How do startups influence the resources commitment of different venture capital investors by communicating disruptiveness?

HOW DO STARTUPS INFLUENCE THE RESOURCES COMMITMENT OF DIFFERENT VENTURE CAPITAL INVESTORS BY COMMUNICATING DISRUPTIVENESS?

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ABSTRACT

Entrepreneurs present their ideas in a favorable light through compelling communications that may shape the investors' impressions about the value of the startup's technology and its potential to disrupt. Assessing such communications, venture capital (VC) investors get an impression of the startup's technology and shape their willingness to commit resources to it. Since diverse kinds of VC investors pursue alternative investment objectives, they may develop different impressions of the startup's technology and accordingly make different resource commitment decisions. This paper aims to investigate the resource commitment decisions of VC investors when financing startups communicating disruptiveness by distinguishing between independent venture capitalists (IVC) and corporate venture capitalists (CVC). Analyzing data about 664 medical device and biotech startups in a 10-year period, we found that communicating disruptiveness decreases the amount of funding committed by IVC, while it has a curvilinear effect on the amount of funding provided by CVC. Our findings contribute to the literature and provide important implications for managers of startups aiming to secure funding from different VC investors.

Keywords: Disruptive Innovation; Corporate Venture Capital; Independent Venture Capital; Impression Management, Interorganizational Learning; Real Option theory.

INTRODUCTION

Disruptive technologies have shaken the venture capital (VC) market, putting investors, such as corporate venture capitalists (CVC) and independent venture capitalists (IVC), in a position to make investment decisions under conditions of extreme uncertainty (van Balen, Tarakci, and Sood 2019; Rossi et al. 2020). Such uncertainty is related to the unlikely ex-ante comprehension about if and when a potentially disruptive startup's technology is likely to become definitely disruptive (Danneels 2004; Adner and Snow 2010; Gans 2016). Before the technology turns out to be disruptive, indeed, VC investors lack tangible results to assess the merit of the startup's ideas because of unproven technologies, unfinished products or services, and unpredictable market acceptance and demand (Parhankangas and Ehrlich 2014). For instance, disruptive technologies introduce products with features formerly unseen in the market, and this makes it uncertain whether or not such innovations will attract customers and thus generate extraordinary financial returns for VC investors (Slater and Mohr 2006; Hang, Garnsey, and Ruan 2015). Moreover, since disruptive technologies leverage novel trajectories, VC investors are also uncertain about their capability to learn about such innovations and thus capture strategic benefits from their investments (Ansari, Garud, and Kumaraswamy 2016).

In such a scenario when VC investors have nothing but a startup's idea to assess, their investment decisions can be influenced by what the startups communicate through pitch decks, elevator pitches, crowdfunding campaigns, promotional brochures, and websites contents (Navis and Glynn 2011; Garud, Schildt, and Lant 2014; Clarke, Cornelissen, and Healey 2019; Falchetti, Cattani, and Ferriani 2022). When factual evidence about the startups and their technologies is unavailable, entrepreneurs must present their ideas in a favorable light through compelling communications that may shape the investors' impressions about the potentiality of the startup's technology (Garud, Schildt, and Lant 2014; Parhankangas and Ehrlich 2014). Thus, by assessing

such communications, VC investors get an impression of the startup's technology potential to disrupt, hence influencing their willingness to commit resources to it (van Balen, Tarakci, and Sood 2019; Falchetti, Cattani, and Ferriani 2022).

Few scholars have previously investigated how communicating technologies' disruption potential influences the resource commitment decisions of VC investors in such an uncertain context; in this regard, some authors suggest that VC investors are willing to commit more resources (Kanze and Iyengar 2017), while others less (van Balen, Tarakci, and Sood 2019). Thus, the literature demonstrates diverging views regarding the effect of communicating disruptiveness on VC funding decisions, opening up room for several research paths aimed to identify possible explanations behind this mixed evidence. In this paper, we take one of the possible research paths to shed new light on the relationship between communicating disruptiveness and VC resource commitment, exploring whether the diverging views observed in the literature can be explained considering that the VC landscape is characterized by diverse types of investors, such as IVC and CVC.

When taking resource commitment decisions under uncertain conditions, IVC and CVC pursue alternative objectives that affect their investment logic (Guo, Lou, and Pérez-Castrillo 2015; Alvarez-Garrido and Dushnitsky 2016). Particularly, IVC aim to benefit from the extraordinary returns generated by startups, while CVC follow strategic learning objectives (Alvarez-Garrido and Dushnitsky 2016). Thus, gaining insights into how different VC investors commit resources to reach different objectives may enable scholars, who have considered VC investors as a homogeneous group thus far, to obtain new insights into the relationship between disruptiveness and VC resource commitment decisions. As such, in this paper, we aim to investigate how the startups' communications about the disruptive potentiality of their technologies intervene in the

resource commitment decisions of VC investors by especially distinguishing between IVC and CVC.

We theoretically grounded this study on the Real Option (RO) theory (e.g., Folta and Miller 2002), the inter-organizational learning literature (e.g., Wadhwa and Basu 2013), and the impression management research (Martens, Jennings, and Jennings 2007; Garud, Schildt, and Lant 2014), arguing that communicating the disruptive potentiality of the startup's technology reduces the amount of resources invested by IVC, while it has a curvilinear relationship with the amount of resources committed by CVC. Empirically, we built an ad-hoc dataset based on 664 innovative medical devices and biotech startups considering a 10-year time window. We gathered data from different sources, including economic and business journal articles, startup websites, LinkedIn, the United States Patent and Trademark Office (USPTO), Crunchbase, and the Thomson Reuter VentureXpert databases.

The results of this study offer important theoretical and practical contributions. First, this paper advances previous literature investigating VC investors' resource commitment decisions by shedding new light on how the effect of communicating disruptiveness varies across different types of investors (Kanze and Iyengar 2017; van Balen, Tarakci, and Sood 2019). Moreover, this paper contributes to previous impression management literature investigating how communications influence funding decisions (Martens, Jennings, and Jennings 2007; Garud, Schildt, and Lant 2014; Pan et al. 2018; Falchetti, Cattani, and Ferriani 2022) by adding that alternative financial and strategic investment objectives also intervene in the resource commitment decisions of diverse VC investors. Finally, this research also offers critical managerial implications to support startups in securing funding from different VC investors by communicating disruptiveness.

THEORETICAL BACKGROUND

Impression management refers to the set of activities individuals and organizations perform in an attempt to influence the image that others have of them and thus reach a specific goal (Bozeman and Kacmar 1997; Bolino and Turnley 1999). Particularly, impression management manifests itself in many diverse activities, including oral and written communications (Clark 2008; Falchetti, Cattani, and Ferriani 2022). Previous literature suggests impression management activities are more prevalent when individuals and organizations interact with a powerful audience to obtain their support and when the uncertainty makes it difficult for the audience to get an idea of such individuals and organizations (Gardner and Martinko 1988; Bansal and Kistruck 2006). Impression management considerations are crucial when investigating the effect of the startups' communications on the investors' resources commitment for two main reasons. First, since startups are highly dependent on fundraising, they engage in impression management efforts, such as framing ad-hoc communications, to influence potential investors to commit resources (Navis and Glynn 2011; Falchetti, Cattani, and Ferriani 2022). Moreover, at the time they make their funding decisions, investors can mainly rely on the uncertain market- and product-related data about the startups, and this makes it difficult to assess the actual opportunities behind the investment (Parhankangas and Ehrlich 2014). In such specific circumstances, investors rely on the images, impressions, and sensemaking that the communication of the startups has generated in their minds to take investment decisions (Martens, Jennings, and Jennings 2007; Garud, Schildt, and Lant 2014; Falchetti, Cattani, and Ferriani 2022).

Then, to understand how different VC investors commit resources when funding startups communicating disruptiveness, we turn to two different theoretical lenses, i.e., RO theory and inter-organizational learning literature (Folta and Miller 2002; Santoro and Mcgill 2005; Smit and

Trigeorgis 2007; Wadhwa and Basu 2013). Considering the inherent uncertainty that characterizes a disruptive technology, the RO theory represents an appropriate lens for investigating how IVC make decisions about the level of resources they commit when financing startups that communicate the disruptive potentiality of their technologies. Specifically, the RO theory provides insights into how investment decisions are made under uncertain conditions to preserve or enhance investors' profitability (Folta 1998; Folta and Miller 2002).

Even though the focus on the profitability associated with committing resources is of paramount importance in understanding investment decisions under uncertainty, the RO theory does not consider the achievement of strategic learning opportunities associated with the investment (Wadhwa and Basu 2013). This suggests that the RO theory is not able to comprehensively explain the reasonings behind the resource commitment when objectives other than the financial ones guide the investment decisions. This is precisely the case of CVC who aim to gain strategic learning opportunities from their investments (Rossi et al. 2020). Thus, a further theoretical lens is needed to conduct our investigation. Particularly, we reason that drawing from the inter-organizational learning literature (Santoro and Mcgill 2005) is beneficial for understanding how CVC solve the dilemma of how much resources to commit when investing in potentially disruptive innovations. Focusing on the learning opportunities that characterize cross-border relationships, the inter-organizational learning literature emphasizes the importance for partners to engage in close cooperation when capturing such opportunities is uncertain (Santoro and Mcgill 2005; Wadhwa and Basu 2013).

