JOURNAL OF MANAGEMENT STUDIES

Journal of Management Studies ••:•• 2016
doi: 10.1111/joms.12207

Taking a Second Look in a Warped Crystal Ball: Explaining the Accuracy of Revised Forecasts

Violetta Bacon-Gerasymenko, Russell Coff and Rodolphe Durand

Oregon State University; University of Wisconsin-Madison; HEC Paris

ABSTRACT The fundamental questions we address are whether firms with a higher initial forecasting ability are able to accurately revise the exit forecasts of their investments; and how co-investment partners and value-adding commitment with their investment influence the main effect. We explore these questions with novel and unique data collected via mixed research methods on venture capital firms' forecasts of 114 portfolio companies. We find that venture capital firms that are better at making initial forecasts are less effective in revising their forecasts. In addition, while the number of co-investment partners positively moderate this relationship, venture capital firms' value-adding commitment moderates it negatively. Our findings contribute to the literature on organizational forecasting as well as inter-organizational knowledge transfer and knowledge creation. They also provide novel insights into venture capital literature and practice.

Keywords: forecasting, syndication, value-adding commitment, venture capital

> *'If you have reason to think that yesterday's forecast went wrong, there is no glory in sticking to it'. Nate Silver*

INTRODUCTION

Most strategic decisions that organizations make – starting from acquisition of resources to their allocation to a specific product, project or venture – draw on forecasts (Durand, 2003; Makadok, 2002; Makadok and Walker, 2000). Forecast accuracy lies at the core of the resource-based explanations of competitive advantage (Barney, 1991, 1995), since firms with more accurate predictions can invest more effectively (Ahuja et al., 2005; Makadok and Barney, 2001; Makadok and Walker, 2000). As Hogarth and Makridakis

Address for reprints: Violetta Bacon-Gerasymenko, Oregon State University, College of Business, 320 Austin Hall, Corvallis, OR 97331, USA (violetta.gerasymenko@oregonstate.edu).

(1981, p. 116) have stated: 'erroneous forecasts can kill the best plans'. Although sophisticated quantitative forecasting methods are available, most forecasting processes rely on human judgement (Lawrence et al., 2006; Sanders and Manrodt, 2003; Sanna and Schwarz, 2006; Wright et al., 1996). Since bounded rationality (Cyert and March, 1963) and attention (Ocasio, 1997) constrain managers' ability to perceive and assimilate information, variation in such abilities is a key source of firm heterogeneity. Even subtle changes in the ways that tasks or information are presented can undermine the accuracy of experts' predictions (Andreassen and Kraus, 1990). Furthermore, even simple forecasting efforts can be biased by organizational context (Durand, 2003; McNamara and Bromiley, 1997). Such hazards systematically hinder accurate initial forecasts and underscore the need to reconsider or *revise* forecasts over time. By accurately revising forecasts, organizations may achieve higher performance (Makadok and Walker, 2000; Makridakis et al., 2009) and can reallocate their time, attention and other scarce resources more effectively.

Given this strategic importance, it is surprising that previous research has devoted scarce attention to understanding why some organizations are more effective at revising forecasts than others. Our premise is that organizational forecast revision does not necessarily rely on the same ability as making an initial forecast. Initial forecast formation draws on activities related to noticing, analysing and processing information, thereby forming initial predictions for the outcomes of new investments (e.g., in resources, products or ventures). Forecast revision refers to noticing new information over time, reflecting on it and subsequently maintaining or changing previous forecasts (Moritz et al., 2014). The former forecast may obfuscate how the new information is dealt with and incorporated in a revised judgement. High ambiguity of new information and bounded rationality make revisions challenging. Managers may erroneously alter forecasts that should have been maintained and preserve those that should have been changed. Managers' confidence in their initial forecasts may lead to self-efficacy bias (Kahneman and Tversky, 1973, 1979), routine effects (Tripsas and Gavetti, 2000) and confirmatory bias (Bukszar and Connolly, 1988; Cassar and Craig, 2009), and use of improper heuristics that reduce accuracy of their revised forecast. Therefore, we argue that initial forecasting ability is negatively related with revised forecast accuracy. We examine the extent to which this relationship is favourably moderated by two main sources of additional information: complementary information from experts and first-hand commitment with the investment.

We explore these questions in French venture-capitalist firms (VCFs) by relying on a mixed research method. We first conducted exploratory interviews with VCFs and entrepreneurs, followed by analysis of unique quantitative data collected via questionnaires from 23 VCFs regarding their revised forecasts of 114 investments and supplemented by financial reports of VCFs and public sources (Bartunek et al., 1993; Bitektine and Miller, 2015).

Indeed, forecast accuracy is especially critical in the venture capital setting (Gerasymenko and Arthurs, 2014). Venture capitalists invest outside equity in entrepreneurial ventures from a professionally managed venture capital firm. Usually venture capitalists co-manage multiple funds over time. The limited lifespan (approximately 10 years) and high capital requirements mean that VCFs are highly focused on increasing the value of their portfolio companies (PFCs). In doing so, both the time and type of exit are of paramount importance. For instance, whether a company exits the VCF portfolio via an IPO (Initial Public Offering) or a Trade Sale (e.g., M&A) has significant consequences for its return on investment (Giot and Schwienbacher, 2007). The general partners we interviewed confirmed that forecasting and planning for the most likely type of exit is critical. They also concurred that new external information through syndication (e.g., on markets, external shocks) and their many interventions on PFC (about organizational resources, business models, etc.) change the outlook (Gerasymenko et al., 2015); prompting the need to revise forecasts to guide PFCs toward different types of exits (De Clercq and Sapienza, 2006).

As predicted, we found initial forecasting ability to be *negatively* associated with revised forecast accuracy. Since co-investors bring complementary information and knowledge (Wright and Lockett, 2003) and value-adding activities supplemented to portfolio firms help reduce interest and knowledge asymmetries, we expected that both a larger syndicate and more value-adding activities favourably moderate the main relationship. While we were able to confirm the initial moderation, we found the opposite to be true for the latter scenario.

This paper makes several contributions: First, we contribute to the literature on organizational forecasting by examining the relationship between initial forecasting ability and forecast revision. While previous research focused on initial and subsequent forecasts, we find that when organizations make better initial forecasts, they are less effective in revising forecasts. This advances the literature by showing that effective forecast revision is not only hindered by initial beliefs and cognitive limitations, as reflected in the decision-making and psychology literatures, but is also hampered by the initial forecasting ability. This highlights that organizational forecasting is composed of several distinct abilities, the mastery of which requires specific attention, analysis and processes. Second, we show how the VCFs' value-adding interventions in their PFCs and syndication respectively hinder and advance the accuracy of their revised forecasts. These results indicate that forecast revision is more likely to be accurate in the presence of complementary external information (from expert partners) than from internal information (from direct engagement with ventures). Finally, our study brings novel insights to the entrepreneurship and venture capital literature. While prior studies explored the value-adding role of VCFs (Arthurs and Busenitz, 2006), we demonstrate a previously unknown drawback of VCF interventions.

We begin by presenting the reasons that lead organizations to change forecasts and the associated challenges of forecast revision. We then explore forecast revision in the venture capital firm context and develop specific hypotheses. This is followed by a description of our mixed methods, analysis and key findings. Finally, we conclude with an extended discussion of the theoretical and practical implications of our results, as well as identify some fruitful areas for future research.

THEORY

Reassessment of Organizational Forecasts: Reasons and Challenges

Forecasting new ventures is at the heart of entrepreneurial and investor commitment decisions. Whereas in stable environments organizations may rely on the established rules of rational decision-making (Cyert et al., 1998), under volatile and highly uncertain conditions, managerial judgement and interpretation become far more important (Bazerman and Moore, 2008; Cyert et al., 1998). Such judgemental forecasts are integral to organizational decisions about the choice of, and commitment to, new projects, products or markets (Durand, 2003). However, research in cognitive psychology and management points out that individuals and organizations typically suffer from *hindsight bias* (Bukszar and Connolly, 1988), specifically, a tendency to believe their forecasts are more accurate than they actually are. Some scholars have expressed concern that hindsight bias may seriously prohibit forecast revision and improvement in organizational forecasting ability even when feedback on actual outcomes becomes available (e.g., Cassar and Craig, 2009). In order to understand why some organizations excel at forecast revision (Shumsky, 1998), we separate initial forecasting ability from forecast revision. We also analyse how third-party expert informants and direct engagement with projects influence forecast revision.

Many scholars have emphasized that effective forecast revisions are challenging for individuals in organizations for several reasons: First, managers are known to fall into a trap of 'over-thinking', thereby adjusting initial forecasts while they should have been kept the same, or 'under-thinking', whereby preserving those forecasts unchanged that should have been altered. Indeed, managers have bounded rationality (Cyert and March, 1963) which poses limits on organizational capacity to effectively make sense of diverse, ambiguous and novel information (Weick, 1969; Weick et al., 2005). This in turn hinders interpretation and integration of the impact of new internal and external environment stimuli (Christianson et al., 2009) on the outcomes of organizational projects or investments, undermining the accuracy of revised forecasts.

Second, individuals reveal a tendency towards anchoring bias in the face of time-series forecasts (Andreassen and Kraus, 1990) and preserve their initial judgemental forecasts even when new and potentially more accurate information appears. Specifically, an anchoring bias has been often cited as a major impediment to effective adjustments of prior beliefs and behaviours in time-series tasks (Bromiley, 1987). For instance, Lim and O'Connor (1995) adopted a three-stage approach under which they examined an initial judgemental forecast, then considered statistical forecasts and finally revised the initial estimate. The researchers found that people have considerable difficulty in reacting appropriately to the reliability of additional information provided in statistical forecasts. Not only did people fail to decrease their reliance on their own initial judgemental forecast as they witnessed the greater accuracy of the statistical forecast provided to them, but people generally tended to increase their reliance on their initial forecasts over time.

Third, managers tend to exhibit cognitive inertia (Dobrev et al., 2003; Fredrickson and Iaquinto, 1989) that limits their ability to revise forecasts and undertake necessary changes over time. One of the best known examples is the case of Polaroid, discussed in detail by Tripsas and Gavetti (2000). Although the company managers could have foreseen the initial success of instant imaging and photos, they failed to adjust their forecasts in favour of digital photography and subsequently redirect their resources to this domain. The organization creates rules, norms, and a context that conditions their members to perceive and judge prospects in a given manner (McNamara and Bromiley, 1997).

