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Abstract

We investigate the impact of 'learning from peers' on the fundraising abilities of start-up companies. Employing data on the financing rounds of privately owned portfolio companies, we find that companies observe the round amounts of their most successful peers and learn to negotiate higher round amounts with venture capital investors. We further show that the number of common directors or venture capital firms between portfolio companies and their most successful peers has a positive impact on the round amounts of these portfolio companies, which supports the existence of conversational learning. Moreover, observational learning from peers is higher in hot markets, where investors rely on less costly information on peers. Our findings confirm that both observational and conversational learning allow portfolio companies to be in a better negotiating position, thus enhancing their ability to secure funding and invest in their growth.

Key words: Peer effect, portfolio companies, learning, venture capital funding, exit.

JEL classification: G24, G32, G41.

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“Money is the fuel of a company.”
Simon Sinek, Jul 19, 2018,
The National Society of Leadership and Success

1. Introduction

Firms learn from their peers (Foucault and Fresard, 2014; Leary and Roberts, 2014); they observe or communicate with each other to learn and make decisions (Sorensen, 2006; Cai et al., 2009). Their choices also depend on the outcome of decisions made by others (Kaustia and Rantala, 2015). Despite the rich peer effect literature, little is known about peer influence on private firms during the fundraising process. In this paper, we investigate whether private firms learn from their successful peers to secure higher venture capital (VC) funding and whether they use specific conversational learning channels to enhance their fundraising abilities.

Money is the lifeblood that enables a startup to cover its costs and grow. Startups are usually constrained by limited financial history and tangible assets, as well as high uncertainty about their expected cash flows (Aldrich and Fiol, 1994). These constraints limit their access to traditional external financing (Admati and Pfleiderer, 1994; Gompers, 1995) and push them toward the VC market (Rajan, 1992). VC investors have high information-processing capabilities (Lerner, 1995) and spend considerable time screening and selecting new investment opportunities (Gorman and Sahlman, 1989; Sørensen, 2007).[1]

[1] Gompers et al. (2020) find that an average VC firm invests in four out of 200 screened companies per year, and that the selection process is mostly based on the quality of the management/founding team and the nature of the business.

Funding relationships between entrepreneurs and VC firms suffer, however, from agency conflicts that constrain information production (Aghion and Bolton 1992, Gompers 1995, Lerner 1994). Entrepreneurs may act opportunistically (Neher 1999; Casamatta, 2003) and manipulate information (Cornelli and Yosha, 2003). This increases the costs faced by VC firms and deters the selection process of promising startups,[2] thus leading VC firms to use their monopsony power to reduce the value assigned to a startup. The funding amount is thus the outcome of negotiations between startups and VC investors. These negotiations are usually subject to the characteristics of startups, the terms of the contracts between startups and VC firms, as well as fads and fashions that influence the overall value and funding levels of certain industries (Ewens et al., 2022). The negotiation exercise would thus require a close understanding of investors' appetite in the VC market.

With their limited history and high levels of uncertainty, startups tend to refer to and imitate peer firms that have secured the highest funding, i.e., their most successful peers. From a "technical-rationale" perspective, the most successful peers are perceived to possess superior information, and, from a "social-rationale" perspective, they gain a legitimate taken-for-granted status (Lieberman and Asaba, 2006). This perspective is consistent with Strang et al. (2014) who propose a model for innovation adoption and abandonment by consultants and firms, and argue that bounded rational actors imitate their most successful peer, i.e., the firm "associated with highest performance outcome in the just-completed round" (Strang et al., 2014).

[2] To mitigate this issue, VC firms typically stage their financing commitment over multiple rounds (Sahlman, 1990; Tian, 2011) to be able to abandon or better monitor their portfolio companies (Gompers, 1995). This exerts pressure on entrepreneurs to achieve their goals (Admati and Pfleiderer, 1994), allows investors to collect information and monitor portfolio companies (Gompers, 1995), and alleviates potential agency problems (Neher, 1999).

Hence, from an observational learning perspective, startups observe their peers and seek an available representative company to which they assimilate themselves.[3] We postulate that startups are likely to mimic successful peers and negotiate similar amounts of funds when seeking VC funding. This helps startups, especially those with noisy information, to improve their perceived quality and obtain the funds required to compete and grow. In this context, we argue that private companies have a greater cognitive bias towards the highest round amount raised in their peer group. The choice of the peer with the highest round amount could be driven by two foundations: on the one hand, this choice could be the outcome of a rational learning exercise in which past observations are relevant and used to estimate the unobservable qualities of the company raising funds; and on the other hand, the choice of the peer with highest round amount could be considered as an anchor employing heuristic rules (Prat and Uctum, 2018).

Although not necessarily a relevant signal, this anchor could be used as a psychological starting value in the negotiation of round amounts (Tversky and Kahneman, 1974). While we do not examine the foundations of this choice, we argue that a company is likely to be influenced by available information and uses its most successful peer with the highest financing round as an anchor or benchmark. Building on the benchmarking literature, the best-in-class company allows portfolio companies to learn about the investment interest of VC investors and hence to negotiate their own round amounts more effectively. Therefore, we predict that the round amount of a portfolio company increases with the round amount of its most successful peer firm.

If learning exists, portfolio companies are also likely to benefit from the information embedded in their peer firms. Prior research suggests that board interlocks enable information transfer across

[3] Prior research examines the influence of average corporate peers in public markets on individual behavior (Manski, 1993), executive compensation (Albuquerque et al., 2013), corporate disclosure decisions (Seo, 2021), investment decision-making (Bustamante and Frésard, 2021), and the decision to go public (Aghamolla and Thakor, 2022).

firms (Chiu et al., 2013). Firms may thus communicate and learn from their peers through board interlocks and connections (Westphal et al., 2001; Brown and Drake, 2014; Helmers et al., 2017; Cheng et al., 2021). Beyond the observational learning from peers, we argue that the presence of common directors or VC investors represents a conversational learning channel, which enhances the learning process and helps companies better negotiate their round amounts. Hence, we predict that a larger number of common directors or VC investors between a portfolio company and its most successful peer increases the round amount and further mediates the positive association between the round amount of the portfolio company and that of its most successful peer.

However, the positive association between round amounts could be due to a "financial-fashion" (Brealy and Myers, 2003) or to a "money-chasing-deals" phenomenon driven by an excess supply of capital in the VC market (Gompers and Lerner, 2000). Also, the use of an anchor as a source of low-cost information is more likely to be used in an optimistic context (Kleinert and Hildebrand, 2024). The negotiation of the round amount may thus be differentially affected by market conditions. Hence, we predict that observational learning is more significant in hot markets.

We find support for our predictions using data on VC financing rounds for a large sample of US privately-owned portfolio companies between 1980 and 2018. Specifically, the round amount of a portfolio company increases with the round amount of its most successful peer, and with the number of common directors or common VCs. Additionally, the association between the round amount of a portfolio company and that of its most successful peer is mediated by the number of common directors or common VC investors. This suggests that learning goes beyond the simple observation of the most successful peer and could be mediated by potential conversational learning channels. However, our mediation analysis shows that observational learning is more significant economically than conversational learning in this context. We also find that learning from peers becomes more important during hot market conditions, where access to VC funding becomes more difficult. Our empirical evidence is valid for portfolio companies going through their first round of financing, which rejects potential endogeneity and/or reflection concerns or a simple correlation across portfolio companies. And our results remain valid using matched sub-samples through an entropy balancing technique and to various robustness tests.