HYPOTHESES DEVELOPMENT

The venture capital landscape comprises heterogeneous types of investors that differ along several dimensions (Colombo and Murtinu 2017). The distinction that has attracted the most attention from

scholars is the one between IVC and CVC (Bertoni, Colombo, and Grilli 2013). IVC are management companies responsible for handling one or more funds of capital, and they are structured as limited-liability partnerships raising capital from both institutional and individual investors (Alvarez-Garrido and Dushnitsky 2016). IVC are solely dedicated to their investments and do not run other businesses or operations, and gaining financial returns from investments is the sole objective guiding their investment decisions (Alvarez-Garrido and Dushnitsky 2016) (Chemmanur, Loutskina, and Tian 2014). On the other hand, CVC are structured as investment arms or business units of nonfinancial established parent corporates that, representing the only provider of capital, critically influence the CVC investment decisions (Dushnitsky and Lenox 2006). Due to the presence of the nonfinancial parent corporates, CVC investment decisions are mainly driven by strategic objectives (Maula and Murray 2002). Indeed, as widely highlighted by the literature, CVC investments provide a window to new technologies and are pursued to enhance the competitive advantage of parent corporates by allowing them to learn about such technologies (Benson and Ziedonis 2009; Basu, Phelps, and Kotha 2011; Ceccagnoli, Higgins, and Kang 2018). Thus, in the following, we develop two distinct hypotheses about how these two different investors commit resources when funding startups that communicate disruptiveness.

Communicating disruptiveness and IVC resource commitment

The perceptions and impressions of IVC about the potentiality of the startups are largely shaped by how startups communicate their entrepreneurial ideas (Lounsbury and Glynn 2001; Huang and Pearce 2015). When the startups' communications are related to the disruptive potentiality of their technologies, IVC may associate the image conveyed by the startups with that of an uncertain investment opportunity (Navis and Glynn 2011; van Balen, Tarakci, and Sood 2019). For example, communicating disruption may lead IVC to expect unpredictable market acceptance and low initial

performance related to the disruptive technologies (Adner and Snow 2010; Gans 2016). Indeed, potentially disruptive technologies push into the market visionary products characterized by new functionalities unseen in the market so far (Slater and Mohr 2006). Due to the drastic revolution of such products, conservative customers may fail to understand and appreciate their benefits and thus tend to avoid purchasing (Heiskanen et al. 2007). This circumstance makes it challenging to commercialize and make profits from such new-to-the-world and potentially disruptive products. Moreover, communication of disruption may instill a fear in IVC that the startups need to diverge from their initial plans since the development process of disruptive technologies, which run along unexplored technological trajectories, is characterized by unforeseen fatal flaws (Maxwell, Jeffrey, and Lévesque 2011).

We reason that the images and the perceptions that startups generate in the minds of IVC when communicating disruptiveness affect the IVC resource commitment (Mount, Baer, and Lupoli 2021; Falchetti, Cattani, and Ferriani 2022). Since the impression of disruption implies challenges in delivering to the market, commercializing, and generating profits, IVC may be concerned about the possibility that committing extensive resources hampers the financial profitability of their investment opportunities (Folta and Miller 2002). In such a circumstance, IVC are likely to commit a low level of resources to acquire the right, but not the obligation, to eventually engage in more extensive commitment when information that reduces or resolves the uncertainty emerges (Folta, 1998; Folta and Miller 2002). For example, the publication of a prototype disclosure may clarify doubts about the feasibility of the startup's disruptive idea and its commercial chances (Audretsch, Bönte, and Mahagaonkar 2012). Furthermore, through the public claim of data about their technologies during the patenting process, startups may reassure investors about their ability to generate profits from them (Zhang, Guo, and Sun 2019). Moreover, a startup can also reduce IVC's uncertainty surrounding the investment by announcing relationships with

other partners such as other investors (Ozmel, Reuer, and Gulati 2013; Roma, Messeni Petruzzelli, and Perrone 2017; Ragozzino and Blevins 2021).

In sum, we argue that communicating disruptiveness affects the impressions of IVC and downsizes the amount of resources they are willing to commit to that startup. Particularly, IVC will commit a low level of resources while awaiting more information about the startup and its technology before exercising the option to commit a larger amount of money. Accordingly, we state the first hypothesis of the study as follows:

Hypothesis 1. Communicating disruptiveness has a negative effect on IVC resource commitment.

Communicating disruptiveness and CVC resource commitment

The communications of startups also affect the impressions developed by CVC about the opportunity to invest in startups (Navis and Glynn 2011; Falchetti, Cattani, and Ferriani 2022). By communicating disruptiveness, startups can foster the CVC mindset that investing in the startups will provide them with important strategic learning opportunities (Slater and Mohr 2006; Martens, Jennings, and Jennings 2007; Benson and Ziedonis 2009). For instance, communication of disruption may lead CVC to think that they may expand their businesses and reach new markets by learning from startups, which develop disruptive products able to fulfill customers' latent needs (Slater and Olson 2002; Hang, Garnsey, and Ruan 2015). Additionally, communication of disruption may alert CVC about possible technological discontinuities, which they need to embrace to avoid being thrown off from the market by potential new entrants (Lucas and Goh 2009; Karimi and Walter 2016; Eggers and Park 2018). In fact, disruptive technologies that exploit novel trajectories can substitute the current innovations and thus alter the market equilibrium changing the leadership at the expense of established organizations (Bergek et al. 2013).

As such novel and potentially disruptive technologies unveil new markets, novel technological frontiers, and innovative R&D approaches, CVC may be concerned that their capabilities to learn from such investment opportunities are limited (Wan, Williamson, and Yin 2015; Cohen and Levinthal 1990; Wadhwa and Basu 2013). Indeed, when the development of new ideas and technologies requires novel and exploratory search processes, learning can be arduous and uncertain since CVC have to deal with pieces of knowledge that they may not be familiar with and lack the absorptive capacity necessary to insource from such new opportunities (Cohen and Levinthal 1990). Under such circumstances, making large investments is essential for CVC to build quality relationships that resolve learning uncertainties related to investment opportunities (Hamel 1991; Kale and Puranam 2004; Wadhwa and Basu 2013). Effective learning requires, in fact, close collaborations and strict cooperation between the CVC and the startups (Zollo, Reuer, and Singh 2002). To generate cooperative behaviors and facilitate learning processes, it is essential for a startup that the investor demonstrates a high degree of resource commitment by investing a large amount of money (Wadhwa and Basu 2013). Two main mechanisms explain why greater resource commitment enables CVC to learn from a startup. First, higher CVC commitment makes the startup more inclined to share its knowledge. Usually, startups are concerned about possible opportunistic behaviors undertaken by CVC since they may leverage their dominant positions to misappropriate the startup's intellectual property (Dushnitsky and Shaver 2009). Thus, by investing a larger amount of money CVC can alleviate the startup's concern and build trust that increases the startup's propensity to share knowledge (Parkhe 1993; Mesquita, Anand, and Brush 2008). Second, higher resource commitments create mutually beneficial relationships between the CVC and the startup by increasing the dependence of the latter on the former (Young-Ybarra and Wiersema 1999). Since startups are usually limited in terms of resource availability, their dependency on CVC investments pushes them to maintain and strengthen these relationships. Thus, when CVC commit

a higher amount of money, the startup is more likely to be willing to extend their relationships into more committed ones that permit knowledge transfer and learning processes to happen (Wadhwa and Basu 2013). Furthermore, more extensive resource commitment allows CVC to preempt the moves of others avoiding the possibility that competitors learn about the new technologies (Kim et al. 2016). Indeed, by committing a higher amount of funding to the startup, CVC can gain more power in the startup's boards of directors, thus limiting the possibility for others to access the startup's technologies and safeguarding their competitive positions in the market (Ceccagnoli, Higgins, and Kang 2018).

However, if a startup's communications convey an exceedingly disruptive image in the mindset of CVC, CVC may not recognize the investment as a strategic learning opportunity. When the development of new ideas and innovations runs along disruptive technological trajectories that are too far away from the existing ones, CVC may not be able to understand and assess the value of such ideas and innovations due to their cognitive limitation (Henderson 2006). In this scenario, CVC may fail to recognize the opportunities they could get by learning from investing in disruptive startups whose products far exceeded the current customer needs (Kumaraswamy, Garud, and Ansari 2018). Moreover, CVC may also misjudge the impact that disruptive technologies may have on the competitive pattern, thus underestimating the threat to be thrown out of the market by the disruptive startups (Lucas and Goh 2009). If CVC do not recognize the critical value of the learning opportunities, they will avoid committing a high amount of resources to the startup (Santoro and Mcgill 2005). Deeming it unnecessary to establish close cooperation and build trust to incentivize the sharing of information and activate learning processes, CVC will engage in low-resource commitment, which can offer them a level of investment that is commensurate with poor learning opportunities (Kale and Puranam 2004; Wadhwa and Basu 2013). In this circumstance, CVC may base their investment decisions on the financial returns associated with such investments. When

disregarding the strategic learning benefits of the investment and focusing prevalently on their financial returns, the funding decisions of CVC may resemble those of IVC. Thus, CVC will be more concerned about the challenges in the commercialization and profitability of technologies characterized by exceedingly high disruptive potentiality than the possibility to exploit new strategic learning opportunities. Therefore, similar to IVC, CVC will also be discouraged to invest a high amount of funding, preferring to postpone more committed investments when the level of acceptance and profitability of the technologies is less uncertain (Folta and Miller 2002; Smit and Trigeorgis 2007).