It is also important to acknowledge that revising initial forecasts imposes additional costs and can divert attention away from other tasks. Disruptions may be particularly strong when initial forecasts led to significant financial and other resource commitment, and specifically in cases where changes in forecast would imply the commitment of additional resources (Guler, 2007; McNamara et al., 2002; Staw and Fox, 1977). Because of limited attention (Ocasio, 1997), unplanned changes and resource commitments – these may reduce the time organizations are able to give to other important tasks. Such attention and time-related costs can be particularly taxing in small organizations (Ocasio, 2011) where forecasts and resource-allocation decisions are carried out by the same individuals.

Prior research's primary interest focused on how individuals revise their forecast without allowing for how organization-specific factors interfere with forecast revision. Here, we aim to shed light on this critical issue. As organizations with a higher forecasting ability are more likely to suffer from self-efficacy bias, inertia, and heuristics' use, they will revise their forecast less accurately than others. We expect that firms with exposure to more expert partners involved in the projects in point, and firms that commit actively with the projects will gain additional relevant information that will curb positively the main negative association between initial forecasting ability and revised forecast accuracy. We present the empirical context of our study: venture capital firms – and develop our hypotheses.

Venture Capital Setting and Hypotheses

The venture capital industry is one of many appropriate settings for studying organizational forecasting. First, venture capital firms invest in entrepreneurial projects in growing high-tech industries, which are subject to high volatility, renewal and changes (Allen and Hevert, 2007). Understanding the determinants of accurate forecast revisions is therefore highly relevant under such conditions where forecasts would need to be changed regularly, and cognitive biases and organizational influences are likely to penetrate judgemental forecasting. Second, VCFs focus on young ventures that often need to change the course of their initial strategy or business model (Gerasymenko et al., 2015), thus requiring flexibility from VCFs in terms of both predictions and actions. In other words, the need to revise forecasts may come not only from external environmental changes but also from changes within portfolio companies themselves.

Third, evidence from both research and practice underscores that VCFs expect a relatively high return on investment and that the continuation of their funding is subject to specific milestones, intermediary objectives and expectations that their portfolio companies must meet. While setting up different performance metrics and monitoring is undoubtedly important, the key caveat to realizing a return on investment is for a VCF to assure an exit from a portfolio company via one of the potential exit mechanisms: Initial Public Offering or a Trade Sale being among the most common (Gifford, 1997). Because the requirements and venture characteristics required for one exit or the other are very different (Gerasymenko and Arthurs, 2014), the type of exit forecast is a vital strategic forecast that VCFs form upon investment and review as their PFCs progress over time (Giot and Schwienbacher, 2007).

Fourth, VCFs' forecast revision is coupled with some critical actions and interactions within which they are engaged. Indeed, VCFs often co-invest or syndicate their investments with other VCFs (Bygrave, 1987; Lerner, 1994) and therefore rely on joint decision-making when it comes to revising their forecast. Moreover, in addition to providing capital, VCFs are recognized for having a 'hands-on' approach toward their investments through advising their PFCs in different areas (Hsu, 2006). For instance, VCFs are known to advise their portfolio companies in financial, strategic, marketing, business model and other important business-related issues (MacMillan et al., 1989). The information that VCFs would learn about PFCs during such value-adding relationships (De Clercq and Sapienza, 2005) is also likely to shape how VCFs revise their initial forecasts.

Initial Forecast Ability Hinders Forecast Revision

Given multiple external and internal challenges for making accurate predictions, a key question is whether a VCF with a superior initial forecasting ability is more or less accurate in revising its initial forecasts. Three main factors help to explain why forecast revisions are likely to be undermined by the quality of the VCFs' initial forecasting.

First, VCFs devote substantial attention and effort to the initial due diligence and forecasting. The amount of effort exerted by individuals is known to be directly related to the perceived self-efficacy in a given task, e.g., initial forecasting. While self-efficacy characterizes one's belief in performing well a specific task and is usually positively related to the actual performance (Kickul et al., 2009), it is likely to discourage managers of VCF with a higher initial forecasting ability from questioning their initial forecasting ability; as a result, this increase the likelihood of maintaining initial forecasts when changes would be needed, creating an anchoring bias.

Second, it is important to recognize that the VCFs' initial exit forecasts serve as a directing force behind their future attention and value allocation to each portfolio start-up (Gerasymenko and Arthurs, 2014). For instance, a VCF is more likely to hire a new CEO for a venture that is going to go public than for one to be acquired. Because each type of exit requires different value-adding activities from a VCF, VCFs with a higher initial forecast ability will experience stronger behavioural inertia than less able firms. This inertia is often accompanied by a confirmatory bias (Bazerman and Moore, 2008) whereby VCF managers notice novel information that confirms their initial beliefs and forecasts, and disregard information that reveals contradictory signals. This confirmatory bias in turn undermines both the occurrence of and quality of forecast revision for firms with a higher ability to make accurate initial forecasts.

Finally, in addition to due diligence and new project outcome forecasting, VCFs carry multiple other activities at the same time, such as fundraising, advising their portfolio companies, networking and exiting, which in turn limits the amount of attention they can devote to forecast revision. Hence, VCFs tend to rely on simplified heuristics and other mental shortcuts (Bazerman and Moore, 2008) instead of carefully considering new signals and information. This may undermine the accuracy of such revisions (Kahneman and Tversky, 1973). The firms with a higher initial forecasting ability will tend to rely on their original estimates to a greater extent and focus their available attention on other actions and activities. VCFs with a higher forecasting ability are therefore more susceptible to paying insufficient attention to forecast revision; and hence to drawing on imperfect heuristics that reduce their revised forecast accuracy.

Overall, due to self-efficacy bias, inertia, and the reliance on heuristics, we expect to find a negative relationship between the VCFs' initial forecasting ability and the accuracy of revised forecasts.

Hypothesis 1: There will be a negative relationship between the venture capital firms' initial forecasting ability and the likelihood of making accurate revised forecasts.

Impact of Additional Information on Forecast Revision

This relationship will be influenced by two main sources of additional information: external and internal. Notably, scholars documented that more accurate forecasts are made in partnership with other groups and organizations (Lawrence et al., 2006). Soon and O'Connor (1991) and Sniezek (1990) studied the group dimension in forecasting and concluded that a group of individuals does produce more accurate forecasts than the simple averaging the individual pre-group judgements. Accordingly, from a knowledge-based view of the firm, each partner within a specific inter-organizational structure (e.g., an alliance, a syndicate) informs its decision-making and improves its performance by either accessing or acquiring each other's knowledge. This theoretical lens portrays each organization as a pool of knowledge and resources that can be accessed or transferred to another organization, as a function of its absorptive capacity (Lane and Lubatkin, 1998). Hence, external sources of expert information can help one to improve forecasting.

VCFs are known to rely on the knowledge of syndicate partners (whereby one or more investors jointly invest in the same venture) as a way to improve investment outcomes. Earlier research has primarily emphasized two benefits of syndication for VCFs: better project selection as additional venture capitalists provide a second opinion, and greater post-investment value added due to complementary knowledge and competencies that co-investors share with the venture. In addition, Wright and Lockett (2003) found that relationships between syndicate members enhance the decision-making process and, unlike the investor-investee relationship, are not influenced by the lead or non-lead position in a syndicate. Empirical evidence showed that venture capital firms select syndicate partners with whom they can work and share a high level of trust (Wright and Lockett, 2002), and that the decision-making is based primarily on discussion and reaching a consensus (Wright and Lockett, 2003). Relatedly, one of the general partners of a venture capital firm that we interviewed commented:

> While initial forecasts are a strong indication for us of the potential direction of the venture, we usually don't stick to them for more than two years following investment. Changes in the environment and other uncertainties often oblige us to review the direction that a venture will take. We often invite new investors on board when there is a new round of funding, which is an important occasion for us to review and defend or change our initial beliefs and predictions.

Intra-syndicate exchanges based on trust and consensual decision-making may moderate the relationship between initial forecasting ability and forecast revision. First, syndication is likely to decrease the self-efficacy bias spurred by a focal VCF's extensive effort put at initial forecasting since such effort is shared among several co-investors. As external experts, syndicate partners help broaden the source of valid knowledge from which to draw on and as such combat reliance on self-efficacy.

Second, syndicate partners partake not only in decision-making but also in value-adding activities. Sharing value-adding activities among several VCFs is likely to diminish inertial pressures on a focal VCF. Focusing their advising on a restrained set of activities requires a lower degree of time and effort dedicated to a particular PFC and facilitates the ability to change a course of action. As syndicate partners contribute to a greater cognitive diversity in the decision-making process, co-investors highlight different examples from their investment experience. Hearing and discussing such diverse opinions among trusted members decreases confirmatory bias of VCFs with a superior initial forecasting ability, making them more open to reconsidering their initial forecasts. Earlier research shows that confirmatory bias of an individual or organization is decreased when the subject is presented with a somehow related yet different situation from the original experience (Bazerman and Moore, 2008). Because VCFs seek co-investors with complementary knowledge yet possessing enough shared knowledge to work well together (De Clercq et al., 2008), it is likely that the examples that syndicate partners highlight will correspond to the case in point, thereby decreasing confirmatory bias of the focal VCF.

Finally, because a focal VCF is able to delegate part of its activities to syndicate members, this VCF will be able to devote more attention to forecast revisions than another VCF surrounded by less expert knowledge and fewer partners. More available attention to reconsider prior beliefs and forecasts combined with a richer information exchange and debate is likely to encourage deeper cognitive processing rather than reliance on heuristics and other mental shortcuts.

Overall, the presence of multiple external experts (i.e., co-investors in our context) moderates the negative relationship between the VCFs' initial forecasting ability and revised forecast accuracy:

> *Hypothesis 2*: The number of co-investors in a PFC together with the focal VCF will moderate the relationship between venture capital firms' initial forecasting ability and revised forecast accuracy such that this (negative) relationship will be weaker.

A second source of privileged information concerns first-hand data collection obtained through direct commitment of a firm within a PFC. Venture capitalists provide multiple value-adding services to their PFCs, with differing degrees of intensity (Sapienza, 1992). In our interviews, both venture capitalists and the CEOs of venture-backed firms emphasized the importance of advising on a frequent basis, not limited to board meetings. This 'hands-on' involvement in portfolio companies may affect the relationship between VCFs' initial forecasting ability and revised forecast accuracy.

