverage and promoter data are available for sub-samples (374 and 177 firms respectively), while the outcome, innovation, and controls span the full sample. Innovation is strikingly sparse: the mean of the log innovation measure is 0.036, reflecting that patents or trademarks appear for only a small fraction of firms. The average venture has around 1.5 founders, and promoter shareholding, where observed, is high (mean 89.3 per cent).

Table 2. Descriptive statistics.

Variable	N	Mean	SD	Min	Max
Venture-funded (outcome)	1726	0.147	0.354	0.000	1.000
Media, ln(1+articles)	374	1.712	1.120	0.693	5.037
Innovation, ln(1+patents+trademarks)	1726	0.036	0.271	0.000	4.357
Number of founders	600	1.505	0.809	1.000	6.000
Promoter share (%)	177	89.270	20.971	0.298	100.000
Promoter share, centred	177	0.000	20.971	-88.972	10.730
Firm age (standardised)	1726	0.000	1.000	-0.848	7.620
Industry breadth (standardised)	1726	0.000	1.000	-1.709	4.831

Notes. *N differs across variables because signals are observed for different sub-samples: media (374), number of founders (600), promoter share (177); the outcome, innovation, and controls cover the full sample (1,726). Firm age and industry breadth are standardised (mean 0, SD 1). Promoter share is mean-centred.*

Table 3 shows how different pairs of variables are linked. These links are generally modest; none of the correlations is strong, as no value is higher than 0.32 in either direction. This means that multicollinearity, or the problem of predictors overlapping too much, is not an issue here. For example, promoter shareholding is negatively related to media visibility (−0.21), innovation (−0.25), and founding-team size (−0.27). In simple terms, firms where promoters own more of the company tend to be less visible in the media, less innovative, and have smaller founding teams. The control variables only show weak connections to the main signals.

Table 3. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Media	1.00					
(2) Innovation	0.32	1.00				

(3) Number of founders	0.14	0.16	1.00			
(4) Promoter share (centred)	-0.21	-0.25	-0.27	1.00		
(5) Firm age	-0.01	0.11	-0.14	0.07	1.00	
(6) Industry breadth	-0.09	0.01	-0.07	0.10	0.10	1.00

Notes. *Pairwise correlations. Because variables cover different sub-samples, correlations use all available complete pairs.* $|r| \geq 0.10$ *is significant at* $p < 0.05$ *in the full sample*

4. Findings

The results are presented as odds ratios, which help us understand how different factors affect the chances of a firm receiving funding. An odds ratio above 1 means higher odds of getting venture capital, while a value below 1 means lower odds, always compared to a chosen reference category (solar and other cities). **Table 4** provides a summary of the findings from all five models, offering a clear overview of the main effects.

Table 4. Firth penalised logistic-regression results (odds ratios with 95% confidence intervals).

Predictor	Model A (H1)	Model B (H2)	Model C (H3)	Model D (H4)	Model E (H5)
Signals					
Innovation, ln(1+IP)	0.79 [0.36, 1.75]	—	—	—	—
Media, ln(1+articles)	—	1.82*** [1.44, 2.33]	—	—	—
Promoter share (centred)	—	—	0.98* [0.96, 1.00]	—	—
Number of founders	—	—	—	—	1.83*** [1.46, 2.33]
Sector (ref. Solar)					
Electric Vehicle	—	1.94* [1.03, 3.66]	—	2.40*** [1.61, 3.57]	1.90* [1.13, 3.19]
Energy Storage	—	1.21 [0.11, 7.87]	—	0.30† [0.03, 1.17]	0.57 [0.05, 3.37]
Other Cleantech	—	4.46 [0.60, 37.25]	—	2.75† [0.85, 7.89]	1.57 [0.34, 6.16]
Other Renewables	—	1.12 [0.33, 3.32]	—	1.68 [0.82, 3.23]	1.85 [0.62, 5.17]