Considering the above arguments, we hypothesize an inverted U-shape relationship between communicating disruptiveness and CVC resource commitment. The startup's communications of disruption encourage the resource commitment of CVC, who, by associating the image of the startup with critical learning opportunities, are willing to commit a high amount of funding to establish close cooperation that activates learning processes. However, if the startup communications shape exceedingly disruptive perceptions, CVC won't be able to recognize and assess the strategic learning opportunities associated with the startups' technologies and will be thus less inclined to commit a high amount of funding. Accordingly, we state the second hypothesis of the study:

Hypothesis 2. Communicating disruptiveness has an inverted U-shape effect on the CVC resource commitment.

DATA AND METHODS

Research setting and data collection

To investigate the relationship between communicating disruptiveness and the resource commitment of different VC investors (i.e., IVC and CVC), we built a unique dataset considering

a time window from 2005 to 2014. We selected our sample by focusing on the innovative medical devices and biotech startups that have received their first investment from IVC or CVC in the aforementioned period. We specifically chose such a sector due to the critical role that disruptive technologies play in enhancing life expectancy, quality of life, and diagnostic and treatment options, as well as in providing efficiency and cost-effectiveness to the overall healthcare system (Christensen, Bohmer, and Kenagy 2000). Leveraging the Standard Industrial Classification (SIC) codes, we defined the medical devices and biotech startups by considering three different SIC codes: the SIC code "3845" related to the "Electromedical & Electrotherapeutic Apparatus" industry; the SIC code "2836" related to the "Biological Products" industry; and the SIC code "3841" related to the "Surgical & Medical Instruments & Apparatus" industry.

We used the VentureXpert database published by Thomson Venture Economics to select the startups' sample and gather information about the investments they have received since it contains comprehensive coverage of information about both IVC and CVC investments and is frequently used by scholars investigating the VC market (Dushnitsky and Lenox 2006; Van De Vrande and Vanhaverbeke 2013). Considering such a database, we obtained an initial sample of 846 medical devices and biotech startups that have received their first investment in the period under observation. However, often VC investors do not disclose the amount of funding they commit. Thus, we excluded from our sample the innovative startups for which the amount of money received is unknown. The final sample included 664 startups. Specifically, 33% of the sampled startups operate in the "Electromedical & Electrotherapeutic Apparatus" industry (SIC code 3845), 35% in the "Biological Products" industry (SIC code 2836), and 32% in the "Surgical & Medical Instruments & Apparatus" industry (SIC code 3841).

Then, considering the final sample, we leveraged VentureXpert to retrieve information about the IVC and CVC (e.g., previous investment experience and their preferred investment areas), the

startups (e.g., age and nationality), and the amount of funding that the startups have received from IVC and CVC in their first investment. Additionally, data collected from VentureXpert have been triangulated through the Crunchbase website. Moreover, following previous studies (van Balen, Tarakci, and Sood 2019), we gathered information about the communications of the startups in our sample by collecting their mission statements. Particularly, since startups' mission statements are subject to revisions over time as startups acquire further information about their technologies and incrementally achieve their objectives (van Balen, Tarakci, and Sood 2019), we retrieved the cached copies of the startups' webpages at the year before the first investment received. Furthermore, we also leveraged the startups' web pages and LinkedIn to access information about their founders, including their experience and educational background (e.g., Mazzola, Perrone, and Kamuriwo 2016). Finally, patent information was collected using the United States Patent and Trademark Office (USPTO) database.

Moreover, since syndication is commonplace for VC investors that usually co-invest together (Lerner 2014), for each startup in the sample, we distinguished the lead investor type from which it has received its first round of investment (i.e., IVC or CVC). Specifically, we assigned the investor type considering the lead investor as reported in the VentureXpert database and on the Crunchbase website. As recognized by previous scholars, the lead investor is the most committed investor in a syndicate and the most actively involved in monitoring the startup since providing the largest amount of money and being the one sitting on the startup's board of directors (Wright and Lockett 2003; Hochberg, Ljungqvist, and Lu 2010). Thus, since the commitment of the lead investor in a syndicate is the highest, to avoid bias in the estimation of the amount of money invested by different investors, we followed previous scholars and focused our analysis on the lead investors only, excluding non-lead members of the investment syndicate from the analysis (Elango et al. 1995).

Measures

We operationalized two different dependent variables to assess the resource commitment of IVC and CVC: *IVC commitment* and *CVC commitment*. These two variables assess the resource commitment of IVC and CVC by specifically focusing on the amount of resources committed during the first investment round since at that moment, their decisions are not influenced by previous investments (Ross, Fisch, and Varga 2018). Indeed, the literature highlights how previous investments can be used by IVC and CVC to assess the startups' quality and make investment decisions (Dimov and Milanov 2010; Hoenen et al. 2014; Hopp and Lukas 2014). As such, *IVC commitment* measures the amount of funding in millions of US dollars that a startup has received from IVC. Similarly, *CVC commitment* measures the amount of funding in millions of US dollars that an innovative startup has received from CVC.

Regarding the independent variable, we followed the approach adopted by van Balen et al. (2019) to measure the level of disruptiveness communicated by startups in our sample by assessing the framing of their mission statements. Particularly, we measured our independent variable *Disruptiveness* along four dimensions assessing whether a startup leverages the mission statement to (1) promote drastic changes in the market, (2) describe a future that contrasts with the status quo delineating deficiencies in the market, (3) suggest achieving the conventional market objectives in a completely different way, and (4) promote new functions compared to those offered by the current products in the market.

Two graduate assistants read the mission statement of each startup (some extracts of startups' mission statements are reported in the Appendix) to measure the *Disruptiveness* communicated by a startup when describing its innovation. After three instruction meetings to align disagreements on a trial set of mission statements, the two graduate assistants proceeded autonomously in the

evaluation activity. The evaluation procedure of the startups' mission statements demonstrated an adequate degree of agreement between the two graduate assistants (Cohen's κ coefficient equal to 84%) (Cohen 1960). The differences were discussed with the authors to reach a consensus.

At the end of the evaluation procedure of the startups' mission statements, we performed some checks on the *Disruptiveness* dimensions. First, we checked the pairwise correlations among the dimensions shaping the *Disruptiveness* measure to avoid the possibility of considering the four dimensions as proxies for one another. The results indicate that all the values of the correlations are strongly significant ($p < 0.001$) and lower than 0.6. This finding is in line with previous studies on disruptive innovation (van Balen, Tarakci, and Sood 2019; Zhang, Guo, and Sun 2019), suggesting that disruption is a complex concept that needs to be assessed through a multidimensional approach. Particularly, the four dimensions assessed can be considered different facets that characterize the communication of disruptiveness.

Moreover, we also computed the internal reliability for the dimensions shaping the independent variable by using a confirmatory factor analysis (CFA). The CFA's results were as follows: dimension (1) "promotes drastic changes in the market" has a factor loading equal to 0.67; dimension (2) "describes a future that contrasts with the status quo delineating deficiencies in the market" has a factor loading equal to 0.77; dimension (3) "suggests achieving the conventional market objectives in a completely different way" has a factor loading equal to 0.71; dimension (4) "promotes new functions compared to that offered by the current products in the market" has a factor loading equal to 0.68. Since all the dimensions shaping the disruptive innovation have a factor loading greater than 0.6, the results provide evidence for the reliability of the individual items (Hair et al. 2006). We have also computed the value of Cronbach's alpha, which is equal to 0.74 (the value should range between 0.68 and 0.97), implying that the four dimensions are internally consistent at an acceptable level (Hair et al. 2006). Moreover, the comparative fit index

(CFI) (Bentler, 1990), the Tucker–Lewis Index (TLI) (Tucker and Lewis 1973), and the root mean square error of approximation (RMSEA) (Steiger 1990) were performed to assess how well the four dimensions fit the data. The CFI and TLI evaluate the fit between the sample and model covariance matrices. Particularly, the CFI estimates the relative reduction in the lack of fit, while the TLI assesses the relative improvement per degree of freedom. For both indices, values above 0.9 suggest an acceptable fit (Bentler 1990). The RMSEA considers the degree of discrepancy between the sample and model covariance matrices, and a value below 0.05 indicates a reasonable approximation error (Browne and Cudeck 1992). We obtained a CFI of 0.914, TLI of 0.922, and RMSEA of 0.043, indicating an adequate fit and validating the four dimensions of *Disruptiveness.*

Finally, once the correlations and the internal reliability of the four dimensions were assessed, the variable *Disruptiveness* was measured by combining the evaluations of the four dimensions using a categorical variable that assumes integer values ranging from 0 to 4.