First, apart from adding and transferring knowledge to PFCs, VCFs can decrease information asymmetry in the investor-investee relationships (De Clercq et al., 2006) and gain a deeper understanding of the ventures' prospects. Since ventures go through a series of important changes during their early stages of development (e.g., Gerasymenko et al., 2015), VCF's knowledge transfer in a diverse set of business areas help them form a more complete understanding of the PFC's business. This may mitigate self-efficacy bias by furnishing first-hand information. Moreover, a VCF that is more extensively engaged in PFCs may overcome inertial behavioural pressures more easily. When the two parties are engaged in frequent knowledge exchange and transfer, it is easier for them to reach consensus and agree on a different direction, if necessary. Finally, because extended advising implies a certain degree of trust (Zaheer et al., 1998), VCFs gain access to PFC managers' hidden motivations and expected outcomes (Nonaka, 1994). As De Clercq and Sapienza (2006) highlighted from their interviews with VCFs' managers, commitment to enhancing ventures' value creates a good social relationship that allows the PFCs' managers to be more open about challenges and motivation. This improved understanding helps VCFs to gain deeper insights into the future prospects of PFCs' exit outcomes, diminish VCF managers' tendency to rely on mental heuristics and shortcuts (Shepherd et al., 2003), and adjust their initial forecasts. Therefore, value-added activities devoted to PCFs reduce the effect of the different biases that explain the negative relationship between initial forecasting ability and revised forecast accuracy. As a result:

Hypothesis 3: VCFs' value-adding commitment to portfolio companies will moderate the relationship between venture capital firms' initial forecasting ability and revised forecast accuracy such that this (negative) relationship will be weaker.

DATA AND METHOD

We tested these hypotheses in the context of venture capital firms operating in France and their investments in start-up companies. Since it is very hard to accurately and effectively value the investments in start-ups, assessments of future prospects (Sanders and Boivie, 2004) and especially of exit outcomes (Gerasymenko and Arthurs, 2014) play a central role in VCFs' investment strategy. We describe our data, measures and methods below.

Sample

To address our research question we relied on mixed methods research (Bryman, 2006; Plano Clark and Creswell, 2008). Because we were collecting our data about venture capital firms and their portfolio companies in France, a previously-understudied empirical setting, we realized that relying just on quantitative research would be insufficient for gaining a more accurate understanding and data. We relied on a sequential methodology known as exploratory sequential design that enabled us to use the findings of one methodology (e.g., qualitative) to inform the issues to be addressed in the subsequent evaluation (e.g., quantitative) (Greene et al., 1989, p. 262). We first conducted preliminary exploration with venture capitalists and entrepreneurs via qualitative semi-structured interviews to make sure that we were aware of all venture capital interventions and exit forecasts that we would subsequently measure in the quantitative study. This building stage was very important because most research is focused on VCFs in the USA: by relying on exploratory sequential design we were able to validate that the value-adding activities carried out by VCFs in the American context were also carried out by VCFs in France, as well as identify some value-adding activities and exit forecasts that were not previously mentioned by the studies conducted in the American context (Creswell, 2015). For instance, our preliminary interviews showed that some VCFs were spending considerable time advising their portfolio companies regarding public grants and other forms of financial aid available in France. Internationalization appeared as another important area of advising by French VCFs. It is possible that this issue was more prominent in France than in the USA given a significant size difference in the home market. While in this particular study we focus on IPO and Trade Sale exits, secondary sales to other private equity firms appeared to be a viable alternative exit route for French VCFs.

In total, we conducted 15 exploratory semi-structured interviews with VCFs and CEOs of portfolio companies to assure that we had a complete understanding of the relationships between VCFs and their investments, and in particular, of the non-financial interventions that VCFs were involved in following the investment round. In addition, we also relied on these interviews to pre-test our questionnaire to ensure its clarity and the alignment of VCFs' definitions of concepts with our own. Finally, we recognized that because early-stage venture capital activity was relatively recent in France at the start of data collection (2006), it was important to differentiate between professionally-managed VCFs and those that were still in the process of fundraising or staffing. Following recommendations that we received during our interviews with several general partners, we limited our sample to VCFs with 10 million euros under management and above. In sum, these interviews were therefore critical for illustration and clarification of our constructs and potential findings (Greene et al., 1989). The average length of an interview with a general partner was 65 minutes, ranging from 30 minutes to two hours total.

In order to avoid a single source bias, we collected data on different variables from different sources. For instance, in addition to our questionnaire and public sources, we used the early-stage VCFs' semi-annual reports that they provided to their shareholders to collect information on some of our control and independent variables. From this source, we gathered VCF and start-up characteristics. Specifically, we obtained information on the VCF's team size and number of syndicate partners per start-up, as well as information on the VCF's exit deals, enabling us to evaluate their success and failure experience. In terms of the start-up related information, we gathered information on the start-up's valuations, total amount of capital received and employee growth.

As our next sequential research step, we then collected information regarding VCFs' interventions, such as areas in which they actively advised their PFCs or provided other value-adding activities, and their forecasts of the outcomes of the portfolio companies. We sent our questionnaire by email to the 32 French early-stage VCFs in May 2006, representing the complete early-stage venture capital market in the country at that time. In order to maximize response rate, our questionnaire was accompanied by a letter explaining the importance of the study, guaranteeing confidentiality and promising to share summary results. We also followed Dillman (2000) and sent reminders two and five weeks after the initial email. Despite these steps, only two VCFs replied to our questionnaire within this time frame. However, 22 other VCFs showed availability to meet us to reply to our questionnaire in person. Collecting questionnaires in this way enabled us to additionally validate the consistency of the responses and obtain further information about the VCFs' investments by interviewing general partners.

By October 2006 we had collected responses from 24 VCFs, but one was excluded due to incomplete information. In the end, we had complete information from 23 VCFs (a 72 per cent response rate) regarding 300 start-ups they had financed; accordingly, this study is one of the first to collect primary data on the entire portfolios of multiple VCFs. All the VCFs had seats on the boards of the portfolio companies (according to the VCFs' financial reports), which ensured that they were knowledgeable about the companies. To assure that we collected information that was as complete as possible, we asked general partners of VCFs to reply to our questionnaire regarding only the portfolio companies on whose boards they were personally present. It is important to note that although this information was collected from individuals (general partners), the forecasts they indicated reflected the prediction of the venture capital firm as a whole. In their responses, the VCFs indicated for each of these start-ups the likely exit mode and estimated timeframe for each exit they predicted. In addition, the VCFs' general partners indicated the areas in which their VCF provided advice to ventures and connected them to other potentially valuable agents in the market. In total, the VCFs' value-adding involvement covered 18 different areas (e.g., finance, strategy, marketing, human resource management, business plan preparation, networking with experts, investors, etc.) that we detail in our discussion of the variables below.

Because the central question of our study is to understand how VCFs' ability to make initial accurate forecasts (forecasts made upon first investment in a new start-up) is related to the accuracy of revised forecasts of their ongoing investments, we conduct our regression analysis of the VCFs' revised forecast accuracy on those ventures that had been in VCFs' portfolios in 2006 for more than two years. While after two years the outcome of such investments was still uncertain, the period of time that the focal VCFs had spent on board was long enough to have revised their initial forecasts. As we defined earlier in our paper, forecast revision may result in alteration of the initial forecast or may lead VCFs to the conclusion that their initial forecast should be preserved. Earlier research showed that individuals and organizations may commit both types of errors: alter predictions that were correct and preserve those that needed to be changed. While the information we gathered from the VCFs does not allow us to capture the direction of the VCFs' errors in forecast revision, we are able to measure if the VCFs' forecast reassessment was accurate or not. In our interviews VCFs confirmed that they tend to rely on their initial forecast for up to two years after initial investment. After that time, internal policy, often combined with a new investment round, lead VCFs to re-assess the exit prospects of their portfolio companies. At the time of our data collection, 69 per cent of the 300 start-up ventures were still in VCFs' portfolios. Thirty-five per cent of these ventures were recently made investments and therefore reflected initial forecasts made by the VCFs. The remaining 65 per cent, or 135, PFCs reflected the VCFs' revised forecasts, of which 114 consisted in IPOs or trade sales – the remaining 21 being

MBOs and secondary sales. Therefore, our final sample included 114 ventures (backed by 18 VCFs) projected to go public or be acquired by another firm that were still active investments in 2006 and had remained in VCFs' portfolios for more than two years. In 2011, via public online sources, we collected precise up-to-date information on the actual VCF exit outcomes for these start-ups. Thanks to these internal policies, we can therefore separate the accuracy of the revised forecasts of 2006 for each of the 114 firms (our dependent variable) from the VCF's initial forecasting ability measured on the other firms in portfolio (our independent variable).

Dependent Variable: VCF Revised Forecast Accuracy

In order to estimate the *VCF Revised Forecast Accuracy*, we focused on those 114 ventures that by 2006 had stayed in the VCFs' portfolios for at least two years and for which we had a revised forecast of the expected type of exit. IPOs or trade sales of start-ups in VCFs' portfolios in 2006 were expected to occur between 2007 and 2009. In order to evaluate the accuracy of the VCFs' revised forecasts made in 2006, in 2011 we collected information on the actual exits that took place. We considered the revision of the forecast accurate if the VCF exited via IPO or Trade Sale as reflected in their revised forecast. We also took into account if the exit occurred during the predicted year (that includes one year before or after the forecast year of exit). Because one of the key indicators of VCF performance (and investments in general) is internal return on invested capital, which varies with the time that it takes to receive a pay-back (Kaplan and Schoar, 2005), it was important to consider not only the type of exit, but also the time when the exit occurred. For instance, if a VCF general partner forecast an IPO in 2007, we considered the forecast accurate if the VCF did exit through IPO and it happened during 2006–08. Other type of exit, or an IPO after 2008, or no exit from the portfolio in 2011 (the case of so-called 'living dead' companies which remain in portfolio) were considered as inaccurate forecast revisions.