Waste & Recycling	—	1.97† [0.92, 4.21]	—	1.18 [0.78, 1.77]	1.51 [0.88, 2.58]
City (ref. Other cities)					
Bengaluru	—	1.88 [0.86, 4.13]	—	3.03*** [1.95, 4.70]	2.07* [1.15, 3.76]
Chennai	—	3.44† [0.95, 13.83]	—	3.39*** [1.81, 6.18]	3.50** [1.52, 8.01]
Mumbai	—	0.88 [0.36, 2.12]	—	2.23** [1.29, 3.80]	1.60 [0.75, 3.33]
Delhi-NCR	—	0.64 [0.31, 1.30]	—	1.77** [1.18, 2.66]	1.16 [0.67, 2.00]
Hyderabad	—	1.10 [0.37, 3.29]	—	1.96† [0.96, 3.81]	1.49 [0.62, 3.49]
Ahmedabad	—	1.31 [0.37, 4.52]	—	1.48 [0.68, 2.96]	1.83 [0.65, 4.89]
Pune	—	0.60 [0.18, 1.88]	—	1.17 [0.62, 2.13]	0.89 [0.37, 2.02]
Controls					
Firm age (standardised)	0.20*** [0.04, 0.62]	0.25*** [0.14, 0.42]	0.01*** [0.00, 0.07]	0.25*** [0.17, 0.35]	0.45*** [0.28, 0.67]
Industry breadth (standardised)	1.37 [0.71, 2.98]	0.99 [0.77, 1.29]	1.06 [0.71, 1.60]	0.83* [0.69, 0.98]	0.96 [0.79, 1.17]
Sample and fit					
N	45	374	177	1,726	600
Funded firms (events)	23	137	44	254	176
McFadden pseudo-R^2	—	—	—	0.163	—
AUC	—	—	—	0.781	—
Hosmer–Lemeshow p	—	—	—	0.184	—

Notes. *Firth penalised logistic-regression odds ratios; 95% confidence intervals in brackets. An odds ratio above 1 raises, and below 1 lowers, the odds of funding. Reference categories: Solar (sector) and Other cities (city). Firm age and industry breadth are standardised. Fit statistics are for the full-sample model (D). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.*

4.1 Media coverage is the strongest signal (H2 supported)

Media coverage stands out as the clearest and most reliable positive signal of funding. In Model B, each increase in media attention (measured as a one-unit rise in log media coverage) raises a firm's chances of receiving venture capital by about 82 per cent (odds ratio 1.82, $p < 0.001$). These findings support H2 and reinforce the idea that media attention acts as a signal to investors, helping them find promising firms and boosting a company's visibility (Petkova et al., 2012).

4.2 Funding varies sharply by sector and city (H4 supported)

Model D provides strong evidence for H4. Companies in the electric-vehicle sector are more than twice as likely to secure funding compared to those in the solar sector (odds ratio 2.40, $p < 0.001$), making electric vehicles the only sector that stands out distinctly. The impact of location is even more pronounced: firms based in Chennai (3.39), Bengaluru (3.03), Mumbai (2.23), and Delhi-NCR (1.77) all have much higher chances of getting funding than firms located outside the main city hubs. **Table 5** shows these differences as adjusted probabilities, making the findings easier to interpret.

Table 5. Model-adjusted predicted funding probabilities, by sector and city.

Rank	Sector	P(fund) %	Rank	City	P(fund) %
1	Other Cleantech	11.6	1	Chennai	14.4
2	Electric Vehicle	10.7	2	Bengaluru	13.2
3	Other Renewables	7.5	3	Mumbai	10.0
4	Waste & Recycling	5.5	4	Hyderabad	8.7
5	Solar (reference)	4.7	5	Delhi-NCR	8.1
6	Energy Storage	1.0	6	Ahmedabad	6.7
			7	Pune	5.4
			8	Other cities (reference)	4.7

Notes. *Predicted probabilities from Model D (full sample), computed with the other categorical set held at its reference (sector at Solar; city at Other cities) and continuous controls at their means. These are model-adjusted probabilities, not raw funding rates.*

4.3 More founders raise funding odds (H5 supported)

The number of founding team members is a robust positive signal. Controlling for firm age, sector and city, the extra founder increases the likelihood of the firm being funded by approximately 83 per cent (1.83, $p < 0.001$) in Model E. This is beneficial for H5 and the human-capital account: bigger teams convey complementary skills and reduce the execution risk; investors value it (Hsu, 2007). Media attention, together with team size, is among the most trustworthy firm-level indicators in the sample.

4.4 Innovation is inconclusive; ownership is marginal and fragile (H1 not supported, H3 marginally supported)

H1 is not supported. In Model A, the odds ratio for innovation is 0.79 (95% CI 0.36–1.75, $p = 0.551$), indicating there is no clear link between innovation and funding. We consider this result is due to the limits of the data: only 2.6 per cent of firms hold any patents or trademarks, and Model A rests on just 45 firms, 23 of them funded too few to detect an effect even if one exists. The substantive finding is therefore about the setting itself: formal intellectual property is so rare in Indian cleantech at the venture stage that it cannot function as a common signal, unlike in developed markets where patents carry more weight (Audretsch et al., 2012; Hsu & Ziedonis, 2013).