This paper offers several contributions to the literature. First, we expand prior research on the peer effect in the context of publicly listed firms (Leary and Roberts, 2014), financial institutions (Lee et al., 2017), or among sovereign-bond issuers (Chahine and Chidambaran, 2023), and we examine how peer effects act as a channel in startup funding. Specifically, our paper furthers our understanding of the determinants of VC funding, which is usually the outcome of a negotiation between startup owners and VC investors based on a firm's business plan covering management, market, and product criteria (Timmons, 1981). We also complement the work of Aghamolla and Thakor (2022) who investigate IPO peer effects in the drug development industry and find that firms are more likely to raise above-median VC funding after observing a peer doing so. [4]

Second, we contribute to previous studies on social learning, which refers to the use of the choices and experiences of others to make decisions (Bikhchandani et al., 1998; Young, 2009), by confirming the role played by conversational learning in peer effects. We therefore extend the debate on the relational agency framework focusing on the impact of prior co-investments in VC syndicates (Bellavitis et al., 2020). We also contribute to research on knowledge-based view and the role played by knowledge spillover (Liu et al., 2010). We show that a larger number of common

[4] Our results are also consistent with prior research on peer effects as a source of information, which influences corporate decisions. This research includes, among others, evidence on peer effects in formulating financial structure (Leary and Roberts, 2014; Francis et al., 2016), investment decisions (Foucault and Fresard, 2014, Dessaint et al., 2018), and dividend policies (Kaustia and Rantala, 2015; Grennan, 2019).

directors (or common VCs) mediates the observational learning that occurs between a portfolio company and its most successful peer, which helps increase its round amount. This suggests that common directors (or VC investors) act as channels by which firms share information about strategic decisions.[5] Our findings confirm the role of common directors and VCs as a source of knowledge spillover in facilitating information transfer across firms. While common directors advise and bring knowledge and experience gained elsewhere (Fama and Jensen, 1983), they usually cannot, by regulation, be drawn from direct competitors (Brown and Drake, 2014).[6] Our paper contributes to this literature by providing evidence that sharing board members (or VCs) influences companies' ability to raise funds, grow, and compete.

Finally, our findings contribute to the anchoring theory in finance (Tversky and Kahneman, 1974; Kahneman and Tversky, 1982). Prior research shows that anchoring matters in investment decision-making, negotiation, auctions, or the determination of a reference price for consumers (Galinsky and Mussweiler, 2001; Furnham and Boo, 2011). We expand this literature in the context of VC funding and argue that the round amount of the most successful peer could be used as an anchor or benchmark. Beyond rational learning, economic agents with bounded rationality are likely to imitate their most successful peers when dealing with limited and biased information (Strang et al., 2014). Emulating the most successful peer suggests that benchmarking to the best-in-class generates knowledge at the level of portfolio companies and increases the round amount.

[5] While the Clayton Act expressly prohibits director interlocks among direct competitors, it does not prohibit intra-industry interlocks (Mizruchi 1996). We employ an industry classification schema from Barth et al. (1998) that has 15 broad categories to avoid our intra-industry interlocks being interpreted as competitor interlocks (Zajac, 1988).

[6] Linck et al. (2008) document that more than 64% of board directors in US public firms were outsiders during the 1990s and 2000s. Chiu et al. (2013) further indicate that a typical S&P 500 firm had a median of five interlocks with other boards during this same period. Both factors suggest that social learning via interlocked directors is widespread.

In the remainder of the paper, we develop our hypotheses in the context of existing relevant literature in section 2. We report our data sources and discuss our methodologies in section 3. We present our empirical results and verify support for our hypotheses in section 4. We follow up with robustness tests in section 5 and further analysis in section 6. We conclude in section 7.

2. Literature Review and Hypothesis Development

As a scarce resource, capital is especially important during the early stages of the life of a startup, when the business generates limited or even no revenues. It helps startups pay salaries and bills and cover research and development expenditures that improve the quality of their goods and services. Capital is therefore a critical asset that helps ensure a startup's success and fund competitive choices to challenge rivals (Fresard, 2010). However, startup owners are likely to have an optimistic bias in the assessment of the valuation of their firms and may try to maximize their round amounts. As investors, VC firms try to maximize the return on their funds. This leads to a potential conflict of interest and an agency concern in the negotiation process. VC firms usually ask startups to forecast their financial statements to determine their capital requirements and predict the business's future value (Stancill, 1987). The estimation of the required amount of capital funding is one of the main dilemmas faced by entrepreneurial firms.

2.1. Observational Learning from the Round Amount of the Most Successful Peer

Given the uncertainty related to financial forecasting of privately owned companies with limited history and experience, the owners of portfolio companies do not have the opportunity to "learn by doing." They may, however, learn vicariously from the experience of other portfolio companies and thereby build new capabilities (Denrell, 2003). In observing other portfolio companies' VC funding rounds, the owners of a portfolio company identify the representative group of peers and acquire knowledge about the appetite of VC investors (Lane and Lubatkin, 1998). In this private market context, we argue that owners are likely to rely on a limited number of heuristics to simplify their complex decision on the funding amount. They are biased towards the information available about their peer with the highest round amount, used as an "anchor" (Tversky and Kahneman, 1974). This anchoring bias is likely to impact the VC funding process and lead to excessive weight on vivid information and overconfidence (Thaler, 1985). The owners of portfolio companies are thus likely to refer to the most successful peer and try to obtain similar amounts of capital to compete and grow. As economic agents, they may consider that their available information is noisy (Banerjee, 1992) and that making optimal choices could be time-consuming (Conlisk, 1980). As such, they use their most successful peer, i.e., the peer firm with the highest financing round during the previous year, as a benchmark value or anchor.

First, portfolio companies may adopt a technical rationale and follow their most successful peers whose experience has "technical value" (Abrahamson and Rosenkopf, 1993). Specifically, the owners of portfolio companies observe and update their prior beliefs in a Bayesian manner based on the actions of their successful peers (Romer, 1993). They learn that their most successful peers are likely to have access to better information or have more significant expertise than other peer firms (Bikhchandani et al., 1998). Second, portfolio companies may adopt a social rationale and mimic their successful peers, benefitting from their leadership status, to enhance their own perceived type (Scharfstein and Stein, 1990) and legitimately negotiate higher funding amounts (Hannan and Carroll, 1992). The negotiation of the required round amount for a portfolio company will thus be adjusted and pulled toward the round amount of the most successful peer.

Accordingly, the negotiation of a funding amount depends on the portfolio company's characteristics as well as its prior beliefs which are based on observed actions by the most successful peer. We argue that the owners of portfolio companies learn about the funding abilities of VC investors from their most successful peers. They identify the highest funding amount raised by the best-in-class company during the last calendar year, use it as a benchmark, and learn to negotiate their round amounts. We therefore predict a positive relationship between the round amount of a portfolio company and that of its most successful peer firm, after controlling for the portfolio company's characteristics. Hence:

H1: The round amount of a portfolio company is positively associated with that of its most successful peer firm.

2.2. Learning from Peers through Conversational Channels

From a social learning perspective, prior literature suggests that organizations try to become similar to other organizations in their environment, referred to as "isomorphism" (DiMaggio and Powell, 1983). Building on the knowledge-based view and social capital theory, Liu et al. (2010) find that human mobility across national borders and multinational firms facilitates international knowledge spillovers and enhances innovation. Thus, learning from peers goes beyond the simple observation of the VC funding amount and the positive association between round amounts. Information and knowledge could be shared between companies through board connections and interlocks. A large body of literature has shown that firms are likely to adopt financial decisions comparable to those of firms with common directors (Bouwman, 2011). More recently, Foroughi et al. (2022) find evidence on the existence of peer effects in adopting antitakeover provisions among board-interlocked firms. Board interlocks facilitate the dissemination of earnings management and financial disclosure (Chiu et al. 2013; Cai et al. 2014; Jiang et al. 2018). The information transmitted through board interlocks positively impacts merger and acquisition activities (Westphal et al., 2001), research and development (R&D) and patenting (Helmers et al., 2017), tax-avoidance (Brown and Drake, 2014), and investment in technology (Cheng et al., 2021).

We argue that the presence of a common director or VC investor between a portfolio company and its peer represents a channel through which firms communicate and learn the details and impacts of their decisions (Chiu et al., 2013). Such channels strengthen knowledge spillover and social interaction, i.e. conversational learning, which facilitates the learning process (Westphal et al., 2001; Brown and Drake, 2014; Helmers et al., 2017; Cheng et al., 2021). As a conversational learning channel, the presence of a common director or VC investor may complement the observational learning efforts of portfolio companies. It is thus likely to allow portfolio companies to better mimic their most successful peers and negotiate higher round amounts. Hence:

H2a: The round amount of a portfolio company is positively associated with the number of common directors or VC investors with its most successful peer firm.

H2b: The Number of common directors or VC investors mediates the positive association between the round amount of a portfolio company and the one of its most successful peer firm.

2.3. Observational Learning and Market Conditions

While we argue that fundraising is an outcome of negotiations between the startup and VC investors, we do not form hypotheses on the negotiation process between both parties. Indeed, the round amount may depend on the information held by all involved parties as well as on potential VC agency problems (Chahine et al., 2020).