Our dependent variable (*VCF Revised Forecast Accuracy*) is therefore coded as 1 if the VCF managers correctly predicted the type, either IPO or Trade Sale, and period of exit, and 0 if either or both criteria were not met. The overall accuracy of the VCFs' revised forecast is about 20 per cent. While VCFs overestimated potential IPO and Trade Sale exits after revising their forecasts, their ability to sort out potential IPO from Trade Sale exits is high (80 per cent and above). The accuracy of prediction also varies across VCFs: 14 made accurate Trade Sale forecasts, two made accurate IPO forecasts and two VCFs made accurate predictions of both IPO and Trade Sale exits.

Independent and Moderating Variables

VCF Initial Forecasting Ability. The variable *VCF Initial Forecasting Ability* is estimated by comparing the IPO and Trade Sale forecasts that VCFs reported for their newly made investments (those start-ups that by the date of our data collection had stayed in the VCFs' portfolios for less than two years) with the actual exit outcomes collected in 2011. If the predicted exit materialized, we coded the variable as 1, and 0 otherwise. By summing up the total number of accurate initial forecasts and dividing it by the total number of initial forecasts per each VCF, we obtained a proportion of initial accurate forecasts for each VCF. We then multiplied the number by 100 per cent to express it as a percentage, for ease of use. While some VCFs correctly predicted up to 50 per cent of exits upon initial investment in a start-up, others failed to make any accurate initial exit predictions. As a result, *VCF Initial Forecasting Ability* captures the VCFs' ability (or inability) to make initial accurate exit forecasts.

VCF Syndication. Our first moderating variable, *VCF Syndication*, was measured as a number of co-investors in a PFC together with the focal VCF. As a robustness test, we also coded *VCF Syndication* as a binary variable equaling 1 if a VCF had one or more co-investors and 0 if none. Such variable transformation did not change the direction or significance of our findings and we report results with the number of co-syndicates.

VCF Value-Adding Commitment. In our questionnaire, venture capitalists indicated areas in which they provided competent value-adding advising and network connections to each start-up in their portfolio. It is common for start-ups to lack functional expertise in one or more areas and, to some extent, this may be provided by VCFs via advising and networking (Beckman and Burton, 2008). These value-adding services could be in such areas as finance, strategy, marketing, human resource management, business plan, business model, networking with different types of agents (Hsu, 2006; Sorenson and Stuart, 2008), public aid, recruitment of management talent (Boeker and Wiltbank, 2005), and international management. From our literature review and our pre-test questionnaire, we detailed 18 different areas of VCF involvement. The PFCs we interviewed considered such advising to be critical since most of them faced disadvantages in accessing external knowledge of this sort (Almeida et al., 2003).

Respondents were asked to include only interventions that they deemed to be competent and value creating. On this basis, we refer to them as areas in which VCFs had some relevant knowledge and capabilities, regardless of the frequency with which they were deployed. To validate this further, whenever possible we asked respondents to give additional explanation and clarification of the interventions they made and the value these interventions added to the portfolio companies. We recognize that validating capabilities using external or third party data is preferred. However, self-reported data on specific resources and capabilities have been the norm in much of the literature (Durand, 2003; Hall, 1993; Nag and Gioia, 2012). Scholars interested in understanding the nature and impact of the VFCs' competencies on performance of their portfolio companies have followed this path (Busenitz et al., 2004; MacMillan et al., 1989). A very high similarity of replies collected from VCFs and CEOs of portfolio companies regarding the value of VCFs' advising (Sapienza and Gupta, 1994) provide additional evidence of the high reliability of the self-reported data in this context. Each area in which a VCF implemented a set of (knowledge sharing) actions by advising a PFC was coded 1 (0 otherwise). By summing up these binary variables to estimate the number of areas in which each start-up was advised by a focal VCF, we obtained our final *VCF Value-adding Commitment* measure for each portfolio company.

Controls

We controlled for a number of contextual factors associated with each start-up. First, because traditional performance measures such as profit or sales growth are not suitable for early-stage start-ups, we relied on several other performance measures that were established as most representative of ventures' development. Consistent with prior studies (Fitza et al., 2009; Hsu, 2004; Lerner and Gompers, 2001) we use the change in company valuation between two funding rounds to control for the company performance. Upon initial investment, this valuation occurs through a negotiated process between the current company owners and new investors to the start-up. Therefore, the *Start-up Valuation* variable is the percentage increase (or decrease) between the firm valuation at the focal VCFs' initial investment round and the start-up valuation in 2006. We obtained this variable from the VCFs' reports to their limited partners in which they were providing the update of each portfolio start-up valuation on a semi-annual basis. Because of over-dispersion of this variable, after adding one to the variable to avoid negative or zero values, we used natural logarithm to make the distribution of the variable closer to normal. Because not all venture-backed startups generate profit or even revenue during initial stages of development, a change in the number of employees over time has also been considered as a reliable performance measure. Therefore, in line with earlier research, to control for the start-up's performance, *Start-up Growth*, we included the change (logged) in the number of employees in 2006 compared to the year of the VCFs' initial investment. We also accounted for some critical VCFs' characteristics. We controlled for the number of general partners in each VCF, *VCF Team Size*, to account for the cognitive diversity and input that each VCF benefits from when making forecasts. Because the accuracy of at least initial forecasting is influenced by failure experience that encourages more in-depth review of the VCFs' beliefs and practices, we controlled for *VCF Failure Experience*, defined as the number of prior investments a focal firm made that were liquidated, sold at a loss or declared bankrupt. Other variables were not kept in models as not being significant: VCF age as well as start-ups' characteristics such as geographic location (in France or abroad) and sector of activity (information and communication technologies versus biotechnologies).

Model

Considering that our dependent variable is binary, we relied on a probit regression model to test our hypotheses (Hoetker, 2007). We compared the model fit for probit and logit, using functions estimates store and estimates stats in STATA. AIC and BIC values were slightly smaller for probit than logit, suggesting that probit was a slightly better fit. Overall, our results are similar for probit and logit. We used robust standard errors (Huber, 1967) in an effort to be conservative in our estimates, since robust standard errors are usually larger than non-robust standard errors, and clustered the errors on VCFs to control for the potential differences among them. Because macroeconomic conditions may influence the forecast accuracy, we used year dummies to control for year effects at the time of VCFs' initial investment in portfolio companies.

However, because our dependent variable is a limited dependent variable (LDV) (i.e., binary) we still have to interpret our results with caution before drawing final conclusions. As several researchers pointed out, in regressions with a LDV, the significance of coefficients of explanatory variables is not sufficient to draw conclusions about the impact of the variables on the predicted outcome. That is because, unlike ordinary least squares (OLS) regressions, LDV models are nonlinear, meaning that an explanatory variable's marginal effect (the effect of a unit change in an explanatory variable on the dependent variable) does not equal the variable's model coefficient. Also, the marginal effect in a LDV varies with the value of other variables in the model. For these reasons, 'an explanatory variable's coefficient can rarely be used to infer the true nature of the relationship between the explanatory variable and the dependent variable' (Wiersema and Bowen, 2009, p. 628). Additional analysis is often required, and assessment of the marginal effect and associated z-statistic value is best done graphically by plotting these values against the predicted value of the dependent outcome. Following the procedure suggested by Wiersema and Bowen, we relied on the *predictnl* STATA command for our further analysis. The results of the analyses of marginal effects and z-statistic of *VCF Initial Forecasting Ability* and interaction coefficients with the *VCF Syndication* and *VCF Value-adding Commmitment* were significant and had signs similar to our results in the probit regression model. We do not report these graphs for the sake of brevity, but they are available from the authors upon request. Taking into consideration these additional analyses, we conclude that our findings of the probit regression model discussed below are robust.

Endogeneity

It is important to recognize that the reasons why VCFs remain on the boards of some companies longer than others are not random (Heckman, 1979). If the same non-random factors influence VCFs' decisions to keep companies in their portfolio and their forecast accuracy, endogeneity is present, and the coefficients found in the regression model predicting forecast accuracy may be inaccurate (Hamilton and Nickerson, 2003). To correct for this potential endogeneity problem, we used a two-stage procedure similar to a standard Heckman model (Sartori, 2003). We calculate the Inverse Mills ratio from a first-stage probit model, which in our case predicts whether a start-up was in a VCF's portfolio or not during 2006, the year of data collection. This dummy variable, *Portfolio Start-up*, takes 1 if a VCF was sitting on a start-up's board in 2006 and 0 if the VCF had exited beforehand. By 2006, the year of our data collection, the VCFs had exited from 31 per cent of the 300 startups in portfolio, or 93 of their investments. As per the Heckman procedure, we include the Inverse Mills ratio in the second-stage probit regression model to account for the potential bias associated with endogeneity.

The logic behind this specification is that start-ups from which VCFs exited earlier (before 2006) may have differed systematically from those that remained in VCFs' portfolios by 2006 in terms of some characteristics that we are unable to control in our regression model. Since this difference could affect our results as VCFs try to predict outcomes for start-ups that had not exited prior to 2006 (e.g., the outcomes for the ventures in the VCFs' portfolios in 2006 may be systematically harder or easier to predict), our first stage uses data on all 300 start-ups to model the likelihood that a VCF was on board with a given start-up in 2006 (Table II). We next introduced the Inverse Mills ratio in our second-stage model to control for the potential endogeneity, predicting the accuracy of the VCFs' forecast revisions for our PFCs under consideration (Table III).

RESULTS

Table I shows descriptive statistics for the sample and correlations. Correlation coefficients among other variables do not exceed 0.4, thus present low risk of collinearity. Also, since none of the variance inflation factor statistics exceed 4, which is much below the established threshold of 10, the collinearity should not be a concern in our sample.

Table II presents the results for the first-stage probit model of the Heckman procedure – a model predicting whether VCFs were on board or exited from a company by 2006. According to the Heckman method, we identified and included four variables that influenced the likelihood of being in the VCFs' portfolio but not the VCFs' forecast accuracy. These variables were *VCF Age*, *Start-up Sector (ICT = 1)*, *Start-up Location (France = 1)*, and *Start-up Age*. The results of the first-stage model pointed out that older start-ups, with a higher valuation, located abroad and operating in the biotech industry, were less likely to remain in the VCFs' portfolio.

Table III shows the results of second-stage probit regressions predicting *VCF Revised Forecast Accuracy* regarding the type and time of exit of start-ups from their portfolios. We included the Inverse Mills ratio from Table II for the startups under consideration.