H3 is also moderately supported and should be read with caution. In Model C, each additional percentage point of promoter shareholding lowers the odds of funding by about 1.9 per cent (odds ratio 0.981, 95% CI 0.962–1.000, $p = 0.048$), aligning with the existing literature claims that firms with more promoter shareholding are less willing to cede governance to outside investors (Jensen C. Michael, 1979). Three things temper this. The estimate rests on 177 firms with only 44 funded; it sits right at the edge of significance, with an upper confidence bound of 1.000; and it disappears once media coverage is added to the smaller overlapping sample (odds ratio 0.99, $p = 0.392$). The direction is suggestive, but the effect is best treated as a tentative pattern rather than a firm result.

4.5 Model performance and robustness

The diagnostics for the full-sample model (Model D). The model sets the funded and unfunded ventures apart well: the area under the ROC curve is 0.781 (Figure 2), i.e., above the 0.5 we would expect from chance alone. This explanatory power is what we would expect for a cross-sectional model of one-off decisions (McFadden pseudo-$R^2 = 0.163$). The model is also properly calibrated. The Hosmer–Lemeshow statistic is 11.32 on 8 degrees of freedom ($p = 0.184$). The test signals poor fit through a low p-value, the high value here is the reassuring one. The predicted and observed funding rates line up closely across risk groups, as Figure 3 shows. Multicollinearity does not threaten the estimates either, since no two predictors correlate above 0.32 in absolute value (Table 3).

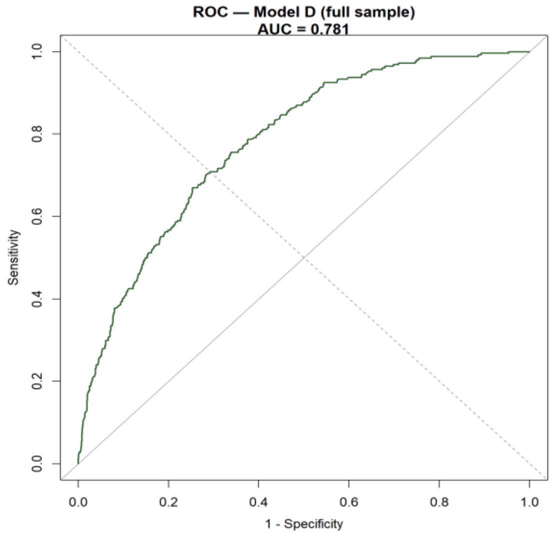

Figure 2. ROC curve for Model D (full sample); AUC = 0.781, indicating discrimination well above chance (the diagonal).

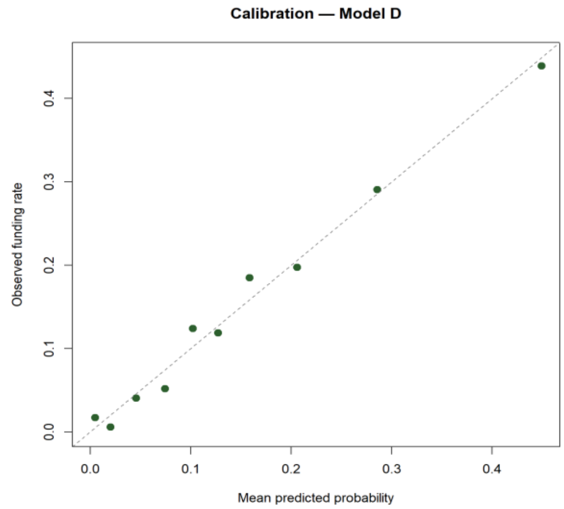

Figure 3. Calibration plot for Model D: mean predicted probability versus observed funding rate across ten bins (Hosmer–Lemeshow p = 0.184).

Further, three other checks support the results. First, the largest Cook's distance is 0.071, far below the general threshold of 1, and the sector and location effects remain almost the same when we drop the ten most influential firms. Second, when we collapse the seven city indicators into a single metropolitan dummy, the location effect holds firmly (odds ratio 2.13, $p < 0.001$), so the finding is not an artefact of how we split the cities. Third, dropping the two thinnest sector categories leaves the electric-vehicle premium and the metropolitan effects intact.