The outcome of negotiations may also be differentially affected by market conditions. Gompers and Lerner (2000) indicate that higher inflows of capital into VC funds increase the valuation of new VC investments, thus creating a "money chasing deals" problem. Kleinert and Hildebrand (2024) argue that VCs' information processing could be altered by market conditions. They explain that VCs track signals in cold markets and emphasize less costly talks consistent with the overall market optimism in hot market conditions. VCs' readiness to accept higher funding amounts may thus differ in a hot vs. cold market. For example, a hot market is usually characterized by greater capital inflows into VC funds (Gompers et al., 2008), with an increasing competition among VCs for good quality portfolio companies (Zhelyazkov and Tatarynowicz, 2021). A larger number of startups are likely to use this opportunity to seek funding than in normal or cold periods, and this could exceed the amount of available liquidity for startup investments. The quality of companies looking for funding may also be lower in hot markets than in normal market conditions. While the average round amount is likely to be low in cold markets, we predict a lower average round amount in hot markets compared to normal market conditions.

Furthermore, economic agents with cognitive limitations often focus on the most salient available information and ignore less salient information. Hirshleifer (2001) argues that individuals tend to rely on heuristics to simplify complex decisions, and this is more likely in firms faced with high uncertainty and limited information. In this context, economic agents are likely to overweight highly accessible information and use it as a potent anchor (Kahneman, 2002). Compared to cold or normal market periods, investors are less cautious in hot markets (Gulati and Higgins, 2003), and portfolio companies are likely to rely in their negotiations on the available information given by the round amount of their most successful peer. We thus expect the anchoring effect to be stronger in hot periods in which investors are faced with increasing asymmetric information on the quality of the startup and its valuation. Hence:

H3a: The round amount of a portfolio company is lower during hot markets than in normal or cold markets.

H3b: The association between the round amount of a portfolio company and the one of its most successful peer firm is stronger in hot markets than in normal or cold markets.

3. Data and Methodology

We employ the entire sample of 192,775 investment rounds of VC-backed portfolio companies from 1980 to 2018 found in the VentureXpert database. We adjust all USD amounts for inflation, and winsorize variables at the top and bottom 1% of the distribution in all sample years to mitigate the effect of outliers. Table 1 shows the distribution of portfolio companies per industry and shows that 57.3% of portfolio companies are within the information technology (high-tech) sector, 25.3% are within the low-tech sector, and the remaining 17.4% are in the medical sector. This distribution is almost the same across the sample period, with some high-tech waves around the dot-com bubble between 1999 and 2001 and during the market-recovery period following the subprime crisis from 2014 to 2018. Companies within the high-tech and medical subsectors, representing approximately 48% and 55% of all companies, respectively, follow similar trends in similar periods.

To test our predictions, we develop a simple learning model that includes a portfolio company and a peer firm (Leary and Roberts, 2014). We assume that corporate managers have private information about market conditions, their firms' characteristics, as well as the round amounts and publicly known characteristics of peer firms. We estimate the following regression specification on peer-mimicking effects:

$$Ln\ Round\ Amount_{i,t} = Ln\ Max\ Round\ Amount_{j,t-1} + Controls_t + e_t \qquad (1)$$

The dependent variable, $Ln\ Round\ Amount_{it}$, is the natural logarithm of the round amount of portfolio company (i) at time (t). $Ln\ Max\ Round\ Amount_{jt,t-1}$ is the natural logarithm of the round amount of portfolio company (j) with the highest round amount (the most successful peer) within the same 2-digit industry classification (SIC) in the year before the financing round date (t-1). In

Table 1. Frequency of Financing Rounds by Industry and Year

Distribution of portfolio companies by industry and year. The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. The table follows industry classification as per the VentureXpert database, and reports industry distribution (*Frequency*) in percentage points for the whole sample and by sample year.

	Main Industries			*Tech-Sector*	
	Information Technology	Low-Technology	Medical	Hi-tech	Medical-Tech
Frequency	57.3	25.3	17.4	47.6	55.4

Round Year	Information Technology	Low-Technology	Medical	Hitech	Medical-Tech
1980	47.44	38.75	13.81	48.47	57.46
1981	53.53	33.42	13.05	52.35	60.99
1982	53.66	34.15	12.20	51.65	59.98
1983	60.73	26.21	13.07	56.81	64.85
1984	63.31	22.36	14.33	59.24	65.99
1985	60.58	23.65	15.77	59.09	65.18
1986	54.08	29.24	16.68	53.59	60.27
1987	49.39	30.75	19.85	49.36	56.71
1988	46.86	33.23	19.91	45.56	53.81
1989	47.13	32.00	20.87	46.46	54.22
1990	46.59	31.28	22.13	48.59	54.71
1991	45.20	33.41	21.39	42.60	49.05
1992	46.55	28.37	25.07	45.77	51.03
1993	43.02	34.64	22.34	42.42	47.10
1994	45.15	32.04	22.81	42.52	45.82
1995	47.48	32.44	20.08	44.98	49.03
1996	48.24	33.28	18.48	45.37	50.28
1997	52.13	28.97	18.90	49.49	54.11
1998	54.41	28.46	17.12	51.34	57.81
1999	66.96	21.37	11.67	55.53	63.32
2000	70.94	19.27	9.79	57.53	68.15
2001	61.54	25.35	13.11	52.51	61.90
2002	59.91	22.60	17.50	54.55	61.36
2003	56.40	24.17	19.43	53.85	59.62
2004	55.73	24.64	19.62	53.61	58.20
2005	51.16	28.09	20.75	50.00	54.25
2006	48.86	31.62	19.51	46.40	46.41
2007	48.97	31.32	19.70	45.59	45.61
2008	49.82	30.70	19.49	47.46	47.48
2009	48.69	28.49	22.82	47.19	47.22
2010	49.00	30.07	20.93	47.11	47.14
2011	52.82	28.06	19.12	48.43	48.46
2012	55.52	26.16	18.33	50.46	50.51
2013	59.84	22.00	18.16	54.16	54.19
2014	64.13	19.39	16.49	57.48	57.53
2015	66.64	17.58	15.78	56.83	56.94
2016	65.65	18.05	16.30	58.21	58.26
2017	65.33	17.82	16.85	56.67	56.71
2018	66.46	17.55	15.99	57.60	57.63

section 5, we repeat our core test using the most successful peer in the same 4-digit SIC and the average round amount of peer firms within an industry-year, excluding the portfolio company (i).

To test our second hypothesis on whether conversational learning channels accentuate observational learning, we add the natural logarithm of the number of common directors or common VC investors between the portfolio company and its most successful peer to our empirical investigations:

$$\textit{Ln Round Amount}_{i,t} = \textit{Ln Max Round Amount}_{j,t-1} + \textit{Ln (Nb. Common Directors or Common VCs)}_{t} + \textit{Controls}_{t} + e_{t} \qquad (2)$$

To test our third hypothesis on the differential effect of market conditions, we define indicators of hot and cold VC markets as in Yung et al. (2008). To do that, we consider that the number of financing rounds in each quarter reflects the condition of the VC market. We therefore classify financing quarters as hot, cold, or normal by comparing the moving average of financing rounds in each quarter to the historic average of all financing rounds across all quarters all the way to 1980; the hot (cold) market indicator then takes a value of one if the moving average is 50% above (below) the historical average, zero otherwise. Quarters that are neither hot nor cold are classified as normal. The test for our third hypothesis therefore becomes:

$$\textit{Ln Round Amount}_{i,t} = \textit{Hot Market} + \textit{Cold Market} + \textit{Ln Max Round Amount}_{j,t-1} \times \textit{Hot Market} + \textit{Ln Max Round Amount}_{j,t-1} \times \textit{Cold Market} + \textit{Ln Max Round Amount}_{j,t-1} \times \textit{Normal Market} + \textit{Controls}_{t} + e_{t} \qquad (3)$$

In terms of control variables, our empirical tests control for firm-, industry- and VC-level characteristics. All variables are defined in Appendix A.

First, we control for the characteristics of portfolio companies and include an indicator of the quality of corporate governance, *Corporate Governance Index (CG Index)*. Building on prior research in Gompers et al. (2003), we construct the *CG Index* with data typically used in the corporate-governance literature, and we calculate it based on the data available for each funding round.[7] La Porta et al. (2000) show that effective corporate governance is a critical milestone to protect minority shareholders, especially when a company seeks funds from outside investors. The structure and composition of a portfolio company's board of directors are key oversight mechanisms. There is also evidence on the existence of peer effects in adopting antitakeover provisions as an example of diffusion of corporate governance practices for firms in the same networks (Foroughi et al., 2022). Given the cost they bear for a suboptimal governance framework, existing shareholders are likely to optimize the company's board structure during a financing round. Our *CG Index* therefore includes the following four board-of-director characteristics: size, proportion of independent members, proportion of women, and proportion of doctoral degree holders. We assign a score of one for each characteristic whenever its value is higher than the median value over the entire observation period, and zero otherwise. As such, our composite *CG Index* ranges from 0 to 4. We expect the round amount of portfolio companies seeking VC funding to be positively associated with more robust corporate governance.