We first introduce only the control variable of our probit regression in Model 1 (Table III) and then add our independent variable *VCF Initial Forecasting Ability* in Model 2 (Table III), test the moderating effect of the *VCF Syndication* and *VCF Value-adding Commitment* respectively in Models 3 and 4 and present our full probit regression in Model 5

Table I. Correlation and descriptive statistics

N	*Variables*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	VCF Revised Forecast Accuracy									
2	VCF Initial Forecasting Ability	−0.156								
3	VCF Syndication	0.001	−0.001							
4	VCF Value-adding Commitment	−0.062	0.012	0.252*						
5	Start-up Valuation (ln)	0.161*	0.005	0.120	−0.102					
6	Start-up Growth (ln)	0.139	−0.224*	0.025	0.169	−0.002				
7	VCF Team Size	0.098	−0.090	−0.144	0.126	−0.175	0.154			
8	VCF Failure Experience	−0.087	0.067	0.229*	0.200*	0.329*	0.117	−0.055		
9	Heckman value	0.061	−0.125	−0.003	−0.247	0.534*	−0.156	−0.220	-0.101*	
	Mean	0.20	8.62	2.09	5.60	0.48	3.10	6.53	1.40	0.71
	Std. Dev.	0.40	17.29	2.86	2.03	1.57	0.81	2.89	2.09	0.34
	Min	0	0	0	0	0	0	2	0	0.08
	Max	1	50	14	10	6.98	4.87	11	11	2.11

N = 114, coefficients significant at $p < 0.05$ are marked with *.

Table II. Probit regression predicting the likelihood of start-ups to be in VCF portfolio

Variables	*Portfolio Start-up*
VCF Age	−0.263**
	(−2.69)
VCF Size (ln)	−0.229†
	(−1.65)
Start-up Sector (IT=1)	−0.719**
	(−2.66)
Start-up Valuation (ln)	−0.155**
	(−2.95)
Start-up Location (France=1)	−0.581*
	(−2.32)
Start-up Age (ln)	−0.051*
	(−2.07)
Year Dummies	Yes
Constant	4.388***
	(−4.85)
Pseudo R-squared	0.168
chi2	90.82***

N = 300. z-statistics are shown in parentheses.
†p <0.10.
*p < 0.05.
**p <0.01.
***p < 0.001.

(Table III). As we can see from Table III, the coefficient for *Start-up Valuation* is positive and significant ($p < 0.01$), suggesting that an increase in the venture's value is associated with a more accurate forecast revision. Likewise, the coefficient of *Start-up Growth* is also positive but marginally significant ($p<.10$) in Model 1. The coefficients of these two variables suggest that overall VCFs are more accurate at predicting exits of better performing ventures. We also notice that the coefficient of the *VCF Failure Experience* is negative and significant ($p<.05$). The Inverse Mills ratio (*Heckman Value*) is insignificant in Model 1, suggesting that endogeneity should not be a concern in interpreting our findings.

Model 2 shows support for our first hypothesis, which predicted a negative relationship between the *VCF Initial Forecasting Ability* and the *VCF Revised Forecast Accuracy*: the coefficient of the *VCF Initial Forecasting Ability* is negative and significant ($p<.05$), suggesting that a greater ability to make initial forecasts reduces the ability to revise forecasts. Before testing our moderating hypotheses, we mean-centred our variables to ease interpretation of the findings. In our second hypothesis we predicted that the *VCF Syndication* will positively moderate the relationship between *VCF Initial Forecasting Ability* and *VCF Revised Forecast Accuracy*. The interaction coefficient is positive and highly significant ($p<.001$) in Model 3, suggesting potential support for our second hypothesis. Finally, we test our third hypothesis that *VCF Value-adding Commitment* will positively moderate the relationship hypothesized in our first hypothesis. We first introduce the interaction term in Model 4 and then present a complete model with two interaction terms in Model 5. Contrary to our expectations, the interaction coefficient is negative and highly

Table III. Probit regression of VCF revised forecast accuracy

Variables	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
VCF Syndication	−0.002	0.052	3.259***	0.126	19.30***
	(−0.01)	(0.95)	(5.86)	(0.84)	(24.62)
VCF Value-adding Commitment	−0.020	−0.075	−0.069	−0.284	−5.906***
	(−0.29)	(−0.88)	(−0.78)	(−1.40)	(−16.52)
Start-up Valuation (ln)	0.344***	0.434***	0.357***	0.223*	0.340**
	(3.85)	(4.74)	(3.38)	(2.21)	(3.24)
Start-up Growth (ln)	0.343†	0.239	0.316	0.234	0.343
	(1.76)	(1.16)	(1.38)	(1.13)	(1.47)
VCF Team Size	0.074	0.051	0.087	0.026	0.075
	(1.34)	(0.92)	(1.28)	(0.41)	(1.13)
VCF Failure Experience	−0.197*	−0.194*	−0.179†	-.046	−0.201*
	(−2.02)	(−2.09)	(−1.90)	(−0.51)	(−2.09)
Heckman value	−0.714	−1.543*	−1.278†	−0.713	−1.201
	(−1.52)	(−2.42)	(−1.79)	(−1.01)	(−1.62)
VCF Initial Forecasting Ability		−0.025*	−6.012***	−3.377**	−31.16***
		(−2.33)	(−6.65)	(−3.62)	(−25.99)
VCF Initial Forecasting Ability * VCF Syndication			6.288***		37.88***
			(5.49)		(24.62)
VCF Initial Forecasting Ability * VCF Value-Adding Commitment				−10.99***	−11.42***
				(−19.28)	(−24.92)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	−2.020*	−1.140	−4.719***	−1.847*	−17.82***
	(−2.08)	(−1.06)	(−3.77)	(−2.14)	(−12.77)
Pseudo R-squared	0.146	0.176	0.241	0.195	0.265
chi2	26.72***	54.28***	701.1***	1024.91***	1172.8***

N = 114. z-statistics are shown in parentheses.
†p <0.10.
*p < 0.05.
** p <0.01.
*** p < 0.001.

significant (p<.001), suggesting that our third hypothesis is disconfirmed. As explained above, we cannot rely on a single coefficient to determine support but need to complement our interpretation with a graphical representation. Both interaction effects are graphically presented on Figures 1 and 2.

In Figure 1 we notice that the slope of the interaction between *VCF Initial Forecasting Ability* and *VCF Syndication* at 1 standard deviation above the mean is positive, whereas at low levels of syndication (1 standard deviation below the mean) the slope of the curve is negative. As a result, the moderation effect of VCF Syndication is even stronger than we expected since the negative relationship between VCF Initial Forecasting Ability and VCF Forecast Revision becomes positive in the presence of a high number of co-investors. The slopes in Figure 2 confirm that the interaction between *VCF Initial Forecasting Ability* and a high level of *VCF Value-adding Commitment* (1 standard deviation above the mean) decreases the likelihood of accurate forecast revision, whereas the interaction between *VCF Initial*

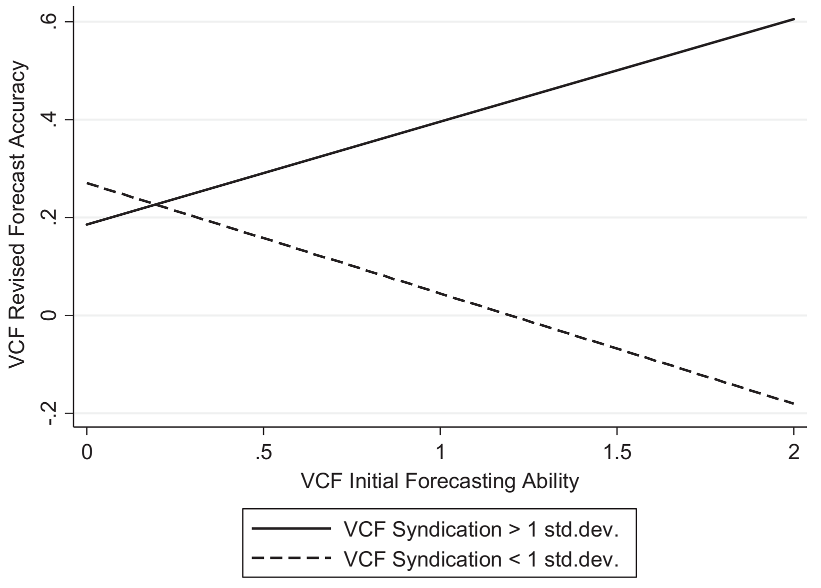

Figure 1. Moderating effect of the VCF Syndication on the VCF's ability to revise its forecast

Forecasting Ability and a low level of *VCF Value-adding Commitment* (1 standard deviation below the mean) increases the likelihood of making a more accurate revised forecast.

In sum, we found that organizations with a higher initial forecasting ability are less accurate than others at adjusting their forecasts over time. We also found that addition of external knowledge (through expert partners, or co-investors) moderate this negative relationship up to a point where it flips over the total effect as shown in Figure 1.

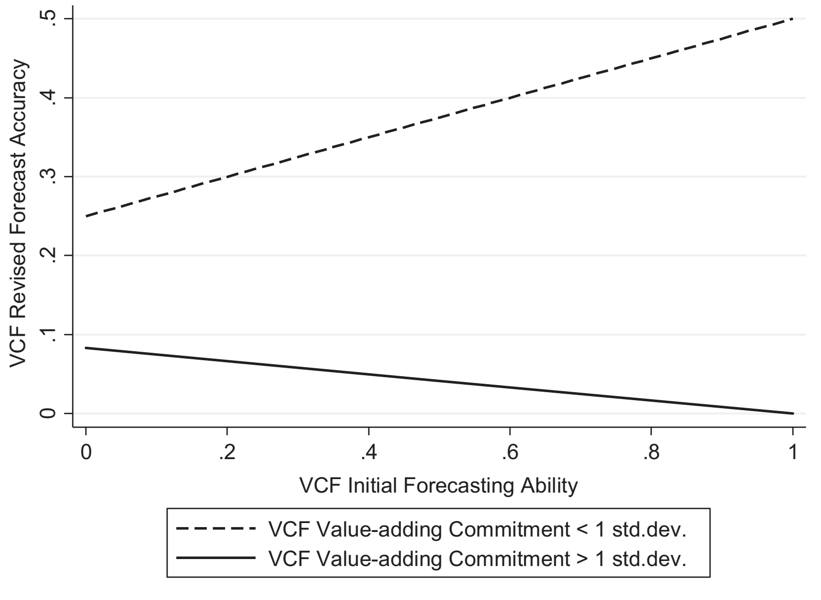

Figure 2. Moderating effect of VCF Value-adding Commitment on the VCF's ability to revise its forecast

Contrary to our hypothesis, we found that VCFs' high value-adding commitment to portfolio companies reinforces the negative relationship between initial forecasting ability and revised forecast accuracy. Adding internal information does not incapacitate the self-efficacy, routine, confirmatory and heuristics biases that explain the main effect.