Finally, we analysed whether the signals work in combination rather than independently, the question RQ3. We examined the twelve theory-based interactions in advance. Only one of them reached nominal significance on its own, Founder team size combined with metropolitan location ($p = 0.048$), but with twelve tests we would expect roughly one such result by chance, and it did not survive correction for multiple testing (adjusted $p = 0.575$). The signals therefore appear to work additively. Each contributes over and above the others, and the effect of one does not measurably depend on the level of another. We put this cautiously, though, because interactions demand far more statistical power than main effects, and 254 funded firms may simply be too few to reveal them. Our data cannot fully separate a genuinely additive process from an underpowered test of a combined one.

5. Discussion

Testing five signals based on established theory within a single framework gives a clear answer to the central question of this study. For Indian cleantech companies, visibility (especially media coverage), the strength of the founding team, and location in a major city are the signals most closely linked to receiving venture funding. In contrast, formal technology credentials are mostly missing from the market, and ownership concentration is only weakly related to funding.

Media coverage turns out to have the biggest effect in the study (odds ratio 1.82, $p < 0.001$). An increase in media attention—measured as a one-unit rise in the log number of articles is linked to an 82% higher chance of funding. Funded firms have a median of seven articles written about them, compared to just two for those that did not get funding. This supports the idea that media attention acts as a third-party endorsement, making it easier for investors to notice promising ventures and trust their quality. However, this finding should be interpreted carefully. It is possible that firms receive more media coverage after they get funding, not just before, and the study's cross-sectional design cannot separate cause from effect. For this reason, we describe the link between media coverage and funding as an association, not a definite cause. This issue of reverse causality is a key limitation in interpreting the results.

The effect of the founding team is strong (odds ratio 1.83, $p < 0.001$) and less likely to be biased by timing, since the team is usually set at the beginning, before any funding is received. Each additional founder boosts the chance of funding by 83 per cent. This supports the idea that a broader team signals a wider mix of skills—technical, business, and regulatory—that are valuable for cleantech companies. Investors often look at the founders' backgrounds first, especially when there is little product or financial information to go on. In cleantech, where companies face challenges in technology, policy, and building a market at the same time, it makes sense that investors value teams with a broad skill set.

Location effects are large and robust. Outside the hubs, the odds of being funded are about one-third of the odds for ventures in Bengaluru (3.03, $p < 0.001$), and are also significant in Chennai (3.39), Mumbai (2.23), and Delhi-NCR (1.77); predicted probabilities range from 14.4 per cent in Chennai to 4.7 per cent outside the hubs. These occur when the thinnest sector cells are lost. This pattern is an example of agglomeration reasoning, which includes lower monitoring costs, deal flow via the network, and tacit information transfer on quality (Chen et al., 2010; Sorenson &

Stuart, 2001). The mechanism is stronger in an emerging-market context than in developed economies, where the formal verification mechanism is weaker (Khanna & Palepu, 2000); instead, ecosystem membership serves. The sector gradient is the same as the reading, with the odds of electric-vehicle businesses being 2.40 times higher than solar's, possibly due to their deep-tech nature, the policy momentum, and the fact that they may have a much longer growth runway than the more mature solar business in India.

The innovation outcome requires the most careful statement. It is a coefficient below 1 and not significant; it does not mean that patents are not important. There are patent and trademark records for just 45 firms (2.6 per cent of the sample), and a test of 23 funded firms cannot detect any effect at the realistic size either way. Results from the literature vary: patents predict funding in developed-market samples (Conti et al., 2013; Hsu & Ziedonis, 2013), while null and negative findings are reported (Hoenig & Henkel, 2015). The straightforward answer is this study does not answer the question. What the scarcity does confirm is a reality of the sector: at the time Indian cleantech ventures seek venture capital, formal intellectual property is largely absent and thus cannot serve as a readily available indicator where it is present.

The ownership result is weakly negative and suggestive. Taken at face value, each additional point of promoter ownership slightly lowers the odds of funding, consistent with the entrenchment interpretation of the relationship between concentrated ownership and the reluctance of the promoter to sell off ownership or allow outside governance (Jensen C. Michael, 1979), but not the commitment signal interpretation that is associated with concentrated ownership (Brealey et al., 1977). There are three cautions to note here: it is at the conventional threshold; it is based on 44 funded cases among 177 firms, and it does not hold up when media coverage is added in an overlapping subset of firms. It is reported as a tentative pattern for qualitative follow-up and not a supported hypothesis.