Moreover, since the level of commitment of both IVC and CVC could also be affected by other factors than the startups' communications about the disruptive potentiality of their innovations, we included several control variables in our models. Particularly, we controlled for temporal effects, including a dummy variable for each year of the studied period. Furthermore, we controlled for several effects related to the startups and the VC investors. Concerning the startups, as our sample includes medical devices and biotech startups operating in three different industries, we controlled the *Industry* of the startup. As such, *Industry* was operationalized through three dummy variables representing the industry of the startup according to the SIC codes (i.e., "Electromedical & Electrotherapeutic Apparatus" "Biological product" and "Surgical & Medical Instruments & Apparatus"). Additionally, we controlled for the possibility that a startup has already released products or prototypes since this circumstance may influence their ability to secure funding by highlighting their quality in the investors' eyes (e.g., Audretsch, Bönte, and

Mahagaonkar 2012). Accordingly, *Released product* assumes the value "1" if, according to the VentureXpert database, the startup has released at least one product/prototype before the first investment received, and "0" otherwise. Moreover, it is strongly recognized in the literature that through patenting activity, startups can signal their quality to attract funding from prominent investors (Zhang, Guo, and Sun 2019). Thus, we controlled for the *Patent* of the startup, a binary variable that assumes the value "1" if the startup has filled at least one patent before its first investment according to the USPTO database, and "0" otherwise. Moreover, it is recognized that startups that are active in technology-oriented industries typically file for patent protection, whereas startups that are active in marketing-oriented industries are more likely to file for trademark protection (De Vries et al. 2017). As such, we also controlled for the number of *Trademarks* registered by the startups in our sample. Furthermore, we added the variable *Startup age* to control for the number of months that have passed from the founding date of the startup to the first investments received. Additionally, we controlled for the effect played by the *Startup nationality* on the IVC and CVC resource commitment through a binary variable assuming the value "1" if the headquarter of the startup is in the US, and "0" otherwise. We also controlled the *Growth ambition* of the startup by considering the gender of the startup's founders. Indeed, previous studies recognized how female entrepreneurs are less focused on economic performance and growth (Bird and Brush 2002; Manolova et al. 2012). *Growth ambition* measures the ratio of the number of female founders to the total number of founders for each startup. Following some previous studies suggesting that the startup's human capital influences the funding received (e.g., Gimmon and Lavie 2010), we added three control variables to control for the role played by the startups' founders in attracting potential investors. First, we added the control variable *Founders*, a count variable that measures the number of entrepreneurs that founded the startup. Second, since the literature has highlighted that the educational background of the startups' founders affects the

fundraising of the startups (Baumol, Schilling, and Wolff 2009; Ratzinger et al. 2018), we controlled for the founders' education by checking their profiles on LinkedIn; as such, *Founders education* is a binary variable that assumes the value "1" if at least one of the startup's founders has a Ph.D., and "0" otherwise. Finally, since experienced and novice founders focus differently on novelty (Baron and Ensley 2006), they may differ in their ability to attract funding. Thus, we controlled for the *Founder experience,* a binary variable that assumes the value "1" if at least one of the startup's founders has prior entrepreneurial experience, and "0" otherwise.

Considering the control variable related to the VC investors (both IVC and CVC), we included in our model a dummy variable controlling for the effect that the *Investor industry focus* has on the amount of money committed by the investor. *Investor industry focus* assumes the value "1" if the VC investor has a specific investment focus on the medical devices and biotech sector as retrieved from VentureXpert, and "0" otherwise. Moreover, the funding decision of a VC investor may also be influenced by their previous experience in the capital market (Van De Vrande and Vanhaverbeke 2013). Thus, we also included the variable *Investor experience,* which measures the amount of money in millions of US dollars that the investor has previously committed to entrepreneurial projects. Furthermore, recognizing that IVC and CVC syndicate their investments frequently to pool their efforts, share the risk, and increase the diversity and the number of their investments (Bygrave 1987), we added the control variable *Syndication*, which measures the number of investors that take part in the investment together with the lead. We also controlled for the effect of the *Investor nationality* on the resource commitment decisions of CVC and IVC through a binary variable assuming the value "1" if the headquarter of the VC investors is in the US, and "0" otherwise. Additionally, following the literature on venture capital (Anokhin, Wincent, and Oghazi 2016), we controlled for the investors' preferred round of investment as a measure of their *Risk tolerance*. Seed- and early-stage startups are characterized by a very high-risk investment

opportunity, whereas later-, extension-, or balanced-stage investment startups are associated with lower levels of risk (Anokhin, Wincent, and Oghazi 2016). Thus, we operationalized the *Risk tolerance* of the investor by using a binary variable that considers the investor's previous investments and assumes the value "1" if the preferred investment round for the VC investors is a seed- or early-stage and "0" if the preferred investment round is later-, extension-, or balanced-stage. To measure this control variable, we collected data from both the VentureXpert database and the Crunchbase website.

Finally, only considering CVC, we included a binary variable to control for their primary *Investment objective*. Following the previous work of scholars (Dushnitsky and Lenox 2006), we determined the primary objective of CVC using information disclosed by their parent corporate executives or by CVC personnel. Specifically, we conducted an extensive search for CVC' investment announcements in newspapers, trade magazines, and newsletters. Then, two of the authors independently coded the primary CVC objectives. The coding procedure showed an overall rate of agreement equal to 89%, and the differences were discussed with the third author to reach a consensus (Cohen 1960). *Investment objective* assumes the value "1" if the CVC are seeking strategic objectives, and "0" if the CVC are financially driven.

The descriptive statistics for all the variables are reported in Table 1.

Insert Table 1 here

ANALYSIS AND RESULTS

Table 2 provides the pairwise correlation values for all variables. The pairwise correlation analysis did not disclose any criticality. Moreover, to assess for multicollinearity problems, we also calculated the variance inflation factor (VIF) values (Stevens 1996). The VIF values are below the

threshold of 10; thus, the explanatory variables can concurrently be included in our models (Gujarati 2004).

Insert Table 2 here

To test our hypotheses, we used two ordinary least squares (OLS) regression analyses. The results of the OLS estimations are reported in Table 3. Model 1, Model 2, and Model 3 focus on the effect of communicating disruptiveness on IVC resource commitment. In particular, Model 1 operates as a baseline model, and it includes only the control variables. Model 2 introduces the independent variable *Disruptiveness* to test the first hypothesis of the study. Model 3 includes the quadratic effect of *Disruptiveness* to further confirm the linear relationship (*Hypothesis 1*). Similarly, Model 4, Model 5, and Model 6 assess the relationship between communicating disruptiveness and CVC resource commitment. Model 4 constitutes the baseline model including only the control variables. Then, Model 5 introduces the independent variable *Disruptiveness,* and Model 6 includes its quadratic effect to assess *Hypothesis 2*.

Insert Table 3 here

Concerning the dependent variable *IVC commitment* and starting with the control variables, we focus on Model 1. The control variable *Risk tolerance* is significant and has a positive effect on the amount of money committed by IVC, implying that IVC with higher tolerance to face risks will commit higher amounts of funding. The dummy variables related to the startup *Industry* are not significant, suggesting that when making resource commitment decisions, IVC are not concerned about the differences between "Biological product", "Surgical & Medical Instruments & Apparatus" and "Electromedical & Electrotherapeutic Apparatus" industries. Moreover, the

control variable *Founders* is significant and has a positive coefficient, indicating that when the startup has a higher number of founders, IVC are more willing to commit a higher amount of funding. The control variable *Age* is significant, meaning that the age of a startup affects IVC investment decisions; in this regard, the older the startup is, the higher the amount of funding committed by IVC will be. On the other hand, the control variables *Investor nationality, Startup nationality, Patent, Product released,* and *Growth ambition* do not affect the funding decisions of IVC. Furthermore, *Founders education* and *Founders experience* are significant, and they have a positive coefficient, meaning that startups whose founders have a Ph.D. title and prior entrepreneurial experience receive more funding from IVC. Moreover, both the control variables *Investor experience* and *Investor industry focus* are significant and show a positive coefficient, suggesting that IVC with more experience in the market capital and characterized by a specific focus on medical devices and biotech startups are more willing to engage in high-committed investments. Finally, the control variable *Syndication* is also significant and has a positive coefficient, meaning that the larger the number of co-investors is, the higher the amount of funding committed by IVC will be. In Model 2, the variable *Disruptiveness* is significant and has a negative impact on the *IVC commitment*, thus confirming the first hypothesis of this study. Finally, in Model 3 $Disruptiveness^2$ does not affect the IVC resource commitment, further confirming the linear relationship between communicating disruptiveness and the IVC commitment.

Considering the dependent variable *CVC commitment*, we initially focus on Model 4 to assess the control variables. *Risk tolerance* is significant and shows a positive coefficient, indicating that CVC with higher tolerance to face risk are willing to commit a larger amount of money. The dummy variables “Surgical & Medical Instruments & Apparatus” and “Biological product” are significant and present a positive coefficient. This result suggests that compared to the startups operating in the “Electromedical & Electrotherapeutic Apparatus” industry (omitted

since it is used as a baseline category), those that operate in the "Surgical & Medical Instruments & Apparatus" and "Biological product" industries receive more funding from CVC. Furthermore, the controls *Startup nationality, Founders, Product released, Growth ambition*, *Trademarks,* and *Experience* do not affect the amount of funding committed by CVC. The control variable *Age* is significant and presents a positive coefficient, meaning that the age of the startup increases the CVC willingness to commit a substantial amount of money. Moreover, the control variable *Patents* is significant and positively affects the CVC decision to commit a higher amount of money to a startup that has already filed at least one patent. Additionally, *Founders education* is significant and has a positive coefficient, meaning that startups whose founders have a Ph.D. title receive more funding from CVC. Moreover, the variable *Syndication* is also significant and has a positive coefficient, suggesting that the presence of co-investors has a positive effect on the amount of funding committed by CVC. Last, *Investor nationality, Investor experience, Investor industry focus,* and *Investment objective* are not significant. Considering Model 5, the variable *Disruptiveness* is significant and has a positive impact on the *CVC commitment*. Model 6 also demonstrates that the squared term of the explanatory variable, $Disruptiveness^2$ is significant and has a negative coefficient, thus confirming the second hypothesis of this study.