Given a relatively wide distribution of the *VCF Value-adding Commitment* variable, ranging from 0 to 10 with a mean of 5.6, we also tried an alternative operationalization. We created three distinct categories: *VCF Value-adding Low Commitment* if involvement was 1 standard deviation below the mean, *VCF Value-adding Average Commitment* if involvement was within 1 standard deviation below and above the mean, and *VCF Value-adding High Commitment* if involvement was 1 standard deviation above the mean. Similar to our previous findings, the interaction between *VCF Value-adding High Commitment* and *VCF Initial Forecasting Ability* was negative and significant ($p < .001$). Interestingly, the interaction between *VCF Value-adding Low Commitm*ent and *VCF Initial Forecasting Ability* was positive and significant ($p<.01$), suggesting that having no or a very low level of involvement in a PFC can help VCFs achieve a more objective vision of the venture's future development. This result and our prior finding that goes against our Hypothesis 3 may lead to an alternative explanation: high levels of value-adding commitment lead VCF managers to develop emotional attachments to ventures together with initial beliefs about the outcomes of these ventures, introducing an important bias into forecast revision. We also conducted an additional test to examine if *VCF Syndication* with others could help overcome the negative impact of *VCF Value-adding Commitment* on forecast revision accuracy. Results of a three-way interaction showed a negative and significant coefficient ($p<.05$), suggesting that syndication was not helpful in coping with potential attachment bias of a VCF instilled by a higher level of VCFs' value-adding commitment to PFCs.

DISCUSSION

The fundamental question we address is whether a firm's superior initial forecasting ability facilitates or hinders accurate revision of forecasts. As knowledge exchange with experts and direct information access help redress biases, we investigate whether these two factors moderate the main relationship between initial forecast ability and revised forecast accuracy. We test our hypotheses using a unique dataset of VCFs for which we have the revised forecasts of exit outcomes for startups in their investment portfolio, the degree of syndication for each start-up in portfolio, and the value-adding activities deployed by the VCF in each start-up.

We find that a higher initial forecasting ability is negatively associated with revised forecast accuracy, and that this relationship is positively moderated by the degree of external (expert) knowledge (to the point that the relationship becomes positively oriented) but, contrary to expectations, negatively moderated by direct engagement of the VCF with the start-up. These findings contribute to the literature in several ways.

Initial vs. Revised Forecast Trade-off

First, we theorize and examine organizational forecasting in terms of its two distinct facets that have not been examined concurrently previously: initial forecasting ability and the accuracy of revised forecasts. Drawing on forecasting and decision-making literature, we postulate and find evidence that inertial pressures resulting from effort and time committed to developing one's initial forecasting ability leads to self-efficacy bias, confirmatory bias and heuristics' use that undermine the ability of organizations to effectively revise their forecasts. We therefore extend the forecasting literature by highlighting a potential trade-off that organizations encounter between investing time and effort into initial forecasting versus dedicating attention and resources to noticing, interpreting and collecting new signals and information enabling forecast revision. While earlier research focused exclusively on individuals' commitment to initial beliefs as a barrier to subsequent belief adjustments, we extend this research by showing the degree to which the effort and resources committed to developing a superior organizational initial forecasting ability may create resistance to effective forecast adjustments.

In addition, despite recognition that judgemental forecasting is an essential organizational activity, knowledge about forecasting is primarily informed by lab experiments at the individual level or from very specific empirical settings that may not be generalizable. Rare studies, such as Makadok and Walker (2000), seek to understand if forecasting activity can be considered an organizational competence and explain superior organizational performance. These authors examined forecasting activity in money funds and found that more accurate forecasting significantly increases appropriable economic returns and fund size. Our study follows this path, and contributes to the forecasting literature by extending research on forecasting revision at the organizational level.

The Positive Role of Syndication

Our study also contributes to the literature on venture capital syndicates (De Clercq et al., 2008). Earlier research emphasized the benefits of complementary knowledge of syndicate partners as a way to access a higher quality deal flow (Sorenson and Stuart, 2008) and benefit from a better selection process and richer knowledge to add value to PFCs along the way (Brander et al., 2002). Other studies examined VCFs' decision to enter a syndicate (Manigart et al., 2006), the effect of syndication on VCF performance (De Clercq and Dimov, 2008) and the structural and behavioural antecedents of syndicates (Wright and Lockett, 2003). The key assumption of these studies is that a partner possesses a stock of valuable knowledge that the other partner can access or learn from by assimilating it with its own knowledge base and that this leads to subsequent performance improvement.

We add to this literature by providing evidence that more syndicate partners help a VCF with a higher initial forecasting ability to reestimate correctly the exit outcomes of its PFCs. Collectively, a larger syndicate will have a higher cognitive ability to redress a VCF's biases and help identify, process and integrate new signals and information into more accurate forecast updates. Our findings address an important issue of the power of initial forecasting ability as an anchor (Kahneman and Lovallo, 1993) to subsequent effective revisions of forecasts. Our findings show that such anchoring bias can be overcome by co-investing with other syndicate partners. Because a higher number of syndicate partners are likely to bring more diverse and opposite perspectives on the outcomes of ventures, a high number of co-investors can particularly serve as an effective filter of the VCFs' initial forecasting abilities and beliefs.

The Dark Side of Commitment

Agency and resource dependence theories suggest that VCFs can provide effective monitoring and value-adding services to their ventures (e.g., Bussgang, 2010). Indeed, VCFs' representatives have been predominantly portrayed as highly knowledgeable board members who understand the evolving nature of firms and the industries they invest in (Ozcan and Eisenhardt, 2009). Prior research argued that the higher the VCFs' commitment to the PFC via intensive advising and other value-adding roles such as network sharing and personal coaching, the better will be the outcome (Hsu, 2006; Junming and Chia-Yu, 2008). While De Clercq and Sapienza (2006) recognize that commitment reflects an emotional dimension and a proactive effort, they admit that it is difficult to empirically test the extent to which VCFs' predictions or expectations will be affected by such commitment.

Our study is therefore one of the few to uncover the 'dark side' of the VCFs' value-adding commitment to PFCs. At the intersection of the dynamic theory of organizational knowledge creation (Nonaka, 1994) and decision-making literatures, we show that a high level of value-adding commitment on behalf of VCFs reinforces the rigidity of VCFs' initial vision and prevents effective forecast revision. Contrary to our expectation that access to private information will help curb the biases experienced by VCFs with a better initial forecast ability, we found that a higher commitment leads to less accurate forecast revisions. One possible explanation is that VCF commitment promotes affective or emotional attachment of VCFs' members to startups they invested in. This can interfere with an objective evaluation and become a source of bias. For instance, earlier research showed that affective attachment tends to reinforce previously held beliefs making it particularly challenging for individuals to abandon or review their earlier expectations (Adomzda and Baron, 2013). Such emotional attachment may be further reinforced by social costs (Goffman, 1959) that a VCF would have to incur by decreasing or withdrawing from its value-adding commitment to PFCs. Since people in organizations strategically manage impressions and aim to appear competent to their peers and partners, a VCF may persevere in its value-adding commitment to avoid social tension with PFCs and syndicate partners. Moreover, VCFs are known to overestimate their ability to add value to PFCs that may provide additional explanation for our finding. Because such emotional factors, overconfidence, and over optimism contribute to escalation of organizational commitment (Sleesman et al., 2012) – sticking to a given course of action even in the face of evidence that is suboptimal (Staw and Fox, 1977) – an active value-adding role may further reinforce such tendencies (Guler, 2007). All in all, gaining internal information about ventures does not help VCFs readjust their forecast.

As such, our study speaks to the growing stream of research examining the microfoundations of dynamic capabilities (Augier and Teece, 2009; Felin et al., 2012; Teece, 2012). We study forecasting at the organizational level – exploring how external and internal information sources alter the effects of initial forecasting ability on forecast revision. While our study is at the organizational level, it is influenced by theory at the individual level as well, thereby illuminating a key organizational activity that future research on the micro foundations of dynamic capabilities can explore by disaggregating organizational and individual effects of a firm's forecasting capability (Durand, 2003; Vergne and Durand, 2011).

Practical Implications

Our study reveals substantial heterogeneity in forecast accuracy: while some VCFs have erroneous exit expectations about their PFCs, others are able to accurately predict the exit outcome of as many as 50 per cent of their investments. Our results draw attention to some important factors that may undermine VCF managers' forecasting accuracy. Specifically, VCF managers should be aware that the better they are at identifying targets and forecasting PFCs' exit originally, the more they need to adjust their later stage forecasting. Self-efficacy bias, reliance on routines, confirmatory bias and use of heuristics need to be actively fought.

Syndication with other investors appears to help VCFs revise their forecasts more effectively. As a result, VCFs should be encouraged to seek other expert opinions. Moreover, VCF managers must be cautious about the counter-intuitive effect of a 'hands-on' policy vis-à-vis their PFCs. VCF managers need to be aware that an extended value-adding commitment to PFCs may increase psychological attachment to the ventures, reinforce the anchorage around initial expectations, and undermine efforts to effectively reassess the PFCs' exit outcomes. This, in turn, may lead VCF managers to direct their effort toward the wrong outcomes (e.g., type of exit), which may compromise the firm's expected return. VCF managers should therefore carefully manage their value-adding involvement with PFCs. Finally, our findings have important implications for PFC CEOs. They point to some important limitations that their VCF may have in correctly assessing the best suited exit route. CEOs should therefore consider viewpoints of different investors and other partners when it comes to directing their venture toward one exit outcome over another.

Limitations and Future Research

Our hypotheses were tested in the context of venture capital firms' forecasts of the types of exit pursued by their portfolio companies. While we believe that both this empirical context and our data were highly suitable for examining our research question, the extension of our findings to other contexts should be done with some degree of caution. It is possible that organizations from different industries are subject to more or less cognitive rigidity than VCFs when making forecasts. Also, VCFs are relatively small organizations, and not only should our findings hold, but they may possibly have a bigger magnitude in larger organizations or in organizations operating in less dynamic environments. Replicating our study in a different setting could provide some additional insights on the research topic.