We control for several additional variables used as proxies for the ex-ante uncertainty of the portfolio company. These include the age of the portfolio company at the time of the financing round (*Firm Age*) and the stage of the financing round (*Stage Number*) as proxies for the maturity level of the portfolio company. *Stage Number* is a scale variable that summarizes a portfolio

[7] While we recognize that corporate governance depends on a larger set of factors, we consider these variables as they are provided in the VentureXpert database.

company's four main funding stages. It takes the value of 1 for seed funding, 2 for early stage, 3 for expansion, and 4 for later stage and other bridge or mezzanine funding stages prior to exit. We also control for the presence of a top auditor (*Top Auditor*) to reflect the existence of a high-quality external auditor certifying the accuracy of the portfolio company's financial statements. We further include *Prior Investment*, which is equal to the total amount invested in previous rounds. It reflects the achievement of milestones in past rounds and suggests the resolution of existing uncertainties surrounding the portfolio company's business. We expect firms with lower ex-ante uncertainty, i.e., older firms, at a more advanced stage of financing, involving top auditors, and with larger prior investment, to raise a higher level of funding.

The round amount may also depend on industry trends. Beyond learning from peers, industries with high growth, profitability, and tangible or intangible investments, are more likely to attract VC investors. To control for industry effects, we include control variables related to the industry characteristics of our portfolio companies. Our industry-level variables include the industry average return on assets (*Industry RoA*), which controls for the profitability of the industry, capital expenditures (*Industry CapEx*), research and development (*Industry R&D*), which reflect potential growth opportunities in the industry, and sales growth over a three-year period prior to the financing round date (*Industry Sales Growth*), which captures the industry's past growth. In line with prior research in Chemmanur et al. (2014), we use industry averages of publicly traded firms for all these variables where industry is defined within the 2-digit SIC of portfolio companies and averages are computed in the year prior to the financing round. We expect the financing round amount to increase with industry-level variables (Tian, 2011). Since we expect VC firms to invest less in portfolio companies that are in highly competitive industries (Chemmanur et al., 2014), we control for the degree of competitiveness of the portfolio company's industry using the industry Hirshman-Herfindahl index (*HH Index*) calculated based on sales.

We also control for VC characteristics, including *VC Reputation* and *VC Syndicate Size*. *VC Reputation* is calculated as in Lee et al. (2011) and is a time-variant composite index of commonly used indicators measuring a VC firm's reputation on an annual basis over the sample period. Our index provides a rating from 0 (lowest) to 100 (highest) for each reputation-related criterion, and then creates an equally weighted average of all criteria to generate a score ranging from 0 to 100. The criteria we use are related to the dollar amount and number of investment funds under management, the dollar amount invested in startups and their number, and the number of firms taken public. We assume that portfolio companies would benefit from the presence of reputable VC investors who have incorporated the required learning from previous experience to the focal situation (Kim et al., 2010). We also expect high-level portfolio companies attracting more reputable VC firms to raise higher round amounts. *VC Syndicate Size* is equal the number of VC firms within the VC syndicate. We expect portfolio companies with larger syndicates to be more mature and to obtain higher funding (Tian, 2011). Finally, we include industry and calendar-year fixed effects to control for industry-specific characteristics and time-variant trends in VC funding.

In previous peer effects literature, the dependent variable is usually regressed on the average outcome variable of a group with which there could be a mechanical correlation (Manski, 1993; Angrist and Pischke, 2008; Angrist, 2014). This raises an endogeneity concern as estimates might "reflect" both directions of peer effects (Manski, 1993). Our portfolio companies are, however, privately owned firms with limited information available prior to their fundraising rounds. Also, our empirical study assumes the existence of a time lag between the decision made by a portfolio company and its peers, which results in a dynamic model that does not suffer from a reflection problem if the time lag is appropriately determined (Manski, 1993). Given that our analysis is based on learning from the experience of peers during the year before the financing round date, we do not expect any identification challenges, endogeneity, or simultaneity in the decision-making process of a portfolio company and its peers. Hence, our empirical investigation is unlikely to suffer from a "reflection problem" (Manski, 1993). To support this, in Section 5, we test whether startups going through their first round of financing learn from peers. The choice of the first round of financing is likely to alleviate potential refection or correlation across portfolio companies.

4. Empirical Results

4.1. Descriptive Statistics

Table 2 presents descriptive statistics for the entire sample of VC-backed portfolio companies. Panel A presents the descriptive statistics in mean, median, standard deviation, and 25% and 75% percentiles, and shows an average round amount of approximately $15 million, with an average natural logarithm of 1.34. The most successful peer has an average maximum round amount of $216 million, with an average natural logarithm of 5.23. There are on average 0.01 common directors and 0.58 common VC investors between portfolio companies and their peers. An average portfolio company has a *CG Index* of 3.44 out of 4, and a *VC Reputation* of 15.68 out of 100.

In terms of other control variables, 11% of our portfolio companies raise funds while being audited by a top auditor, with an average number of financing rounds of 2.87. Moreover, the average age for companies in our sample is 7.23 years, with the average VC syndicate consisting of 2.62 VC firms, and an average prior investment amount of $20.57 million. In terms of industry characteristics, the average portfolio company is within an industry that is relatively concentrated, with a 572.83 Hirschman-Herfindahl index. The average industry sales growth equals 6.92%, R&D-to-Total Assets equals 26%, Return-on-Assets equal -3.44%, and capital expenditures equal 5%. In terms of market conditions, around one quarter (23.5%) of funding rounds occurred during hot markets, and a mere fraction of 0.1% during cold markets. A significant fraction of funding rounds (76.4%) took place in normal market conditions.

Panel B shows the average round amount for portfolio companies with or without directors in common with their most successful peers. These data indicate that portfolio companies who share common directors with their most successful peer have an average natural logarithm round amount of around 2, significantly higher than that of companies with no common directors (1.34) ($p < 0.01$). Similarly, Panel C shows an average natural logarithm of the round amount of portfolio companies with common VC investors with their most successful peer of 1.62, which is significantly higher than the average of 1.28 for portfolio companies without common VC investors ($p < 0.01$) [8].

Finally, Panel D presents the distribution of the inflation-adjusted natural logarithm of the round amount per year and shows an increasing number of funding rounds and average amounts over time with the highest figures observed during the dot-com bubble in the years 1999 to 2001.

4.2. Portfolio Companies and Learning from the Most Successful Peer

Table 3 presents the empirical tests of our first and second hypotheses. Models (1), and (2a), and (3a) focus on our first hypothesis on observational learning, while Models (2b) and (3b) examine our second hypothesis related to conversational learning and test whether portfolio companies learn through information sharing via common directors and common VC investors, respectively.

[8] Two-tailed Pearson correlations also show that *Ln Round Amount* is positively and significantly correlated with *Ln Max Round Amount*, and with the number of common directors and common VCs, as per our predictions.

Table 2. Descriptive Statistics

The table presents descriptive statistics of the characteristics of portfolio companies and their financing rounds. The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. Panel A reports statistics for the whole sample. *N* is the number of observations, *std-dev.*, standard deviation, *25th* and *75th* are the bottom and top quartile of the distribution, respectively. Panel B and Panel C summarize the average round amount by presence of common directors or common VC investors, respectively, between a portfolio company and its most successful peer, where the most successful peer is defined as the portfolio company with the highest financing round amount in the same 2-digit industry classification over the past year. *Prob. (Diff.)* reports the p-value of the difference in means test between the subsamples. Panel D presents the distribution of the number and the average natural logarithm of the round amounts per year. The round amounts in Table 2 are adjusted for inflation. Variables are defined in Appendix A.