Both controls are informative and show the behaviour that is expected by the theory. Firm age is consistently negatively related to all models (0.25 in Model D, $p<0.001$), which suggests that venture capital is allocated to young firms, thus reinforcing the need to control for age in the models. Industry breadth is negative and significant in the full sample (0.83, $p = 0.028$), tentatively consistent with the idea that a wide spread of activities dilutes the clarity of a venture's proposition

(Berger & Ofek, 1995); it is not significant in the smaller samples, and since it is a count-based proxy rather than a sales-weighted index, we do not press the interpretation.

5.1 Implications for the multi-dimensional framework

The systematic review from which this study proceeds groups the determinants of cleantech venture capital into five dimensions: Capital Dynamics, Technological Paradigms, Institutional Frameworks, Cognitive Drivers, and Contextual Environments, and proposes that investment decisions rest on these dimensions working together rather than in isolation (Manethiya et. al, under review). This study takes that framework to the firm level, and the evidence is best described as partial.

We measured signals mapping to two of the review's dimensions and added a third that the review did not cover. Contextual Environments, which we capture through media visibility and through sector and location, get the strongest support: all three proxies are significant, and the location effects hold firm. Cognitive Drivers get partial support, since team size, the human-capital proxy, is strongly significant. To these dimensions we added promoter ownership as a governance signal grounded in agency theory, which the review did not include and found only marginally linked to funding, in an entrenchment-consistent direction, and not robust to alternative specifications. We could not test Technological Paradigms informatively, because patent and trademark records exist for too few firms. Nor could we measure Capital Dynamics, since financial-performance indicators are either unavailable for early-stage private ventures or endogenous to the funding decision. And we could not test Institutional Frameworks at the firm level, because the policy-uncertainty index is a national annual series and the only firm-specific date in a cross-section is the funding event itself, so the measure exists only for funded firms (Section 6). The study therefore speaks with confidence to one dimension, partially to a second, adds a governance signal beyond the review, and cannot reach the remaining three.

We present this pattern as a finding, not a weakness. The signals we test are those a venture reveals in public or secondary data before any investment happens: its media presence, its location, and its founding team. The dimensions we cannot test are those that need private financial detail, which most start-ups do not disclose, or data that shift over time, which a single snapshot cannot capture. In other words, secondary sources alone cannot test the framework in full at the firm level. By marking out these limits, we add useful context for the work that follows.

The idea that investors weigh combined or bundled risks, rather than looking at each risk on its own, is not supported by our data. Out of all possible combinations, only one interaction (team size and being in a big city) was close to significant (p = 0.048), and another was nearly so (p = 0.066), but neither remained significant after adjusting for multiple testing. In simple terms, each signal seems to have its own separate effect; there is no evidence that they strengthen each other when they appear together. We are careful in drawing conclusions, though. It's possible that the idea of combined effects just doesn't fit this market, or it could be that our sample of 254 funded firms is too small to detect these patterns. With our current data, we can't tell which explanation is correct, so this question would be better explored with a larger sample or by talking directly to investors.

6. Limitations

This study has several limitations. First, we used the founding team variable by its size, i.e., "Number of Founders", rather than its qualification or experience. Because Crunchbase firm-level data only have the number of founders, but not their individual qualifications, education, or prior venture experience as exportable fields, it may require person-by-person profile collection beyond this study's scope. Therefore, we interpret the team result as evidence that founders' qualifications and experience matter, and investors do not only look at how many founders a venture has. (Bhattacharyya & Subrahmanya, 2024). Second, we do not model the policy environment. The available policy-uncertainty index is a national annual figure that assigns every firm the same value, and the only firm-specific date in the data is the funding event itself, which exists only for funded firms; we therefore cannot construct a firm-level measure without building it from the outcome we are trying to explain (Baker et al., 2016; Gulen & Ion, 2016). Third, we observe only one-sided signals that ventures send, not what investors signal in return, so it cannot be examined whether signalling in this market runs both ways through these databases. Finally, the design is cross-sectional and identifies association rather than causation, and it focuses on media and ownership signals.