We also recognize some methodological limitations of our study. First, while we have taken recommended steps to control for potential endogeneity problems and the Heckman value is insignificant, future studies should draw on longitudinal data to account for potential endogeneity more effectively. Second, we have 18 VCFs, each with different numbers of PFCs. Other models would be desirable with a larger sample of VCFs and more observations for each. Despite this weakness of our data, we conducted extensive robustness tests that reinforce the validity of our findings. Future research should investigate the antecedents of initial forecasting ability, and those of forecast revision accuracy beyond what we already found.

Our study does not address goal congruence between the investor and the PFC. However, goal congruence is one of the critical factors that shape VCF-PFC relationships and performance (De Clercq et al., 2013, 2014). Future work would add significant knowledge to the field by examining how goal congruence between the parties influences forecasting ability and revised forecast accuracy. Also, because CEOs of PFCs may use impression management techniques to influence investors, the extent to which such techniques have impact on VCFs' predictions could be worth examining.

Understanding what characteristics of syndicate partners contribute more meaningfully to VCF forecasting is another potentially fruitful area for inquiry. While our results reveal significant benefits of syndication for VCF forecast revision, it is possible that some syndicate partners, such as more or less experienced ones or those that have prior investment history with the focal VCF, will have a more positive impact than others. Understanding this phenomenon at a more fine-grained level would also illuminate more precise recommendations for practitioners.

Finally, admittedly our study is one of the first to examine organizational forecasting in a way that captures some of its key constituents (e.g., initial forecasting ability and revised forecasts) and the relationships between them. In this study we focused on VCFs' type of exit forecast, which is one of the essential strategic forecasts that VCFs make. In the future, scholars could collect data on other forecasts that VCFs make and try to understand if and how their forecast accuracy varies in terms of indicators they try to predict. Also, scholars could embrace the challenges of collecting forecasting data longitudinally and bring insights on the dynamics of organizational forecasting over time. Doing so would enable to build a more complete model of this essential organizational capability.

ACKNOWLEDGMENTS

We greatly appreciate helpful comments from our three anonymous reviewers and editors of the journal. We are also thankful for valuable insights from Rajshree Agarwal, Glenn Hoetker, Joe Mahoney, Edward Roberts and seminar participants at the University of Wisconsin and the Cass Business School. The authors are listed alphabetically to reflect their equal participation in developing the article.

REFERENCES

Adomzda, G. and Baron, R. A. (2013). 'The role of affective biasing in commercializng new ideas'. *Journal of Small Business and Entrepreneurship*, **26**, 201–17.

Ahuja, G., Coff, R. and Lee, P. (2005). 'Managerial foresight and attempted rent appropriation: insider trading on knowledge of imminent breakthroughs'. *Strategic Management Journal*, **26**, 791–808.

Allen, S. A. and Hevert, K. T. (2007). 'Venture capital investing by information technology companies: did it pay?'. *Journal of Business Venturing*, **22**, 262–82.

Almeida, P., Dokko, G. and Rosenkopf, L. (2003). 'Startup size and the mechanisms of external learning: increasing opportunity and decreasing ability?'. *Research Policy*, **32**, 301–15.

Andreassen, P. B. and Kraus, S. J. (1990). 'Judgemental extrapolation and the salience of change'. *Journal of Forecasting*, **9**, 347–72.

Arthurs, J. D. and Busenitz, L. W. (2006). 'Dynamic capabilities and venture performance: the effects of venture capitalists'. *Journal of Business Venturing*, **21**, 195–215.

Augier, M. and Teece, D. J. (2009). 'Dynamic capbilities and the role of managers in business strategy and economic perfornance'. *Organization Science*, **20**, 410–21.

Barney, J. (1991). 'Firm resources and sustained competitive advantage'. *Journal of Management*, **17**, 99–120.

Barney, J. B. (1995). 'Looking inside for competitive advantage'. *Academy of Management Executive*, **9**, 49–61.

Bartunek, J. M., Bobko, P. and Venkatraman, N. (1993). 'Toward innovation and diversity in management research methods'. *Academy of Management Journal*, **36**, 1362–73.

Bazerman, M. H. and Moore, D. A. (2008). *Judgment in Managerial Decision Making*, 7th edition. Hoboken, NJ: Wiley.

Beckman, C. M. and Burton, M. D. (2008). 'Founding the future: path dependence in the evolution of top management teams from founding to IPO'. *Organization Science*, **19**, 3–24.

Bitektine, A. and Miller, D. (2015). 'Methods, theories, data, and the social dynamics of organizational research'. *Journal of Management Inquiry*, **24**, 115–30.

Boeker, W. and Wiltbank, R. (2005). 'New venture evolution and managerial capabilities'. *Organization Science*, **16**, 123–33.

Brander, J. A., Amit, R. and Antweiler, W. (2002). 'Venture-capital syndication: improved venture selection vs. the value-added hypothesis'. *Journal of Economics & Management Strategy*, **11**, 423–52.

Bromiley, P. (1987). 'Do forecasts produced by organizations reflect anchoring and adjustment?'. *Journal of Forecasting*, **6**, 201–10.

Bryman, A. (2006). 'Inegrating quantitative and qualitative research: how is it done?'. *Qualitative Research*, **6**, 97–113.

Bukszar, E. and Connolly, T. (1988). 'Hindsight bias and strategic choice: some problems in learning from experience'. *Academy of Management Journal*, **31**, 628–41.

Busenitz, L., Fiet, J. and Moesel, D. (2004). 'Reconsidering the venture capitalists' "value added" proposition: an interorganizational learning perspective'. *Journal of Business Venturing*, **19**, 787–807.

Bussgang, J. J. (2010). *Mastering the VC Game: A Venture Capital Insider Reveals How to Get from Start-up to IPO on Your Terms*. Boston, MA: Portfolio, Penguin Group (USA) Inc.

Bygrave, W. D. (1987). 'Syndicated investments by venture capital firms: a networking perspective'. *Journal of Business Venturing*, **2**, 139–54.

Cassar, G. and Craig, J. (2009). 'An investigation of hindsight bias in nascent venture activity'. *Journal of Business Venturing*, **24**, 149–64.

Christianson, M. K., Farkas, M. T., Sutcliffe, K. M. and Weick, K. E. (2009). 'Learning through rare events: significant interruptions at the Baltimore & Ohio railroad museum'. *Organization Science*, **20**, 846–60.

Creswell, J. W. (2015). *A Concise Introduction to Mixed Methods Research*. Thousand Oaks, CA: SAGE Publications, Inc.

Cyert, R. M. and March, J. G. (1963). *A Behavioral Theory of the Firm*. Upper Saddle River, NJ: Prentice Hall/Pearson Education.

Cyert, R. M., Dill, W. R. and March, J. G. (1998). 'The role of expectations in business decision making'. In Maanen, J. V. (Ed), *Qualitative Studies of Organizations*. Thousand Oaks, CA: SAGE Publications, Inc., 5–30.

De Clercq, D. and Dimov, D. (2008). 'Internal knowledge development and external knowledge access in venture capital investment performance'. *Journal of Management Studies*, **45**, 585–612.

De Clercq, D. and Sapienza, H. J. (2005). 'When do venture capital firms learn from their portfolio companies?'. *Entrepreneurship: Theory & Practice*, **29**, 517–35.

De Clercq, D. and Sapienza, H. J. (2006). 'Effects of relational capital and commitment on venture capitalists' perception of portfolio company performance'. *Journal of Business Venturing*, **21**, 326–47.

De Clercq, D., Fried, V. H., Lehtonen, O. and Sapienza, H. J. (2006). 'An entrepreneur's guide to the venture capital galaxy'. *Academy of Management Perspectives*, **20**, 90–112.

De Clercq, D., Sapienza, H. J. and Zaheer, A. (2008). 'Firm and group influences on venture capital firms' involvement in new ventures'. *Journal of Management Studies*, **45**, 1169–94.

De Clercq, D., Dimov, D. and Thongpapanl, N. (2013). 'Organizational social capital, formalization, and internal knowledge sharing in entrepreneurial orientation formation'. *Entrepreneurship: Theory & Practice*, **37**, 505–37.

De Clercq, D., Bouckenooghe, D., Raja, U. and Matsyborska, G. (2014). 'Unpacking the goal congruence-organizational deviance relationship: the roles of work engagement and emotional intelligence'. *Journal of Business Ethics*, **124**, 695–711.

Dillman, D. A. (2000). *Mail and Internet Surveys - The Tailored Design Method*. New York: Wiley.

Dobrev, S. D., Tai-Young, K. and Carroll, G. R. (2003). 'Shifting gears, shifting niches: organizational inertia and change in the evolution of the U.S. automobile industry, 1885–1981'. *Organization Science*, **14**, 264–82.

Durand, R. (2003). 'Predicting a firm's forecasting ability: the roles of organizational illusion of control and organizational attention'. *Strategic Management Journal*, **24**, 821–38.

Felin, T., Foss, N. J., Heimeriks, K. H. and Madsen, T. L. (2012). 'Microfoundations of routines and capabilities: individuals, processes, and structure'. *Journal of Management Studies*, **49**, 1351–74.

Fitza, M., Matusik, S. F. and Mosakowski, E. (2009). 'Do VCs matter? the importance of owners on performance variance in start-up firms'. *Strategic Management Journal*, **30**, 387–404.

Fredrickson, J. W. and Iaquinto, A. L. (1989). 'Inertia and creeping rationality in strategic decision processes'. *Academy of Management Journal*, **32**, 516–42.

Gerasymenko, V. and Arthurs, J. D. (2014). 'New insights into venture capitalists' activity: IPO and time-to-exit forecast as antecedents of their post-investment involvement'. *Journal of Business Venturing*, **29**, 405–20.

Gerasymenko, V., De Clercq, D. and Sapienza, H. (2015). 'Changing the business model: effects of venture capital firms and outside CEOs on portfolio company performance'. *Strategic Entrepreneurship Journal*, **9**, 79–98.

Gifford, S. (1997). 'Limited attention and the role of the venture capitalist'. *Journal of Business Venturing*, **12**, 459–82.