Panel A. Descriptive Statistics

	N	Mean	std-dev.	25th	Median	75th
Round Amount (in $ mil.)	192,775	14.99	34.77	1.26	4.42	12.87
Ln Round Amount	192,775	1.34	1.80	0.23	1.49	2.55
Peer Max Rd. Amount(in $ mil.)	192,351	216.23	74.89	225.81	256.07	256.07
Ln Peer Max Rd. Amount	192,351	5.23	0.71	5.42	5.55	5.55
Number of Common Directors	94,405	0.01	0.35	0.00	0.00	0.00
Number of Common VCs	192,775	0.58	0.88	0.00	0.00	1.00
CG Index	89,976	3.44	0.85	3.00	4.00	4.00
VC Reputation	192,775	15.68	12.82	6.63	12.75	21.55
Top Auditor	192,775	0.11	0.32	0.00	0.00	0.00
Stage Number	192,775	2.87	0.96	1.00	3.00	4.00
Firm Age	153,985	7.23	12.38	2.00	4.00	8.00
VC Syndicate Size	192,775	2.62	2.22	1.00	2.00	3.00
Prior Investment	192,775	20.57	131.25	0.00	1.04	13.83
HH Index	175,839	572.83	702.48	285.16	374.71	605.55
Industry Sales Growth	175,649	6.92	22.20	1.14	2.29	5.13
Industry R&D	174,224	0.26	0.49	0.08	0.18	0.26
Industry ROA	175,837	-3.44	173.55	-3.36	-0.88	-0.20
Industry CapEx	175,837	0.05	0.05	0.04	0.05	0.06
Hot Market	192,775	0.235	0.424	0.000	0.000	0.000
Cold Market	192,775	0.001	0.027	0.000	0.000	0.000

Panel B. Average Round Amount by Common Director

Common Director	Average Ln Round Amount
0	1.337
1	2.113
Prob. (Diff.)	*0.000*

Panel C. Average Round Amount by Common VC Investor

Common VC Investor	Average Ln Round Amount
0	1.283
1	1.618
Prob. (Diff.)	*0.000*

Panel D. The Distribution of Ln Round Amount Per Year

Year	N	Mean	std-dev.	25th	Median	75th
1980	449	0.781	1.309	-0.059	0.827	1.646
1981	751	0.901	1.389	0.099	1.015	1.804
1982	1107	0.710	1.372	-0.248	0.833	1.675
1983	1431	1.022	1.418	0.231	1.107	2.023
1984	1570	0.962	1.452	0.131	1.107	1.982
1985	1522	0.845	1.498	-0.070	0.941	1.944
1986	1679	0.959	1.558	0.010	1.129	2.081
1987	1899	0.880	1.531	-0.006	1.016	1.956
1988	1929	0.926	1.583	-0.114	1.088	2.004
1989	1931	0.812	1.639	-0.145	0.931	1.871
1990	1835	0.435	1.775	-0.734	0.652	1.718
1991	1688	0.205	1.751	-1.000	0.298	1.463
1992	2030	0.307	1.888	-1.012	0.448	1.681
1993	1813	0.386	1.936	-0.988	0.513	1.835
1994	1938	0.605	1.905	-0.673	0.803	2.035
1995	2719	0.876	1.846	-0.196	1.194	2.174
1996	4312	0.919	1.841	-0.223	1.163	2.175
1997	4740	1.097	1.734	0.065	1.367	2.292
1998	5857	1.221	1.748	0.144	1.466	2.420
1999	8324	1.706	1.739	0.635	1.916	2.897
2000	13494	1.784	1.746	0.739	1.988	3.053
2001	8271	1.366	1.769	0.299	1.552	2.653
2002	5784	1.362	1.733	0.336	1.530	2.616
2003	5408	1.343	1.783	0.315	1.541	2.534
2004	5397	1.579	1.700	0.585	1.833	2.660
2005	6400	1.361	1.795	0.255	1.616	2.557
2006	8016	1.296	1.840	0.187	1.509	2.526
2007	7790	1.588	1.741	0.488	1.782	2.736
2008	7568	1.511	1.746	0.457	1.644	2.669
2009	5601	1.346	1.733	0.252	1.531	2.460
2010	6761	1.473	1.698	0.469	1.530	2.530
2011	7441	1.380	1.815	0.188	1.500	2.598
2012	7547	1.230	1.877	0.086	1.272	2.464
2013	7644	1.091	1.852	0.041	1.176	2.361
2014	8424	1.323	1.883	0.058	1.426	2.588
2015	8834	1.408	1.883	0.280	1.447	2.723
2016	8062	1.428	1.804	0.327	1.535	2.657
2017	7693	1.609	1.791	0.556	1.649	2.751
2018	7116	1.969	1.764	0.916	2.061	3.136

Models (1), (2a & b), and (3a & b) show a positive and significant association between the round amount of a portfolio company and that of the most successful peer in the prior year ($p < 0.01$). As predicted in *Hypothesis 1*, this finding suggests that portfolio companies learn from their observation of peers in negotiating their round amounts. Specifically, a one standard deviation increase in the round amount of the most successful peer is associated with approximately 5% to 7% increase in the round amount of the incumbent portfolio company.[9]

To test *Hypotheses 2a & 2b* on learning from conversational channels, Model (2b) repeats Model (2a) and examines the mediating effects of the natural logarithm of the number of common directors, i.e. its effect on the change in the coefficient of the round amount of the most successful peer. In Model (3a), we exclude *VC Syndicate Size* given its high correlation with the natural logarithm of the number of common VC investors. In Model (3b), we repeat Model (3a) to examine the mediating effect of the natural logarithm of the number of common VCs.

In line with *Hypothesis 2a*, both Models (2b) and (3b) confirm the existence of conversational learning. In Model (2b), we find a positive and significant association between the natural logarithm of the round amount and the natural logarithm of the number of common directors ($p < 0.01$). A one standard deviation increase in the natural logarithm of the number of common directors between a portfolio company and its most successful peer is associated with an increase of approximately 25% in the round amount**.** Similarly, Model (3b) shows a positive and significant association between the natural logarithm of the round amount and the natural logarithm of the number of common VC investors between a portfolio company and its most successful peer ($p < 0.01$). A one standard deviation increase in the natural logarithm of the number of common VC investors between a portfolio company and its most successful peer results in an increase in the

[9] External shocks may occur and alter learning curves if the time lag to identify the most successful peer is long. Although not shown in the paper, we repeat our tests using the maximum round amount of the most successful peer over 3-month and 6-month periods. The results remain consistent and strongly significant at the 1% level, and are available upon request.

Table 3. Observational and Conversational Channels of Learning from Peers: Mediation analysis.

Fixed effects regressions of the natural logarithm of the financing round amount of a portfolio company on the natural logarithm of the round amount of its most successful peer as a proxy for observational learning, the natural logarithm of the number of common directors (or common VC investors) with the most successful peer as a proxy for conversational learning, and other control variables. The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. The most successful peer is defined as the portfolio company with the highest financing round amount in the same 2-digit industry classification over the past year. Models (1), (2a), and (3a) focus on Observational Learning, and Models (2b) and (3b) under Conversational Learning test whether portfolio companies learn through information sharing via common directors and common VC investors, respectively. The tested sample in Models (1, 2, and 3) includes firm-level observations for which we were able to identify the round amount of the most successful peer and all control variables. All models have fixed industry and year effects. Standard errors are in italics. *N* is the number of observations. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable:	Ln(RdAmount)				
The context of:	Observational x Conversational Learning				
	(1)	(2a)	(2b)	(3a)	(3b)
Ln Max Round Amount	0.102***	0.071***	0.066***	0.085***	0.080***
	0.010	*0.015*	*0.015*	*0.016*	*0.015*
Ln Number Common Directors			0.263***		
			0.061		
Ln Number Common VCs					0.789***
					0.013
Mediating effect of Com. Dirs. on Max Round Amount			0.070***		
% of total effect mediated			*7.342*		
Mediating effect of Com. VCs. on Max Round Amount					0.059***
% of total effect mediated					*6.433*
CG Index		0.027***	0.020**	0.046***	0.047***
		0.008	*0.009*	*0.008*	*0.008*
VC Reputation		0.002***	0.002***	0.014***	0.010***
		0.000	*0.000*	*0.000*	*0.000*
Top Auditor		0.166***	0.167***	0.310***	0.275***
		0.016	*0.016*	*0.017*	*0.017*
Stage Number		0.175***	0.181***	0.206***	0.225***
		0.007	*0.007*	*0.008*	*0.008*
Firm Age		0.011***	0.010***	0.006***	0.008***
		0.001	*0.001*	*0.001*	*0.001*
VC Syndicate Size		0.253***	0.246***		
		0.002	*0.002*		
Prior Investment		0.000***	0.000***	0.000***	0.000***
		0.000	*0.000*	*0.000*	*0.000*
HH Index		0.000	0.000	0.000	0.000
		0.000	*0.000*	*0.000*	*0.000*
Industry Sales Growth		0.001***	0.001***	0.002***	0.002***
		0.000	*0.000*	*0.000*	*0.000*
Industry R&D		-0.054***	-0.053***	-0.063***	-0.059***
		0.013	*0.013*	*0.014*	*0.014*
Industry ROA		0.001*	0.001*	0.002**	0.001
		0.001	*0.001*	*0.001*	*0.001*

Industry CapEx		0.444***	0.440***	0.465***	0.483***
		0.129	*0.127*	*0.138*	*0.135*
Hot Market		-0.140***	-0.136***	-0.194***	-0.163***
		0.032	*0.032*	*0.035*	*0.034*
Cold Market		0.311	0.180	0.316	0.402
		0.422	*0.444*	*0.451*	*0.441*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	192,351	77,087	77,087	77,087	77,087
Adj. R-sq	0.410	0.599	0.606	0.542	0.562

round amount by approximately 34%. Both common directors and common VC investors are thus likely to share the lessons learned from their experience in financing the most successful peers.