Figure 1 is a graphical representation of previous results. Regarding Hypothesis 1, Figure 1 highlights that the *IVC commitment* is linear and shows a negative slope when increasing the disruptive potentiality communicated by the backed startups. Concerning Hypothesis 2, Figure 1 suggests that an inverted U-shaped relationship exists since the amount of funding committed by CVC first increases with the startups' communication of disruption at a decreasing rate to reach a maximum, after which the amount of funding decreases at an increasing rate. The point at which the curve attains its maximum value is defined as the "turning point", and it needs to be located within the data range (Haans, Pieters, and He 2015). We tested this assumption following the

procedure described in the study by Haans, Pieters, and He (2015), finding further confirmation for the curvilinear inverted U-shaped relationship. In particular, the turning point is positioned at 2.74 (95% conf. interval [2.28–3.07]; p-value 0.000).

Insert Figure 1 here

Endogeneity check and robustness analyses

To adequately address endogeneity concerns related to our independent variable *Disruptiveness*, we used a two-stage model leveraging the Instrumental Variable (IV) method (Wooldridge 2002; Hamilton and Nickerson 2003). Particularly, to account for such endogeneity concerns, we need an IV that correlates with the independent variable but is exogenous from the dependent one (Hamilton and Nickerson 2003). We selected the *Communication skill*s of the startup's founders as a firm-level instrument, suggesting that such communication skills do have not a direct effect on the amount of funding a startup acquires. We reason that the effect of the founders' communication skills on the fundraising of the startups depends on how such skills influence the framing of the startups' communications. Specifically, by gathering data from the LinkedIn profiles of the startups' founders, we measured the IV *Communication skill* as the number of founders that have a (bachelor's or master's) degree in the field of communication studies (e.g., journalism, public relations, and marketing). In addition to the intuitive support for the choice of our IV, we also leveraged more reliant and robust statistical tests to assess the IV relevance and exogeneity (French and Popovici 2011). In this regard, we evaluated the strength of the instrument's effects on the endogenous regressor through the Anderson canonical correlation Lagrange Multiplier (LM) test for instrument relevance. The LM test suggested our IV is highly significant (Anderson canon. corr. LM statistic = 15.895, $p < 0.0001$), highlighting its strong predictive power in the first stage

model (Davidson and MacKinnon 2004). To assess the exogeneity of the IV, we carried out a Sargan-Hansen test for overidentification (Davidson and MacKinnon 2004). Our analysis suggested that the Sargan-Hansen test is statistically insignificant (Sargan-Hansen statistics = 14.463, $p > 0.10$), providing evidence that our IV is less likely to be correlated with the error term in the second-stage model. Combined, the results of the above tests support the empirical validity of the IV *Communication skill*.

The results of the two-stage endogeneity analysis are reported in Table 4. In the first stage of the model, *Disruptiveness* serves as the dependent variable, and *Communication skill* is put into analyses as IV together with other control variables (Model 1 in Table 4). In the second stage of the model, the predicted value of *Disruptiveness*, which we obtained from the first stage, is fitted as an independent variable along with the control variables (Model 2 and Model 3 in Table 4). The results of the two-stage endogeneity analysis are consistent with previous results, thus validating our interpretations.

Insert Table 4 here

Moreover, some additional analyses were carried out to further support our results. First, we performed a new analysis considering the entire sample including all the investors, i.e., IVC and CVC. To assess the different effects of *Disruptiveness* on the resource commitment of the two different types of investors using the entire sample, we included in the analysis the control variable *Investor type.* The variable *Investor type* assumes the value "0" if the investor belongs to IVC and "1" if the investor belongs to CVC. The results for the linear only and U-shaped relationships are reported in Table 5. Model 1 operates as a baseline model, and it includes only the control variables.

In particular, we used the same control variables included in the main analysis (Table 3), except for *Investment objective*, which has been measured for CVC only. Model 2 introduces the linear interaction term between *Disruptiveness* and *Investor type*. Finally, Model 3 includes the quadratic interaction between *Disruptiveness* and *Investor type*.

Insert Table 5 here

The results of this analysis are consistent with those obtained when splitting the sample according to the investor type (Table 3). Indeed, Model 2 demonstrates that the linear interaction term between *Disruptiveness* and *Investor type* has a significant and positive coefficient, suggesting that CVC are more inclined than IVC to engage in extensive resource commitment toward startups communicating that their innovations have disruptive potentiality. Moreover, Model 3 highlights that the quadratic interaction term between *Disruptiveness* and *Investor type* has a significant and negative coefficient. This suggests that the relationship between *Disruptiveness* and resource commitment has a curvilinear inverted U-shaped nature when considering CVC.

Second, we performed further analysis to check for a possible adverse selection issue in our sample related to the circumstance in which startups are forced to accept funding from CVC since they do not receive investments from IVC. For instance, startups with more disruptive potential may have fewer investment options from IVC and may therefore be forced to accept funding from CVC. Thus, to check for such a possible adverse selection issue, we performed further analysis to demonstrate that the startups that receive funding from CVC in our sample also receive funding from IVC. Particularly, since startups usually receive funding from a syndicate of investors (made up of IVC and/or CVC), we examined the composition of the syndicates financing the startups of our sample. We assessed whether the number of IVC who invest in syndicates whose lead investors

are IVC does not differ significantly from the number of IVC who invest in syndicates whose lead investors are CVC. To compare the two groups, a one-way ANOVA was conducted. The test indicates that the two groups' variances do not significantly differ from each other (F equal to 1.26; p-value equal to 0.2616), meaning that, in our sample, there are no differences between the number of IVC who invest in syndicates whose lead investors are IVC and the number of IVC who invest in syndicates whose lead investors are CVC. Thus, in our sample, startups that have received funding from CVC as leading investors do not seem to suffer from an adverse selection problem, at least in terms of other IVC investments.

Third, we conducted a further analysis to explore the innovation of the startups in our sample and assess their disruptiveness at present. This exploration aims to investigate if there is a link between what was communicated in the mission statements in terms of disruptive potentiality and the actual disruption that the technologies from these startups have created currently. Indeed, startup entrepreneurs may be excessively optimistic about the potentialities of their innovations and may communicate a disruptiveness that does not necessarily turn out to be actual. We collected additional secondary data from scientific articles published in peer-reviewed journals that have conducted empirical studies on the startups' products/technologies. In this regard, we searched on Google Scholar for articles published in the last 10 years that cite the name of the startups and/or their products/technologies. We gathered results for 505 startups in our sample. Then, two researchers independently read these articles and assessed the disruptiveness of the startups' technologies along the four dimensions identified by van Balen et al. (2019). To compare the disruptiveness communicated by the startups in the mission statements and that emerged from the scientific articles, a one-way ANOVA was conducted. The test indicates that the two groups' variances significantly differ from each other (F equal to 3.86; p-value equal to 0.004), suggesting that there are differences between startups' communication of disruptive potentiality and the

evaluation of independent and external experts of the actual disruptiveness observed at present. In particular, we performed a Welch test to assess differences in the means of the two groups with unequal variances (Wilcox 2007). The results of the Welch test suggest that the level of disruptiveness communicated by the startups (means equal to 2.403) exceeds the actual level of disruptiveness (means equal to 2.242). Thus, these results suggest that overall, what we have measured in our main analyses are just the entrepreneurs' communications about the disruptive potentialities of their technologies, which do not reflect the actual disruptiveness occurring presently.

DISCUSSION AND CONCLUSIONS

Our results confirmed the two hypotheses of the study. First, we found support for the negative effect of communications about disruptions on the resource commitment of IVC. This result is in line with the recent study by van Balen et al. (2019), and it suggests that when a startup communicates the potential of their technologies' disruptiveness, IVC develop the perception that the financial return of that investment is highly uncertain. Pursuing only financial objectives and aiming at gaining returns to recover their investments, IVC care about the significant opportunity costs that may hamper their portfolio return and preclude them from the possibility to finance other initiatives (Alvarez-Garrido and Dushnitsky 2016). Thus, since IVC perceive disruptive technologies as difficult to commercialize and arduous to generate profits from (Hang, Garnsey, and Ruan 2015), they are discouraged from committing substantial resources at least until more information emerges and resolves the uncertainty surrounding the technologies (Folta 1998).

Second, we ascertained confirmations about the curvilinear relationship between communicating disruptiveness and the resource commitment of CVC. In their investment decision-making processes, CVC are mainly guided by strategic objectives, and they aim to learn from

innovative startups to explore novel technological trajectories and detect new opportunities for enhancing the competitiveness of their parent corporates (Chemmanur, Loutskina, and Tian 2014; Alvarez-Garrido and Dushnitsky 2016). Investing in startups claiming disruption allows corporates to make sense of potential learning opportunities related to new business and technological discontinuities (Eggers and Park 2018; Kammerlander, König, and Richards 2018). In particular, this result suggests that to capture learning opportunities from startups communicating disruptiveness, CVC need to establish close cooperation by committing an extensive amount of resources (Santoro and Mcgill 2005; Wadhwa and Basu 2013). Indeed, incentivizing startups to share information and increasing their dependency on the investors to establish close cooperation allows CVC to exploit learning opportunities from the startups (Hang, Garnsey, and Ruan 2015).