Giot, P. and Schwienbacher, A. (2007). 'IPOs, trade sales and liquidations: modelling venture capital exits using survival analysis'. *Journal of Banking & Finance*, **31**, 679–702.

Goffman, E. (1959). *The Presentation of Self in Everyday Life*. New York: Doubleday.

Greene, J. C., Caracelli, V. J. and Graham, W. F. (1989). 'Toward a conceptual framework for mixed-method evaluation designs'. *Educational Evaluation and Policy Analysis*, **11**, 255–74.

Guler, I. (2007). 'Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry'. *Administrative Science Quarterly*, **52**, 248–85.

Hall, R. (1993). 'A framework linking intangible resources and capabilities to sustainable competitive advantage'. *Strategic Management Journal*, **14**, 607–18.

Hamilton, B. H. and Nickerson, J. A. (2003). 'Correcting for endogeneity in strategic management research'. *Strategic Organization*, **1**, 51–78.

Heckman, J. (1979). 'Sample selection bias as a specification error'. *Econometrica*, **47**, 153–61.

Hoetker, G. (2007). 'The use of logit and probit models in strategic management research: critical issues'. *Strategic Management Journal*, **28**, 331–43.

Hogarth, R. M. and Makridakis, S. (1981). 'Forecasting and planning: an evaluation'. *Management Science*, **27**, 115–38.

Hsu, D. H. (2004). 'What do entrepreneurs pay for venture capital affiliation?'. *Journal of Finance*, **59**, 1805–44.

Hsu, D. H. (2006). 'Venture capitalists and cooperative start-up commercialization strategy'. *Management Science*, **52**, 204–19.

Huber, P. J. (1967). 'The behavior of maximum likelihood estimation under nonstandard conditions'. In LeCam, L. M. and Neyman, J. (Eds), *The Fifth Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley, CA: University of California Press, **5**, 221–33.

Junming, H. and Chia-Yu, C. (2008). 'An investment strategy based on the long-run performance of IPOs: venture-backed and non-venture-backed firms'. *Journal of Investing*, **17**, 95–105.

Kahneman, D. and Lovallo, D. (1993). 'Timid choices and bold forecasts: a cognitive perspective on risk taking'. *Management Science*, **39**, 17–31.

Kahneman, D. and Tversky, A. (1973). 'On the psychology of prediction'. *Psychological Review*, **80**, 237–51. '

Kahneman, D. and Tversky, A. (1979). 'Prospect theory: an analysis of decision under risk'. *Econometrica*, **47**, 263–91.

Kaplan, S. N. and Schoar, A. (2005). 'Private equity performance: returns, persistence, and capital flows'. *Journal of Finance*, **60**, 1791–823.

Kickul, J., Gundry, L. K., Barbosa, S. D. and Whitcanack, L. (2009). 'Intuition versus analysis? Testing differential models of cognitive style on entrepreneurial self-efficacy and the new venture creation process'. *Entrepreneurship: Theory & Practice*, **33**, 439–53.

Lane, P. J. and Lubatkin, M. (1998). 'Relative absorptive capacity and interorganizational learning'. *Strategic Management Journal*, **19**, 461–77.

Lawrence, M., Goodwin, P., O'Connor, M. and Önkal, D. (2006). 'Judgmental forecasting: a review of progress over the last 25 years'. *International Journal of Forecasting*, **22**, 493–518.

Lerner, J. (1994). 'The syndication of venture capital investments'. *FM: the Journal of the Financial Management Association*, **23**, 16–27.

Lerner, J. and Gompers, P. (2001). *The Money of Invention: How Venture Capital Creates New Wealth*. Boston, MA: Harvard School Business Press.

Lim, J. S. and O'Connor, M. (1995). 'Judgemental adjustment of initial forecasts: its effectiveness and biases'. *Journal of Behavioral Decision Making*, **8**, 149–68.

MacMillan, I., Kulow, D. and Khoylian, R. (1989). 'Venture capitalists' involvement in their investments: extent and performance'. *Journal of Business Venturing*, **4**, 27–35.

Makadok, R. (2002). 'A rational-expectations revision of Makadok's resource/capability synthesis'. *Strategic Management Journal*, **23**, 1051–7.

Makadok, R. and Barney, J. B. (2001). 'Strategic factor market intelligence: an application of information economics to strategy formulation and competitor intelligence'. *Management Science*, **47**, 1621–39.

Makadok, R. and Walker, G. (2000). 'Identifying a distinctive competence: forecasting ability in the money fund industry'. *Strategic Management Journal*, **21**, 853–64.

Makridakis, S., Hogarth, R. M. and Gaba, A. (2009). 'Forecasting and uncertainty in the economic and business world'. *International Journal of Forecasting*, **25**, 794–812.

Manigart, S., Lockett, A., Meuleman, M., Wright, M., Landström, H., Bruining, H., Desbrières, P. and Hommel, U. (2006). 'Venture capitalists' decision to syndicate'. *Entrepreneurship: Theory & Practice*, **30**, 131–53.

McNamara, G. and Bromiley, P. (1997). 'Decision making in an organizational setting: cognitive and organizational influences on risk assessment in commercial lending'. *Academy of Management Journal*, **40**, 1063–88.

McNamara, G., Moon, H. and Bromiley, P. (2002). 'Banking on commitment: intended and unintended consequences of an organization's attemtp to attenuate escalation of commitment'. *Academy of Management Journal*, **45**, 443–52.

Moritz, B., Siemsen, E. and Kremer, M. (2014). 'Judgmental forecasting: cognitive reflection and decision speed'. *Production & Operations Management*, **23**, 1146–60.

Nag, R. and Gioia, D. A. (2012). 'From common to uncommon knowledge: foundations of firm-specific use of knowledge as a resource'. *Academy of Management Journal*, **55**, 421–57.

Nonaka, I. (1994). 'A dynamic theory of organizational knowledge creation'. *Organization Science*, **5**, 14–37.

Ocasio, W. (1997). 'Towards an attention-based view of the firm'. *Strategic Management Journal*, **18**, 187–206.

Ocasio, W. (2011). 'Attention to attention'. *Organization Science*, **22**, 1286–96.

Ozcan, P. and Eisenhardt, K. M. (2009). 'Origin of alliance portfolios: entrepreneurs, network strategies, and firm performance'. *Academy of Management Journal*, **52**, 246–79.

Plano Clark, V. L. and Creswell, J. W. (2008). *The Mixed Methods Reader*. Thousand Oaks, CA: SAGE Publications, Inc.

Sanders, N. R. and Manrodt, K. B. (2003). 'The efficacy of using judgmental versus quantitative forecasting methods in practice'. *Omega*, **31**, 511–22.

Sanders, W. G. and Boivie, S. (2004). 'Sorting things out: valuation of new firms in uncertain markets'. *Strategic Management Journal*, **25**, 167–86.

Sanna, L. J. and Schwarz, N. (2006). 'Metacognitive experiences and human judgment: the case of hindsight bias and its debiasing'. *Current Directions in Psychological Science*, **15**, 172–6.

Sapienza, H. J. (1992). 'When do venture capitalists add value?'. *Journal of Business Venturing*, **7**, 9–27.

Sapienza, H. and Gupta, A. (1994). 'Impact of agency risks and task uncertainty on venture capitalist-CEO interaction'. *Academy of Management Journal*, **37**, 1618–32.

Sartori, E. A. (2003). 'An estimator for some binary-outcome selection models without exclusion restrictions'. *Political Analysis*, **11**, 111–38.

Shepherd, D. A., Zacharakis, A. and Baron, R. A. (2003). 'VCs' decision processes: evidence suggesting more experience may not always be better'. *Journal of Business Venturing*, **18**, 381–401.

Shumsky, R. A. (1998). 'Optimal updating of forecasts for the timing of future events'. *Management Science*, **44**, 321–35.

Sleesman, D. J., Conlon, D. E., McNamara, G. and Miles, J. E. (2012). 'Cleaning up the big muddy: a meta-analytic review of the determinants of escalation of commitment'. *Academy of Management Journal*, **55**, 541–61.

Sniezek, J. A. (1990). 'A comparison of techniques for judgmental forecasting by groups with common information'. *Group & Organization Studies*, **15**, 5–19.

Soon, A. and O'Connor, M. (1991). 'The effect of group interaction processes on performance in time series extrapolation'. *International Journal of Forecasting*, **7**, 141–9.

Sorenson, O. and Stuart, T. E. (2008). 'Bringing the context back in: settings and the search for syndicate partners in venture capital investment networks'. *Administrative Science Quarterly*, **53**, 266–94.

Staw, B. M. and Fox, F. V. (1977). 'Escalation: the determinants of commitment to a chosen course of action'. *Human Relations*, **30**, 431–50.

Teece, D. J. (2012). 'Dynamic capabilities: routines versus entrepreneurial action'. *Journal of Management Studies*, **49**, 1395–401.

Tripsas, M. and Gavetti, G. (2000). 'Capabilities, cognition, and inertia: evidence from digital imaging'. *Strategic Management Journal*, **21**, 1147–61.

Vergne, J.-P. and Durand, R. (2011). 'The path of most persistence: An evolutionary perspective on path dependence and dynamic capabilities'. *Organization Studies*, **32**, 365–82.

Weick, K. E. (1969). *Sensemaking in Organizations (Foundations for Organizational Science)*. Thousand Oaks, CA: SAGE Publication Series.

Weick, K. E., Sutcliffe, K. M. and Obstfeld, D. (2005). 'Organizing and the process of sensemaking'. *Organization Science*, **16**, 409–21.

Wiersema, M. F. and Bowen, H. P. (2009). 'The use of limited dependent variable techniques in strategy research: issues and methods'. *Strategic Management Journal*, **30**, 679–92.

Wright, G., Lawrence, M. J. and Collopy, F. (1996). 'The role and validity of judgment in forecasting'. *International Journal of Forecasting*, **12**, 1–8.

Wright, M. and Lockett, A. (2002). 'Structure and management of syndicated venture capital investments'. *Journal of Private Equity*, **5**, 72–83.

Wright, M. and Lockett, A. (2003). 'The structure and management of alliances: syndication in the venture capital industry'. *Journal of Management Studies*, **40**, 2073–102.

Zaheer, A., McEvily, B. and Perrone, V. (1998). 'Does trust matter? Exploring the effects of interorganizational and interpersonal trust on performance'. *Organizational Sience*, **9**, 141–59.