Models (2b) and (3b) show evidence of a mediating effect by common directors or common VCs, which provides support to our prediction in *Hypothesis 2b*. Based on prior research in Colak and Korkeamaki (2021), Fedaseyeu et al. (2018), and Baron and Kenny (1986), mediation occurs if the round amount of the most successful peer affects the round amount of a portfolio company through another channel (or variable) called the mediator, which, in our case, is the number of common directors or common VC investors.[10] We perform a mediation analysis and we find that common directors (common VCs) explain up to 7% (6%) of the relation between the natural logarithm of the round amount of a portfolio company and the one of its most successful peer (significant at the 1% level). The mediating effect is equal to the change in the effects of the round amount of the most successful peer with and without the inclusion of the mediator. For example, in the case of common directors, the percentage of total effect mediated is equal to ((0.071 – 0.066)/0.071 = 0.070). Although the mediating effects are low, they are both significant at the 1%

[10] Beyond the direct effect of the maximum round amount and both mediators on the financing round amount, the mediation analysis requires an additional condition in which the maximum round amount should affect the mediator (Fedaseyeu et al., 2018). We have tested this condition and can confirm the negative (positive) and significant effect of the maximum round amount on the number of common directors (common VCs) at the 1% (10%) level. Results are not shown in the paper but are available upon request.

level, and the association between the round amount of a portfolio company and the one of its most successful peer remains significant at the 1% level in both models (2b) and (3b). Moreover, the results in Table 3 show a higher coefficient for the number of common board members compared to the number of common VCs. One explanation is that due to their presence in the boardroom, common board members may act as more effective mediators than common VCs, who do not necessarily sit on boards. Overall, Table 3 provides evidence of the importance of both observational and conversational channels for learning from peers when seeking VC funding; however, our results suggest that observational learning may be more economically significant than conversational learning in negotiations between startups and VC investors.

In terms of control variables, the natural logarithm of the round amount is positively and significantly associated with *CG Index, VC Reputation, Top Auditor*, *Firm Age*, *VC Syndicate Size*, *Prior Investment*, *Stage Number*, *Industry Sales Growth*, and *Industry Capex* ($p < 0.01$), but is negatively related to the Hot market dummy ($p < 0.01$), *Industry R&D* ($p < 0.01$). This suggests that the financing amount is higher in companies attracting more reputable VC firms, larger VC syndicates, and those at more advanced stages of financing, but it is lower in firms within more R&D-intensive industries and during hot periods. In other words, VC firms invest a larger amount in firms with stronger monitoring mechanisms, greater maturity, and more reputable auditors, but the funding amount is lower in firms with higher intangible assets and during hot periods where a higher number of firms are trying to raise funds.

4.3. Learning and the Effect of Market Conditions

Table 4 examines our third hypothesis on the moderating effect of market conditions on the association between the round amount of a portfolio company and the one of its most successful peer firm. In Model (1), we find that the round amount of a portfolio company is significantly

Table 4. Observational Learning and Market Conditions

Fixed effects regressions of the natural logarithm of the financing round amount of a portfolio company on the natural logarithm of the round amount of its most successful peer, and Hot vs. Cold Market dummies. The sample consists of 192,775 firm financing rounds between 1980 and 2018 in the United States. The most successful peer is the portfolio company with the highest financing round amount in the same 2-digit industry over the past year. The models include firm-level observations for which we were able to identify the round amount of the most successful peer and all control variables. All models have fixed industry and year effects and include all controls. Model (1) examines the full sample under different market conditions, while Models (2)-(3) and (4)-(5) look at cross-sections of high vs. low industry sales growth and high vs low industry RoA, respectively. The sub-samples are divided based on the median level observation for sales growth or RoA. Standard errors are in italics. *N* is the number of observations. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable: Ln(RdAmount)

	Full Sample (1)	High Ind. Sal. Growth (2)	Low Ind. Sal. Growth (3)	High Ind. RoA (4)	Low Ind. RoA (5)
Hot Market	-0.531***	-0.276	-0.490***	-0.405***	-0.321
	0.128	*0.235*	*0.17*	*0.139*	*0.452*
Cold Market	2.091*	0.000	1.767	2.122*	0.000
	1.15	*(omitted)*	*1.224*	*1.154*	*(omitted)*
Ln Max Round Amount x Hot Market	0.128***[a]	0.002	0.149***[a]	0.095***[a]	0.073
	0.023	*0.04*	*0.033*	*0.026*	*0.079*
Ln Max Round Amount x Cold Market	-0.601	0.333	-0.585	-0.625	0.000
	0.391	*0.335*	*0.41*	*0.392*	*(omitted)*
Ln Max Round Amount x Normal Market	0.050***[a]	-0.03	0.088***[a]	0.042**[a]	0.034
	0.016	*0.03*	*0.021*	*0.018*	*0.042*
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	77,087	44,179	32,908	37,136	39,951
Adj. R-sq	0.5999	0.623	0.573	0.612	0.59

a: significantly different at the 1% level.

lower during hot funding markets ($p < 0.01$), which supports *Hypothesis 3a*, but it is positively and significantly associated with the round amount of the most successful peer in such markets ($p < 0.01$). A one standard deviation increase in the round amount of the most successful peer is associated with an increase in the round amount of a portfolio company of around 9%. Moreover, while there are no significant effects during cold market conditions, the round amount of a portfolio company is positively and significantly associated with the round amount of the most successful peer during normal markets ($p < 0.01$). A one standard deviation increase in the round amount of the most successful peer in normal periods is associated with an increase in the round amount of the portfolio company by about 3.5%.

Interestingly, in line with *Hypothesis 3b*, a closer look at the empirical results reveals that the interaction coefficient of the round amount of the most successful peer with the hot market dummy is significantly higher than the one with normal market dummy (at the 1% level). The results in Table 4 thus suggest that the bargaining power of portfolio companies decrease in hot periods, but the anchoring effect of their most successful peer strengthens their ability to negotiate a higher round amount, which is consistent with prior results in Kleinert and Hildebrand (2024).

Models (2) and (3) repeat Model (1) by subsamples of high vs. low industry sales growth, respectively, and Models (4) and (5) do so for high vs. low industry RoA, respectively. The sub-samples are divided based on the median level observation for sales growth or RoA. The results in Models (2) and (5) indicate the absence of observational learning in high industry sales growth or in low industry RoA contexts, respectively. In contrast, the results in Models (3) and (5) suggest a stronger anchoring effect in low industry sales growth or high industry RoA contexts, respectively. Similar to Model (1), we find that portfolio companies in low sales growth periods are more likely to learn from their most successful peers to increase their round amounts, and the effect is significantly higher in hot vs. normal market conditions at the 1% level. Moreover, portfolio companies in more profitable industries are more likely to learn from their most successful peers to increase their round amounts, and this is more significant in hot periods than during normal periods (at the 1% level). The coefficients on the rest of the control variables are consistent with those presented in Table 3 and are not reported to save space.