However, our findings also highlight that when communication shapes an exceedingly disruptive perception in the mindset of CVC, they may be discouraged from committing a considerable amount of funding. In fact, since extreme levels of disruption are difficult to recognize and assess, CVC are not able to grasp the strategic learning opportunities related to such investments (Henderson 2006; Lucas and Goh 2009). Thus, in this scenario, CVC will not deem close cooperation with the startups necessary and will be less inclined to commit substantial funding.

Contribution to the literature

Our findings offer two main contributions to the literature. First, this paper enriches the literature addressing how communication of disruption influences the resource commitment decisions of VC investors (Kanze and Iyengar 2017; van Balen, Tarakci, and Sood 2019). These previous studies have reported diverging results when exploring how communicating disruptiveness impacts VC funding decisions. We proposed that a possible explanation for such mixed results may lie in the

fact that previous studies have considered the VC landscape as composed of a homogeneous group of investors without considering their diverse investment objectives. For example, as opposed to the study of van Balen et al. (2019), which highlights a negative effect of communicating disruptiveness on the amount of funding provided by a homogeneous group of investors (i.e., IVC, CVC, and angel investors), our study analyzes how communicating disruptiveness differently influences the investment decisions of diverse investors pursuing varying objectives. Indeed, since previous literature on entrepreneurship has suggested that IVC and CVC pursue financial and strategic objectives, respectively (e.g. Guo, Lou, and Pérez-Castrillo 2015; Alvarez-Garrido and Dushnitsky 2016), we expand on previous investigations (van Balen, Tarakci, and Sood 2019), suggesting that such alternative investment goals differently influence the resource commitment decisions of diverse investors. In this regard, the resource commitment decisions of different VC investors vary significantly in ways that are consistent with the uncertain realization of financial benefits and strategic learning opportunities associated with disruptive technologies. IVC are concerned about the uncertainty related to the expected financial returns associated with potentially disruptive technologies, while CVC evaluate the uncertainty of gaining learning opportunities when funding startups with the potential to disrupt. Thus, by suggesting that communicating disruptiveness reduces the amount of funding invested by IVC but has a curvilinear effect on the amount of funding committed by CVC, we have demonstrated that our assumption that the different results may be ascribed to the diverse nature of VC investors was well founded. In sum, we believe that previous studies could not capture the whole picture of the relationship between communicating disruptiveness and VC resource commitment, whereas our study offers a more accurate and sharpened representation of how communicating disruptiveness affects the funding decisions of IVC and CVC.

Second, this study contributes to the literature on impression management that has investigated how startups' communications shape the sensemaking of different investors and influence the commitment of their resources (Martens, Jennings, and Jennings 2007; Garud, Schildt, and Lant 2014; Pan et al. 2018; Falchetti, Cattani, and Ferriani 2022). In this regard, the literature has highlighted how different investors rely on the images, impressions, and sensemaking that the communications of the startups have created in their minds to make investment decisions (Pan et al. 2018). In this context, we demonstrate that the reactions to these communications may also depend on the type of investors and the nature of their investment objectives. Relatedly, our study extends this stream of the literature, displaying how beyond individual cognitive processes and the level of expertise (Falchetti, Cattani, and Ferriani 2022), different investment objectives such as financial and strategic ones may also influence the investment decisions of diverse investors. Particularly, IVC and CVC differ along several dimensions including their structures, investment time horizons, objectives, managers' compensation schemes, skills and competencies, startup legitimacy judgments, and the support they may offer to the portfolio startups (Guo, Lou, and Pérez-Castrillo 2015; Alvarez-Garrido and Dushnitsky 2016). Proving that communicating disruptiveness differently influences the resource commitment of IVC and CVC, our study contributes to the literature by suggesting that due to strategic investment objectives, the presence of parent corporates, and the exploration-oriented nature, CVC are more inclined than IVC to commit substantial resources when investing in startups that claim to have disruptive technologies/products, at least for low and moderate levels of disruptiveness.

Managerial implications

By demonstrating that communications of disruption differently affect the investment propensity of diverse investors, we offer actionable suggestions to entrepreneurs on how to frame their

communications so that they can strategically persuade different investors in funding their ideas and technologies. In this sense, entrepreneurs should be aware that framing ad-hoc communications to claim the disruptive potentiality of their technologies differently influences IVC and CVC. Since diverse investors can offer different and complementary competencies and assets to support the startups, when informing investors about the disruptive potentiality of their innovations, entrepreneurs should pay close attention to what kind of investors they want to attract.

If the startups need support in recruiting key employees and developing network capabilities, they should encourage IVC to commit substantial resources (Maula, Autio, and Murray 2005; Alvarez-Garrido and Dushnitsky 2016). Startups can maximize the amount of funding received from IVC by avoiding placing high emphasis on the disruptive potentiality of their technologies. By underemphasizing the disruptiveness of their technologies in their communications, startups can lessen the possibility that IVC develop perceptions of uncertainty about the market acceptance of their products and also reduce their concerns about the financial returns associated with the investment.

Conversely, if the startups need support in building their commercial credibility, accessing technological support, and gaining knowledge about the final market, they should adequately frame their communications related to the disruptive potentiality of the technologies to encourage resource commitment from CVC (Guo, Lou, and Pérez-Castrillo 2015; Alvarez-Garrido and Dushnitsky 2016). As such, startups should moderately communicate the disruptive potentialities of their technologies by highlighting the learning opportunities that the CVC can gain when investing a large amount of money.

Limitations and directions for future research

The interpretations of the results of this study should be appraised while considering some limitations. First, our research specifically focuses on the medical devices and biotech sector, which has recently experienced a proliferation of disruptive innovations (Christensen, Waldeck, and Fogg 2017). While it provides a useful context to examine the effect of disruptiveness, these findings should not be generalized to other sectors characterized by, for example, different technological attitudes, patenting activities, and research and development rates. The extension of the model to different contexts will require additional analysis to examine the applicability in those sectors and the possible differences in the behaviors of investors.

Second, since startups acquire new evidence about their technologies during the innovation development process, the communications about the disruptive potentiality of their technologies as described in their mission statements can change and evolve over time (van Balen, Tarakci, and Sood 2019). For example, improvements in the technology during its development process may lead the entrepreneurs to change the mission statement of the startup and communicate higher disruptiveness. On the contrary, the occurrence of failures during the innovation development process may lead startup entrepreneurs to change the mission statement and communicate lower disruptiveness. Since we retrieved the mission statements using the cached copies of the startups' web pages, we do not expect that revisions of the mission statements of the startups can affect our results. However, future research could conduct a longitudinal analysis to examine how changes in mission statements over time influence the funding decisions of VC investors when financing disruptive startups.

Finally, we are aware that before making investment decisions, investors match the information publicly available online with other documents directly provided by the startup during

the due diligence process. We recognized that reading startups' mission statements or checking their pitch decks (De Clercq et al. 2006) can only represent a preliminary screen to select the most promising startups to invest in. However, in this study, we were not able to control the effect of further information on investors' decisions. Thus, we believe that future research can overcome this limitation by directly asking the entrepreneurs what documents/information they showed to investors to influence their resource commitment decisions.

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FIGURES AND TABLES

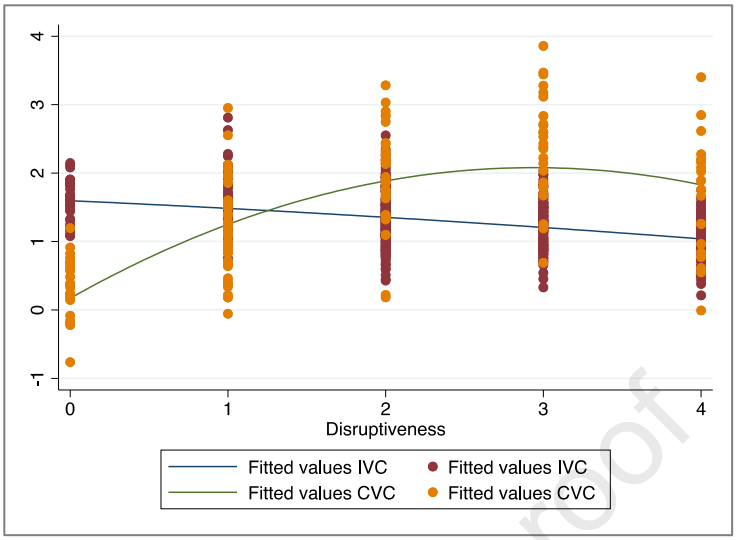

Figure 1. Linear and inverted u-shape relationship

Variable	Mean	St.Dev	Min	Max
IVC funding	1.36	0.85	0.01	5.45
CVC funding	1.30	1.19	0.02	5.02
Startup industry				
Electromedical & Electrotherapeutic Apparatus	0.33	0.47	0	1
Biological Products	0.35	0.48	0	1
Surgical & Medical Instruments and Apparatus	0.32	0.47	0	1
Founders	1.58	0.89	1	6
Age	2.73	1.14	0	6.1
Startup nationality	0.63	0.48	0	1
Patent	0.06	0.24	0	1
Founders education	0.33	0.47	0	1
Product released	0.26	0.50	0	1
Trademarks	1.90	3.68	0	38
Growth ambition	0.18	0.37	0	1
Founders experience	0.28	0.41	0	1
Communication skills	0.22	0.42	0	2
Investor experience	2.20	0.92	0	4.1
Investor industry focus	0.17	0.38	0	1
Syndication	3.98	2.92	1	21
Disruptiveness	2.00	1.18	0	4
Investor type	0.23	0.42	0	1
Investor nationality	0.61	0.49	0	1
Risk tolerance	0.48	0.50	0	1
Investment objective	0.64	0.47	0	1
Year				
Year 2005	0.07	0.25	0	1
Year 2006	0.09	0.28	0	1
Year 2007	0.11	0.32	0	1
Year 2008	0.12	0.33	0	1
Year 2009	0.12	0.32	0	1
Year 2010	0.13	0.33	0	1
Year 2011	0.13	0.34	0	1
Year 2012	0.08	0.27	0	1
Year 2013	0.11	0.31	0	1
Year 2014	0.04	0.21	0	1