7. Conclusion

This study analyses which firm-level signals most influence whether an Indian cleantech venture attracts venture capital. By testing five signals together, the findings suggest that media visibility and human capital matter most; media coverage and founding-team size are positive predictors of receiving funding, and location/hub depends on whether ventures are located in major metropolitan hubs, which are far more likely to be funded than those outside them. The signals work additively rather than in combination. Two further results are informative for what they rule out: formal innovation could not be tested meaningfully, as fewer than three per cent of firms hold any intellectual property, and promoter ownership is only weakly and unreliably linked to funding.

The findings suggest that signals established in developed-economy markets carry over to an emerging-economy market setting only unevenly, such as media visibility, team, and location, while patent-based signals barely register where intellectual property is scarce. In doing so, the study extends signalling research from the country level to the individual venture and offers a transparent, reproducible template for firm-level work in data-scarce markets.

For practice and policy, the concentration of capital is the central concern: with the ten largest ventures absorbing roughly 84 per cent of all investment and only one firm in seven funded at all, ventures that are early-stage, outside the hubs, or low-profile risk being left chronically under-financed a gap that matters for India's net-zero ambitions.

This study analysis shows which signals are linked to funding but not why investors read them as they do; therefore, a planned interview study with cleantech investors will examine how they weigh signals under uncertainty, complementing the outcome-based evidence presented here.

References

Akerlof, G. A. (1970). THE MARKET FOR "LEMONS": QUALITY UNCERTAINTY AND THE MARKET MECHANISM *. In *Source: The Quarterly Journal of Economics* (Vol. 84, Number 3).

Audretsch, D. B., Bönte, W., & Mahagaonkar, P. (2012). Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. *Research Policy*, *41*(8), 1407–1421. https://doi.org/10.1016/J.RESPOL.2012.02.003

Baum, J. A. C., & Silverman, B. S. (2004). Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing*, *19*(3), 411–436. https://doi.org/10.1016/S0883-9026(03)00038-7

Beckman, C. M., Burton, M. D., & O'Reilly, C. (2007). Early teams: The impact of team demography on VC financing and going public. *Journal of Business Venturing*, *22*(2), 147–173. https://doi.org/10.1016/J.JBUSVENT.2006.02.001

Berger, P. G., & Ofek, E. (1995). Diversification's effect on firm value. *Journal of Financial Economics*, *37*(1), 39–65. https://doi.org/10.1016/0304-405X(94)00798-6

Bernstein, S., Korteweg, A., & Laws, K. (2017). Attracting Early-Stage Investors: Evidence from a Randomized Field Experiment. *Journal of Finance*, *72*(2), 509–538. https://doi.org/10.1111/jofi.12470

Bhattacharyya, J., & Subrahmanya, M. H. B. (2024). Determinants of a digital start-up's access to VC financing in India: A signaling theory perspective. *Technological Forecasting and Social Change*, *207*, 123631. https://doi.org/10.1016/J.TECHFORE.2024.123631

Block, J. H., De Vries, G., Schumann, J. H., & Sandner, P. (2014a). Trademarks and venture capital valuation. *Journal of Business Venturing*, *29*(4), 525–542. https://doi.org/10.1016/j.jbusvent.2013.07.006

Block, J. H., De Vries, G., Schumann, J. H., & Sandner, P. (2014b). Trademarks and venture capital valuation. *Journal of Business Venturing*, *29*(4), 525–542. https://doi.org/10.1016/J.JBUSVENT.2013.07.006

Brealey, R., Leland, H. E., & Pyle, D. H. (1977). INFORMATIONAL ASYMMETRIES, FINANCIAL STRUCTURE, AND FINANCIAL INTERMEDIATION. *The Journal of Finance*, *32*(2), 371–387. https://doi.org/10.1111/J.1540-6261.1977.TB03277.X

Bruderl, J., & Schussler, R. (1990). Organizational Mortality: The Liabilities of Newness and Adolescence. *Administrative Science Quarterly*, *35*(3), 530. https://doi.org/10.2307/2393316

Busenitz, L. W., Fiet, J. O., & Moesel, D. D. (2005). Signaling in venture capitalist - New venture team funding decisions: Does it indicate long-term venture outcomes? *Entrepreneurship: Theory and Practice*, *29*(1), 1–12. https://doi.org/10.1111/J.1540-6520.2005.00066.X;WGROUP:STRING:PUBLICATION

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press. https://cameron.econ.ucdavis.edu/mmabook/mma.html