5. Robustness Tests

5.1. Matching through the entropy balancing technique

To better understand the effect of conversational channels on the financing round amount, we use the entropy balancing approach (Hainmueller, 2012; McMullin and Schonberger, 2018). This matching technique provides proper covariate balance between our treated sub-sample (with common directors or common VCs) and control sub-sample (without common directors or common VCs), by weighing observations to generate post-weighing means and variances that are equal for each matching variable between both sub-samples. We match our independent variables (covariates), used in Model (2a) and (3a) of Table 3 for common directors and common VCs, respectively. The results of the entropy balancing approach are presented in Table 5. Our studied sample includes 238 funding rounds with common directors across portfolio companies, and 34,248 funding rounds with common VC investors. After re-weighing our observations, Panel A shows that the differences in means and variances of covariates is almost nil and statistically insignificant. This indicates that a proper entropy balancing was achieved for both models.

Using the entropy balanced sample with post-weighing observations, we run the same regressions as in Models (2b) and (3b) in Table 3. Panel B presents the multivariable regressions which utilize identical distributions of both treated and control observations and that are free of any major biases (Hainmueller, 2012; Chapman et al., 2018). In line with the results in Table 3, both Models (1) and (2) show statistically significant effects of the natural logarithm of the number of common directors or common VCs on the natural logarithm of the financing round amount (at the 1% level). As such, the multivariate entropy balancing technique confirms our findings about the role played by conversational channels. The coefficients on the rest of the control variables are consistent with those presented in Table 3 and are not reported to save space.

Table 5. The Effect of Conversational Channels on Round Amount: An Entropy Approach

Entropy Balancing Test of the effect of conversational channels on the financing round amount. Panel A presents the post-weighing matching estimation, in means and variances, which ensures better covariate balance between treated sub-samples (with common directors or common VCs) and control sub-samples (without common directors or common VCs). Panel B runs the same fixed effects regressions of the natural logarithm of the financing round amount on the natural logarithm of the round amount of the most successful peer, the natural logarithm of the number of common directors in Model (1) (or common VCs in Model (2)), and other control variables, using the post-weighing treated and control observations that were subject to entropy balancing. The most successful peer is defined as the portfolio company with the highest financing round amount in the same 2-digit industry classification over the past year. All models have fixed industry and year effects and include all controls. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A. Differences in observables after entropy balancing

	Common Director dummy					Common VC dummy				
	Treated		Control			Treated		Control		
	N = 238		N = 76,849		Diff. in	N = 34,248		N = 42,839		Diff. in
	Mean	Var.	Mean	Var.	Means	Mean	Var.	Mean	Var.	Means
Ln Max Rd. Amount	3.81	3.28	3.81	6.04	0.00	5.35	0.28	5.35	0.27	0.00
CG Index	3.60	0.47	3.60	0.48	0.00	3.42	0.73	3.42	0.73	0.00
VC Reputation	21.52	381.40	21.52	385.90	0.00	16.99	147.90	16.99	230.10	0.00
Top Auditor	0.24	0.18	0.24	0.18	0.00	0.18	0.15	0.18	0.15	0.00
Stage Number	2.31	0.45	2.31	0.59	0.00	1.99	0.63	1.99	0.67	0.00
Firm Age	11.88	435.50	11.88	388.40	0.00	6.00	86.64	6.00	56.26	0.00
VC Syndicate Size	2.43	5.18	2.43	4.47	0.00					
Prior Investment	209	311895	209	2809425	0.10	24.90	11385	24.90	12262	0.00
HH Index	1391	2068072	1391	4160314	0.00	471	166590	471	149403	0.00
Ind. Sales Growth	6.44	840.60	6.44	776.40	0.00	8.24	517.60	8.24	489.00	0.00
Ind. R&D	0.22	1.75	0.22	0.87	0.00	0.27	0.14	0.27	0.21	0.00
Ind. ROA	-0.75	4.82	-0.75	45.08	0.00	-2.42	31.67	-2.42	35.04	0.00
Ind. CapEx	0.08	0.01	0.08	0.04	0.00	0.05	0.00	0.05	0.00	0.00
Hot Market	0.30	0.21	0.30	0.21	0.00	0.24	0.18	0.24	0.18	0.00
Cold Market	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B. Multivariate regressions after entropy balancing

Dependent Variable:	Ln(RdAmount)	
	(1)	(2)
Ln Max Round Amount	0.144***	0.063***
	0.048	*0.017*
Ln Nb. Common Directors	0.435***	
	0.069	
Ln Nb. Common VCs		0.774***
		0.013
Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N.	77,087	77,087
Adj. R-sq	0.431	0.140

5.2. Learning from Peers, Endogeneity, and Potential Reflection Problems

Beyond the time lag used in our dynamic model to mitigate concerns about potential reflection problems, we rerun our empirical tests focusing solely on portfolio companies going through their first round of financing to mitigate any remaining concerns about reflection or correlation. We argue that a portfolio company raising funds for the first time suffers from higher uncertainty than its most successful peer. As such, both firms cannot be considered perfectly comparable, and the round amount as a dependent variable cannot be simultaneously determined. A positive association between the first round of funding of a portfolio company and the round amount of its most successful peer would therefore reject potential concerns on the existence of a reflection problem and confirm the existence of learning from peers.

Focusing on learning from peers for firms going through their first round of financing has another advantage as it may control for the endogenous effect of the venture quality on the association between VC involvement and the round amount. Given the round amount is subject to the negotiation power of the venture, which also affects VC syndicate size and reputation, it is difficult to find a suitable instrument which affects the round amount but not other explanatory variables.

Table 6 repeats the empirical investigations run in Table 3 on portfolio companies going through their first financing round only. In line with *Hypothesis 1*, all models confirm the positive association between the first round of funding of a portfolio company with the round amount of its most successful peer ($p < 0.01$). This provides evidence that the positive association between both round amounts is driven by learning from peers rather than the similarity between both firms.

Models (2b) and (3b) control for the natural logarithm of the number of common directors and common VCs, respectively. In line with *Hypothesis 2a*, both models show positive and significant

Table 6. Observational and Conversational Learning in the context of the first round of VC funding

Fixed effects regressions of the natural logarithm of the first financing round amount of a portfolio company on the natural logarithm of the round amount of its most successful peer as a proxy for observational learning, the number of common directors (or common VC investors) with the most successful peer as a proxy for conversational learning, and other control variables. The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. The most successful peer is defined as the portfolio company with the highest financing round amount in the same 2-digit industry classification over the past year. Models (1), (2a), and (3a) focus on Observational Learning, and Models (2b) and (3b) under Conversational Learning test whether portfolio companies learn through information sharing via common directors and common VC investors, respectively. Models (2 and 3) include firm-level observations for which we were able to identify the round amount of the most successful peer and on all control variables. All models have fixed industry and year effects. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable:	Ln(RdAmount)				
The context of:	Observational x Conversational Learning				
	(1)	(2a)	(2b)	(3a)	(3b)
Ln Max Round Amount	0.073***	0.079***	0.077***	0.085***	0.083***
	0.014	*0.026*	*0.026*	*0.026*	*0.026*
Ln Nb. Common Directors			1.793**		
			0.885		
Ln Nb. Common VCs					0.275***
					0.026
Mediating effect of Com. Dirs. on Max Round Amount			0.023***		
% of total effect mediated			*2.353*		
Mediating effect of Com. VCs. on Max Round Amount					0.029***
% of total effect mediated					*2.990*
CG Index		0.033**	0.016	0.036**	0.038**
		0.015	*0.017*	*0.015*	*0.015*
VC Reputation		0.000	-0.001	0.006***	0.004***
		0.001	*0.001*	*0.001*	*0.001*
Top Auditor		0.192***	0.201***	0.219***	0.212***
		0.036	*0.037*	*0.037*	*0.037*
Stage Number		0.255***	0.255***	0.226***	0.240***
		0.015	*0.015*	*0.015*	*0.015*
Firm Age		0.006***	0.006***	0.005***	0.006***
		0.001	*0.001*	*0.001*	*0.001*
VC Syndicate Size		0.138***	0.141***		
		0.007	*0.007*		
Prior Investment		0.001***	0.001***	0.001***	0.001***
		0.000	*0.000*	*0.000*	*0.000*
HH Index		0.000**	0.000**	0.000***	0.000***
		0.000	*0.000*	*0.000*	*0.000*
Industry Sales Growth		0.001***	0.001***	0.001***	0.001***
		0.000	*0.000*	*0.000*	*0.000*
Industry R&D		-0.034	-0.037*	-0.037*	-0.035
		0.022	*0.022*	*0.022*	*0.022*
Industry ROA		0.000	0.000	0.000	0.000
		0.002	*0.002*	*0.002*	*0.002*

Industry CapEx		0.298	0.317	0.287	0.290
		0.211	*0.211*	*0.213*	*0.212*
Hot Market		-0.170***	-0.178***	-0.188***	-0.186***
		0.062	*0.063*	*0.063*	*0.063*
Cold Market		0.671	0.657	0.730	0.739
		0.493	*0.524*	*0.497*	*0.495*
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	76,916	24,746	24,746	24,746	24,746
Adj. R-sq	0.427	0.509	0.510	0.501	0.503

associations between the first financing round amount on the one hand and the natural logarithm of the number of common directors ($p < 0.05$) and the natural logarithm of the number of common VCs ($p < 0.01$) with the most successful peer on the other. Models (2b) and (3b) confirm the mediating effect of the number of common directors and common VCs on the positive association between the first financing round amount of a portfolio company and the one of its most successful peer, which validates *Hypothesis 2b*. The natural logarithm of the number of common directors (common VCs) explains up to 2.3% (3%) of the relation between the natural logarithm of the round amount of a portfolio company and the one of its most successful peer (significant at the 1% level).