Table 1. Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)
(1)Commitment	1																														
(2)Investor Nationality	0.02	1																													
(3)Risk tolerance	0.07	-0.06	1																												
(4)Investment objective	0.02	0.08	0.47*	1																											
(5)Year 2005	-0.15	0.14	-0.02	-0.02	1																										
(6)Year 2006	-0.07	-0.06	0.15	0.02	-0.07	1																									
(7)Year 2007	0.21*	0.08	0.07	0.03	-0.07	-0.12	1																								
(8)Year 2008	0.02	0.04	-0.001	-0.07	-0.08	-0.13	-0.14	1																							
(9)Year 2009	-0.14	0.01	0.03	-0.01	-0.07	-0.11	-0.12	-0.13	1																						
(10)Year 2010	-0.11	-0.32*	0.06	-0.01	-0.08	-0.13	-0.14	-0.15	-0.13	1																					
(11)Year 2011	-0.05	-0.08	0.004	0.13	-0.08	-0.12	-0.13	-0.15	-0.12	-0.13	1																				
(12)Year 2012	-0.05	0.17*	-0.10	-0.01	-0.07	-0.12	-0.13	-0.14	-0.12	-0.14	-0.13	1																			
(13)Year 2013	0.13	0.04	-0.13	-0.17*	-0.07	-0.10	-0.12	-0.13	-0.11	-0.12	-0.12	-0.12	1																		
(14)Year 2014	0.23*	0.06	-0.11	0.12	-0.05	-0.08	-0.09	-0.16	-0.10	-0.15	-0.09	-0.09	-0.08	1																	
(15)Electromed&Electrotherap Apparatus	-0.19*	-0.01	0.01	0.02	-0.06	-0.10	-0.04	0.01	0.03	0.07	0.04	-0.08	0.05	0.09	1																
(16)Biological Products	0.18*	0.10	0.05	-0.03	0.05	0.13	0.07	-0.11	0.06	-0.05	0.005	0.02	-0.06	-0.08	-0.50*	1															
(17)Surgical&Medical Instruments and Apparatus	-0.01	-0.10	-0.06	0.01	0.002	-0.03	-0.03	0.10	-0.09	-0.01	-0.04	0.06	0.02	0.002	-0.45*	-0.55*	1														
(18)Sturtup founders	0.06	0.04	0.16	0.04	-0.08	-0.01	-0.04	-0.09	0.04	-0.01	-0.11	0.16*	0.14	-0.02	0.06	0.20*	-0.27*	1													
(19)Sturtup age	0.14	-0.11	-0.15	-0.03	-0.35*	-0.13	-0.08	-0.04	0.02	0.14	0.11	-0.08	0.12	0.22*	0.09*	-0.023	-0.06	-0.09	1												
(20)Startup nationality	0.10	0.76*	-0.04	0.04	0.13	-0.10	0.04	0.08	0.07	-0.20*	-0.13	0.14	0.05	-0.03	-0.15	0.14	0.004	0.06	-0.08	1											
(21)Startup patent	0.31*	0.11	0.05	0.14	0.04	-0.04	0.08	0.05	0.03	-0.13	0.14	0.012	-0.11	-0.09	-0.17*	0.22*	-0.06	-0.06	0.01	0.08	1										
(22)Founders education	0.34*	-0.04	0.02	0.06	-0.05	-0.01	0.06	-0.03	-0.07	-0.02	0.12	-0.11	0.04	0.06	0.05	0.19*	-0.25*	0.11	0.03	-0.06	0.21*	1									
(23)Startup product released	-0.05	-0.03	0.05	0.04	0.12	0.01	-0.06	0.04	-0.01	0.02	0.05	-0.14	0.01	0.002	-0.02	-0.01	0.03	0.005	-0.05	0.05	0.10	-0.15	1								
(24)Trademarks	0.29*	0.07	0.01	0.20*	-0.06	0.002	0.03	0.06	-0.02	0.12	-0.08	-0.10	-0.01	0.02	-0.02	-0.15	0.17*	0.05	0.01	0.19*	0.32*	0.18*	0.01	1							
(25) Growth ambition	-0.06	0.15	0.02	-0.14	-0.07	-0.12	0.05	0.03	0.03	-0.09	0.11	0.01	0.09	-0.09	0.06	-0.03	-0.03	-0.04	0.03	0.12	-0.09	-0.11	-0.03	-0.05	1						
(26) Founders experience	0.16	0.11	-0.01	0.13	-0.14	-0.02	-0.03	0.04	-0.11	-0.02	0.09	0.03	0.10	0.001	-0.09	-0.04	0.13	-0.22*	0.07	0.12	0.17*	0.12	0.13	0.16	-0.03	1					
(27)Investor experience	0.15	0.16	-0.02	0.04	-0.02	-0.07	0.02	-0.03	-0.06	-0.10	0.06	-0.05	0.18*	0.10	0.03	0.01	-0.03	0.002	0.09	0.23*	0.003	0.13	0.10	-0.02	-0.12	0.11	1				
(28)Investor industry focus	0.16*	0.16*	0.002	0.01	0.04	-0.03	0.13	-0.01	-0.04	-0.09	-0.12	-0.01	0.02	0.18*	-0.07	0.24*	-0.18*	0.21*	-0.06	0.07	-0.004	0.09	-0.06	-0.04	0.01	-0.10	-0.16	1			
(29)Syndication	0.34*	0.24	0.06	0.03	0.10	0.08	0.08	0.08	0.14	-0.10	0.06	-0.19*	-0.09	-0.17*	-0.08	0.14	-0.06	-0.001	-0.19*	0.27*	0.37*	0.10	0.05	0.36*	0.01	0.16	0.11	0.01	1		
(30)Disruptiveness	0.48*	-0.04	-0.13	-0.09	0.07	-0.08	0.06	0.02	-0.11	0.05	-0.04	-0.04	0.03	0.07	-0.12	0.06	0.05	0.01	0.11	0.09	0.19*	0.18*	-0.06*	0.29*	0.12	0.19*	-0.005	0.08	0.28*	1	
(31)Investor type	0.11	-0.06	0.04	-0.01	-0.05	-0.04	0.02	0.07	0.09	0.03	-0.09	-0.08	-0.04	0.10	-0.06	0.04	0.02	-0.08	0.07	0.03	0.03	-0.04	0.04	0.03	0.18*	-0.01	0.01	0.16	0.06	0.17*	1
(32)Communication skill	-0.04	0.15	0.03	-0.10	-0.08	-0.13	0.01	-0.01	0.03	-0.05	0.06	0.12*	0.010	-0.10	0.08	-0.01	-0.07	0.23*	-0.02	0.11*	-0.09	-0.02	-0.04	-0.07	0.15*	-0.10	-0.13	0.03	-0.04	0.18*	0.13