Chen, H., Gompers, P., Kovner, A., & Lerner, J. (2010). Buy local? The geography of venture capital. *Journal of Urban Economics*, *67*(1), 90–102. https://doi.org/10.1016/j.jue.2009.09.013

Colombo, M. G., & Grilli, L. (2005). Founders' human capital and the growth of new technology-based firms: A competence-based view. *Research Policy*, *34*(6), 795–816. https://doi.org/10.1016/J.RESPOL.2005.03.010

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011a). Signaling theory: A review and assessment. In *Journal of Management* (Vol. 37, Number 1, pp. 39–67). https://doi.org/10.1177/0149206310388419

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011b). Signaling theory: A review and assessment. In *Journal of Management* (Vol. 37, Number 1, pp. 39–67). https://doi.org/10.1177/0149206310388419

Conti, A., Thursby, J., & Thursby, M. (2013). *PATENTS AS SIGNALS FOR STARTUP FINANCING**.

Cumming, D., Henriques, I., & Sadorsky, P. (2016). "Cleantech" venture capital around the world. *International Review of Financial Analysis*, *44*, 86–97. https://doi.org/10.1016/j.irfa.2016.01.015

Doblinger, C., Surana, K., & Anadon, L. D. (2019). Governments as partners: The role of alliances in U.S. cleantech startup innovation. *Research Policy*, *48*(6), 1458–1475. https://doi.org/10.1016/j.respol.2019.02.006

Gaddy, B. E., Sivaram, V., Jones, T. B., & Wayman, L. (2017). Venture Capital and Cleantech: The wrong model for energy innovation. *Energy Policy, Energy Technology Perspectives*, *102*, 385–395. https://doi.org/10.1016/j.enpol.2016.12.035

Gompers, P. A., Gornall, W., Kaplan, S. N., & Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, *135*(1), 169–190. https://doi.org/10.1016/j.jfineco.2019.06.011

Gompers, P., & Lerner, J. (2001). The Venture Capital Revolution. *Journal of Economic Perspectives*, *15 (2)*, 145–168. https://doi.org/DOI:10.1257/jep.15.2.145

Guldiken, O., Tupper, C., Nair, A., & Yu, H. (2017). The impact of media coverage on IPO stock performance. *Journal of Business Research*, *72*, 24–32. https://doi.org/10.1016/J.JBUSRES.2016.11.007

Haeussler, C., Harhoff, D., & Mueller, E. (2014). How patenting informs VC investors – The case of biotechnology. *Research Policy*, *43*(8), 1286–1298. https://doi.org/10.1016/J.RESPOL.2014.03.012

Heinze, G., & Schemper, M. (2002). A solution to the problem of separation in logistic regression. *Statistics in Medicine*, *21*(16), 2409–2419. https://doi.org/10.1002/SIM.1047;JOURNAL:JOURNAL:10970258;WGROUP:STRING:PUBLICATION

Hsu, D. H. (2007). Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy*, *36*(5), 722–741. https://doi.org/10.1016/J.RESPOL.2007.02.022

Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, *34*(7), 761–781. https://doi.org/10.1002/smj.2037

Islam, M., Fremeth, A., & Marcus, A. (2018). Signaling by early stage startups: US government research grants and venture capital funding. *Journal of Business Venturing*, *33*(1), 35–51. https://doi.org/10.1016/j.jbusvent.2017.10.001

Jensen C. Michael. (1979). *Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure*.

Khanna, T., & Palepu, K. (2000). Is group affiliation profitable in emerging markets? an analysis of diversified Indian business groups. *Journal of Finance*, *55*(2), 867–891. https://doi.org/10.1111/0022-1082.00229;PAGE:STRING:ARTICLE/CHAPTER

King, G., Langche Zeng, G. H. E., Alt, J., Freeman, J., Gleditsch, K., Imbens, G., Manski, C., Mccullagh, P., Mebane, W., Nagler, J., Russett, B., Scheve, K., Schrodt, P., Tanner, M., Tucker, R., Bennett, S., Huth, P., & Zeng, L. (2001). Logistic Regression in Rare Events Data. *Political Analysis*, *9*(2), 137–163. https://doi.org/10.1093/OXFORDJOURNALS.PAN.A004868

Korreck, S. (2019). *The Indian startup ecosystem: Drivers, challenges and pillars of support*. https://www.orfonline.org/research/the-indian-startup-ecosystem-drivers-challenges-and-pillars-of-support