* $p < 0.05$

Table 2. Correlation matrix

	IVC Commitment			CVC Commitment		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Investor nationality	-0.0965	-0.0687	-0.0681	-0.595	-0.361	-0.344
	(0.145)	(0.147)	(0.147)	(0.330)	(0.335)	(0.315)
Risk tolerance	0.104^{+}	0.113^{+}	0.112^{+}	0.432*	0.496**	0.327^{+}
	(0.0783)	(0.0778)	(0.0778)	(0.194)	(0.187)	(0.187)
Biological products	0.230	0.163	0.164	0.475*	0.424*	0.367*
	(0.101)	(0.101)	(0.101)	(0.189)	(0.183)	(0.169)
Surgical&Medical Instruments and Apparatus	0.104	0.0455	0.0454	0.348^{+}	0.268	0.254
	(0.0855)	(0.0854)	(0.0854)	(0.218)	(0.196)	(0.185)
Founders	0.0840**	0.0822**	0.0823^{+}	-0.0233	-0.0377	-0.0660
	(0.0512)	(0.0498)	(0.0498)	(0.0817)	(0.0760)	(0.0724)
Age	0.142***	0.139***	0.138***	0.151^{+}	0.0959	0.128
	(0.0408)	(0.0391)	(0.0388)	(0.0843)	(0.0817)	(0.0818)
Startup nationality	0.151	0.144	0.143	0.300	0.160	0.206
	(0.143)	(0.144)	(0.144)	(0.327)	(0.320)	(0.302)
Patent	-0.146	-0.129	-0.129	0.476**	0.397**	0.253*
	(0.265)	(0.259)	(0.259)	(0.302)	(0.279)	(0.269)
Founders Education	0.156*	0.174*	0.174*	0.510**	0.421*	0.432**
	(0.0872)	(0.0859)	(0.0860)	(0.176)	(0.164)	(0.158)
Product released	-0.0559	-0.0650	-0.0653	-0.0725	-0.0274	-0.0583
	(0.0788)	(0.0776)	(0.0776)	(0.152)	(0.146)	(0.141)
Trademarks	0.0259*	0.0255*	0.0255*	0.0424	0.0270	0.0373
	(0.0100)	(0.0107)	(0.0107)	(0.0373)	(0.0305)	(0.0273)
Growth ambition	0.0640	0.0583	0.0582	-0.0906	-0.333	-0.411
	(0.137)	(0.143)	(0.143)	(0.306)	(0.312)	(0.335)
Founders experience	0.167*	0.144*	0.145^{+}	0.0283	0.00680	-0.0451
	(0.0964)	(0.0973)	(0.0976)	(0.213)	(0.200)	(0.197)
Investor Experience	0.146***	0.145***	0.144***	0.0389	0.0513	0.0280
	(0.0431)	(0.0420)	(0.0419)	(0.0923)	(0.0930)	(0.0853)
Investor industry focus	0.291**	0.253*	0.253*	0.200	0.148	0.148
	(0.109)	(0.107)	(0.107)	(0.190)	(0.184)	(0.172)
Syndicate	0.0495***	0.0478**	0.0478**	0.159***	0.121***	0.115***
	(0.0148)	(0.0145)	(0.0145)	(0.0345)	(0.0326)	(0.0317)
Investment Objective				-0.263	-0.225	-0.152
				(0.197)	(0.193)	(0.188)
Disruptiveness		-0.119***	-0.121**		0.269***	0.991***
		(0.0338)	(0.0388)		(0.0678)	(0.192)
Disruptiveness^{2}			0.00864			-0.182***
			(0.0952)			(0.0449)
Constant	-0.0795	0.184	0.185	-0.931	-1.315*	-1.551**
	(0.249)	(0.248)	(0.248)	(0.578)	(0.564)	(0.493)
N	484	484	484	179	179	179
R^2	0.199	0.224	0.224	0.521	0.579	0.622
adj. R^2	0.147	0.171	0.168	0.419	0.485	0.534
F	4.608	4.974	4.784	8.290	9.953	9.443

Year dummy variables included; Standard errors in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 3. OLS results

	First stage	*Second stage*	
	Disruptiveness Model 1	**IVC Commitment** Model 2	**CVC Commitment** Model 3
Investor nationality		-0.152	-0.124
		(0.146)	(0.384)
Risk tolerance		0.0980^{+}	0.166
		(0.0770)	(0.202)
Biological products	-0.363*	0.136	0.403*
	(0.180)	(0.107)	(0.178)
Surgical&Medical Instruments and Apparatus	-0.411*	0.0710	0.361^{+}
	(0.180)	(0.0929)	(0.203)
Founders	-0.0230	0.0594	0.0512
	(0.0764)	(0.0512)	(0.0920)
Age	0.0473	0.117**	0.165*
	(0.0658)	(0.0379)	(0.0737)
Startup nationality	0.700***	0.229	0.221
	(0.199)	(0.147)	(0.366)
Patent	0.476^{+}	-0.153	0.433
	(0.253)	(0.242)	(0.338)
Founders Education	0.128	0.140	0.518**
	(0.151)	(0.0876)	(0.190)
Product released	-0.199	-0.0899	-0.180
	(0.145)	(0.0817)	(0.150)
Trademarks	0.0283	0.0274**	0.0529
	(0.0205)	(0.00934)	(0.0476)
Growth ambition	0.267	0.0744	-0.0549
	(0.249)	(0.134)	(0.226)
Founders experience	-0.224	0.144	0.158
	(0.180)	(0.0934)	(0.219)
Communication skills	1.160***		
	(0.194)		
Investor Experience		0.127**	0.121
		(0.0443)	(0.102)
Investor industry focus		0.230*	0.323^{+}
		(0.110)	(0.174)
Syndicate		0.0579***	0.0750*
		(0.0143)	(0.0338)
Investment Objective			-0.199
			(0.212)
Disruptiveness		-0.236*	1.740***
		(0.127)	(0.252)
Disruptiveness^{2}			-0.402***
			(0.0536)
Constant		0.556	-2.086***
		(0.357)	(0.513)
N	663	484	179
R^{2}		0.174	0.452
adj. R^{2}		0.137	0.372
F		5.437	11.09
Log-pseudolikelihood	-1011.07		
Wald chi^{2}	50.61		
Prob> chi^{2}	0.0000		

Year dummy variables included; Standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Endogeneity check

	Commitment		
	Model 1	Model 2	Model 3
Investor nationality	-0.203	-0.112	-0.106
	(0.140)	(0.135)	(0.131)
Risk tolerance	0.113*	0.151*	0.111*
	(0.0719)	(0.0685)	(0.0674)
Biological products	0.266**	0.200*	0.182*
	(0.0903)	(0.0860)	(0.0852)
Surgical&Medical Instruments and Apparatus	0.174*	0.101	0.103
	(0.0816)	(0.0773)	(0.0769)
Founders	0.0653*	0.0624*	0.0525*
	(0.0482)	(0.0445)	(0.0436)
Age	0.135***	0.120***	0.124***
	(0.0379)	(0.0361)	(0.0356)
Startup nationality	0.213	0.149	0.161
	(0.141)	(0.134)	(0.130)
Patent	0.225+	0.157+	0.109
	(0.203)	(0.192)	(0.187)
Founders Education	0.260**	0.236**	0.231**
	(0.0810)	(0.0772)	(0.0759)
Product released	-0.0727	-0.0672	-0.0831
	(0.0720)	(0.0689)	(0.0680)
Trademarks	0.0304**	0.0261**	0.0273**
	(0.0103)	(0.0101)	(0.0101)
Growth ambition	0.0923	0.0129	-0.00515
	(0.116)	(0.123)	(0.125)
Founders experience	0.210*	0.178+	0.164+
	(0.0908)	(0.0905)	(0.0894)
Investor Experience	0.134**	0.139***	0.136***
	(0.0430)	(0.0413)	(0.0402)
Investor industry focus	0.334***	0.278**	0.260**
	(0.0931)	(0.0886)	(0.0879)
Syndicate	0.0660***	0.0553***	0.0540***
	(0.0145)	(0.0139)	(0.0135)
Investor type	-0.0278	-0.829***	-1.243***
	(0.0931)	(0.126)	(0.140)
Disruptiveness		-0.120***	-0.121***
		(0.0333)	(0.0333)
Investor type* Disruptiveness		0.460***	1.217***
		(0.0678)	(0.177)
Investor type* Disruptiveness^2			-0.190***
			(0.0437)
Constant	-0.360	-0.00447	0.0650
	(0.222)	(0.228)	(0.220)
N	663	484	179
R^2	0.248	0.314	0.339
adj. R^2	0.211	0.277	0.303
F	7.557	11.14	11.24

Year dummy variables included; Control variable *Investment objective* omitted since related only to CVC investor type;
Standard errors in parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. OLS results (unique sample)

APPENDIX

Extract of startups' mission statements
Abionic has developed a revolutionary nanofluidic technology, providing healthcare professionals with a ultra-rapid, simple and universal point of care diagnostic tool. Our aim is to make ultra-rapid medical diagnosis available everywhere, helping to reduce the number of casualties from a delayed medical response or from potentially fatal misdiagnosis. We believe our cutting-edge technology will lead the future of medical analysis, by providing solutions to a vast amount of current medical challenges. The abioSCOPE is the fastest screening device in the world. Intuitive and easy to use, Abionic's technology is accessible, and the test is painless for the patient. The abioSCOPE is compatible with a wide range of applications. The abioSCOPE process is based on a nanofluidic technology. All Abionic products and tests are clinically proven. All our tests are run with just a few µL of whole blood sample.
Cianna Medical is a women's health company dedicated to the innovative treatment of early-stage breast cancer. When diagnosed early, most women have the option to save their breast by choosing breast conservation therapy (BCT). Our mission is to make BCT available to more women, by developing new approaches to delivering follow-up radiation therapy. The company manufactures and markets the SAVI™ breast brachytherapy applicator. Cianna's SAVI technology allows physicians to precisely target radiation to the area that needs it most, minimizing exposure to healthy tissue. Equally important, women can return to their normal family and work schedules after just 5 days of treatment. Cianna's commitment is to improve care and reduce the burden that breast cancer treatment places on women and their families.
JenaValve is developing a minimallyinvasive, self-expanding aortic heart valve implantation and delivery system that offers a flexible conduit, exact positioning and secure implantation to provide patients with a life-sustaining heart valve replacement. It is a true safe alternative to conventional surgery, especially for elderly patients suffering from co-morbidity. Our product, JenaValve™, is initially aimed at high-risk patients unsuitable for open heart surgery. As the system becomes the AVR procedure of choice, it is expected that its benefits will become equally attractive to all other potential patients.
With the focus on the smallest patients and their families, **Calmark** aims to improve the entire chain of care, reducing waiting times and care costs, and making a significant difference in parts of the world lacking hospital laboratories. By providing point-of-care tests (POC) specialized for newborns, we can enable a safe journey through the first part of life, regardless of where in the world the baby is born.
Neuropure aims to develop and commercialize novel, focused, targeted and logical treatment approaches for patients suffering from a variety of neurological disorders that are presently without cures.

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Authors statement

All the authors have contributed to the paper with multiple roles.