Krishna, H., Kashyap, Y., Dutt, D., Sagar, A. D., & Malhotra, A. (2023). Understanding India's low-carbon energy technology startup landscape. *Nature Energy*, *8*(1), 94–105. https://doi.org/10.1038/s41560-022-01170-y

Li, Y., & Zahra, S. A. (2012). Formal institutions, culture, and venture capital activity: A cross-country analysis. *Journal of Business Venturing*, *27*(1), 95–111. https://doi.org/10.1016/j.jbusvent.2010.06.003

Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. *Journal of Financial Economics*, *110*(2), 403–418. https://doi.org/10.1016/j.jfineco.2013.07.001

Nigam, N., Benetti, C., & Johan, S. A. (2020). Digital start-up access to venture capital financing: What signals quality? *Emerging Markets Review*, *45*, 100743. https://doi.org/10.1016/J.EMEMAR.2020.100743

North, D. (1990). *Institutions, institutional change and economic performance*. 1–27. https://books.google.com/books/about/Institutions_Institutional_Change_and_Ec.html?id=oFnWbTqgNPYC

Owen, R., Brennan, G., & Lyon, F. (2018). Enabling investment for the transition to a low carbon economy: government policy to finance early stage green innovation. *Current Opinion in Environmental Sustainability*, *31*, 137–145. https://doi.org/10.1016/J.COSUST.2018.03.004

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstem, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology*, *49*(12), 1373–1379. https://doi.org/10.1016/S0895-4356(96)00236-3

Petkova, A. P., Rindova, V. P., & Gupta, A. K. (2012). No News Is Bad News: Sensegiving Activities, Media Attention, and Venture Capital Funding of New Technology Organizations. *Https://Doi.Org/10.1287/Orsc.1120.0759*, *24*(3), 865–888. https://doi.org/10.1287/ORSC.1120.0759

Polzin, F., Egli, F., Steffen, B., & Schmidt, T. S. (2019). How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective. *Applied Energy*, *236*, 1249–1268. https://doi.org/10.1016/j.apenergy.2018.11.098

Rajan, R., Servaes, H., & Zingales, L. (2000). The cost of diversity: The diversification discount and inefficient investment. *Journal of Finance*, *55*(1), 35–80. https://doi.org/10.1111/0022-1082.00200;REQUESTEDJOURNAL:JOURNAL:15406261;WGROUP:STRING:PUBLICATION

Rehman, S. (2026). Unveiling the key determinants of cleantech venture capital investment in India: A study using necessary condition and fuzzy set qualitative comparative analysis. *Technological Forecasting and Social Change*, *226*, 124599. https://doi.org/10.1016/J.TECHFORE.2026.124599

Rindova, V. P., Williamson, I. O., Petkova, A. P., & Sever, J. M. (2005). Being Good or Being Known: An Empirical Examination of the Dimensions, Antecedents, and Consequences of Organizational Reputation. *Https://Doi.Org/10.5465/Amj.2005.19573108*, *48*(6), 1033–1049. https://doi.org/10.5465/AMJ.2005.19573108

Samila, S., & Sorenson, O. (2011). Venture Capital, Entrepreneurship, and Economic Growth. *The Review of Economics and Statistics*, *93*(1), 338–349. https://doi.org/10.1162/REST_A_00066

Sorenson, O., & Stuart, T. E. (2001a). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, *10*(6), 1546–1588. https://doi.org/10.1086/321301

Sorenson, O., & Stuart, T. E. (2001b). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, *10*(6), 1546–1588. https://doi.org/10.1086/321301

Spence, M. (1973). *JOB MARKET SIGNALING **. http://qje.oxfordjournals.org/

Stinchcombe, A. L. (1965). Social structure and organizations. In J. G. March (Ed.), *Handbook of Organizations* (pp. 142–193). Rand McNally.

van den Heuvel, M., & Popp, D. (2023). The role of venture capital and governments in clean energy: lessons from the first cleantech bubble. *Energy Economics*, *124*. https://doi.org/10.1016/j.eneco.2023.106877

Woo, H., & Sohn, S. Y. (2022). A credit scoring model based on the Myers–Briggs type indicator in online peer-to-peer lending. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00347-4

Zuckerman, E. W. (1999). The categorical imperative: Securities analysts and the illegitimacy discount. *American Journal of Sociology*, *104*(5), 1398–1438. https://doi.org/10.1086/210178