Results in Table 6 are consistent with the existence of observational learning between a firm and its most successful peer and validate the role played by a common director or VC investor as conversational channels, albeit with a smaller impact on learning than observational channels, as previously observed. More importantly, using the first round of funding of a portfolio company, Table 6 suggests that our results are driven by learning from peers rather than by potential similarities or correlation, i.e. reflection problems, across portfolio companies. It also suggests that our results are not affected by potential endogeneity between venture quality and VC involvement.

Table 7. Observational Learning and the choice of Peers

Fixed effects regressions of the natural logarithm of the financing round amount of a portfolio company on the natural logarithm of the round amount of the most successful peer within the same 4-digit SIC and of the average peer in the same 2-digit industry. The sample consists of 192,775 firm financing rounds between 1980 and 2018 in the United States. The most successful peer is defined as the portfolio company with the highest financing round amount in the same 4-digit industry over the past year. Models (1a) and (2a) focus on the main effect, and Models (1b) and (2b) include control variables. All models have fixed industry and year effects. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable:	Ln(RdAmount)			
	(1a)	(1b)	(2a)	(2b)
Ln Max Round Amount	0.068***	0.037***		
	0.005	*0.008*		
Ln Mean Round Amount			0.482***	0.358***
			0.012	*0.019*
CG Index		0.026***		0.026***
		0.008		*0.008*
VC Reputation		0.002***		0.002***
		0.000		*0.000*
Top Auditor		0.156***		0.153***
		0.016		*0.016*
Stage Number		0.153***		0.162***
		0.006		*0.006*
Firm Age		0.009***		0.010***
		0.001		*0.001*
VC Syndicate Size		0.252***		0.250***
		0.002		*0.002*
Prior Investment		0.001***		0.001***
		0.000		*0.000*
HH Index		0.000		0.000
		0.000		*0.000*
Industry Sales Growth		0.001***		0.001***
		0.000		*0.000*
Industry R&D		-0.053***		-0.044**
		0.014		*0.013*
Industry ROA		0.002**		0.002**
		0.001		*0.001*
Industry CapEx		0.332**		0.390**
		0.140		*0.128*
Hot Market		-0.138***		-0.155***
		0.033		*0.032*
Cold Market		-0.067		0.252
		0.459		*0.420*
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	170,584	75,402	192,351	77,087
Adj. R-sq	0.031	0.193	0.069	0.217

5.3. Learning from Peers and the Choice of Peer Companies

Thus far, our empirical investigations have focused on the most successful peer within the same 2-digit SIC as a benchmark for portfolio companies raising funds from VC firms. Previous studies have, however, focused on the average peer firm rather than the most successful peer. Using the average rather than the highest round amount could mitigate potential issues around round amount inflation. We therefore repeat our tests using the average peer within the same 2-digit SIC. Moreover, for greater accuracy in the choice of comparable peers, we also use the most successful peer within the same 4-digit SIC. Both Models (1) and (2) in Table 7 show a positive association between the average round amount within the same 2-digit SIC or the best-in-class peer in the same 4-digit industry and the portfolio company's round amount. The results in Table 7 therefore confirm the existence of a learning-from-peers effect.[11]

6. Further Investigations

6.1. The effects of VC Reputation Similarity on Observational Learning

Portfolio companies are usually cash-constrained and have limited negotiation power in the choice of VC firms (Heughebaert and Manigart, 2012). Some attractive portfolio companies, however, may be able to select their VC investors and may therefore select more reputable investors to raise higher round amounts. Hence, we expect that high similarity in VC reputation with the most successful peer would have a positive impact on the round amount of a portfolio company.

[11] Although not shown in the paper, given that external shocks are more likely to happen over an extended one-year period and this could alter the learning curve of portfolio companies, we repeat our tests using the round amount of the most successful peer over 3-month and 6-month periods for robustness and find consistent results. The results are available upon request.

However, VC investors may select and invest similar amounts in similar portfolio companies. As such, the association between VC reputation similarity and VC funding amount may simply represent the quality of portfolio companies rather than observational learning across these companies. Yet, a positive association between the round amount of a portfolio company and that of its most successful peer, where VC investors also have comparable reputation, would also mean that observational learning exists across portfolio companies attracting VCs with similar reputation. Accordingly, we argue that if learning exists, portfolio companies will still learn from their peers with similar VC reputations. In other words, a higher VC reputation similarity will strengthen the positive association between the round amount of a portfolio company and that of its most successful peer.

Our empirical investigation in Table 8 adds *VC Reputation Similarity* to our main explanatory variables. In line with our predictions, the results from Models (1) and (2) show that higher *VC Reputation Similarity* significantly increases the natural logarithm of round amount ($p < 0.01$) and strengthens the positive association between the natural logarithm of the round amount of the portfolio company and the round amount of the most successful peer ($p < 0.01$). A one standard deviation increase in *VC Reputation Similarity* is associated with an increase of approximately 4% in the round amount, and it further increases the association between the round amount of a portfolio company and the one of its most successful peer by around 3%, as seen through the interaction between the round amount of the most successful peer and *VC Reputation Similarity*. This suggests that portfolio companies who are able to attract VC firms with comparable reputation to that of the VC firm of the most successful peer are likely to raise a higher round amount.

Table 8. Observational Learning from Peers and VC Reputation Similarity

Fixed effects regressions of the natural logarithm of the financing round amount of a portfolio company on the natural logarithm of round amount of its most successful peer, and the degree of reputation similarity between a portfolio company's VC firms and those of its most successful peer. The sample consists of 192,775 firm financing rounds between 1980 and 2018 in the United States. The most successful peer is the portfolio company with the highest round amount in the same 2-digit industry over the past year. The sample in Model (1) includes observations for which we were able to identify the round amount of the most successful peer and VC Reputation Similarity. The sample in Model (2) includes observations for which we were able to obtain data on all control variables. All models have fixed industry and year effects. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable: Ln(RdAmount)	(1)	(2)
Ln Max Round Amount	0.109***	0.074***
	0.010	*0.015*
VC Reputation Similarity	0.104***	0.072***
	0.007	*0.010*
Ln Max Round Amount x VC Reputation Similarity	0.055***	0.063***
	0.007	*0.011*
CG Index		0.024***
		0.008
VC Reputation		0.002***
		0.000
Top Auditor		0.151***
		0.016
Stage Number		0.161***
		0.006
Firm Age		0.010***
		0.001
VC Syndicate Size		0.250***
		0.002
Prior Investment		0.001***
		0.000
HH Index		0.000
		0.000
Industry Sales Growth		0.001***
		0.000
Industry R&D		-0.054***
		0.013
Industry ROA		0.001*
		0.001
Industry CapEx		0.459***
		0.128
Hot Market		-0.138***
		0.032
Cold Market		0.305
		0.421
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	192,351	77,087
Adj. R-sq	0.063	0.215

6.2. Peer Effects and Firm Characteristics

Table 9 examines whether learning from peers is affected by the level of ex-ante uncertainty of portfolio companies. In this context, we divide our sample by quartile of a portfolio company's age, by companies in high- vs. low-tech industries, and companies with or without a top auditor. We consider that less (more) uncertain portfolio companies are those in which age is higher (lower) than the median value. Also, less (more) uncertain portfolio companies are in low-(high-) tech industries and (do not) employ a top external auditor.

The models in Table 9 show that the effect of the most successful peer round amount is more significant for less uncertain portfolio companies. Interestingly, when defining their round amount, old, low-tech, and portfolio companies with a top auditor are more likely to learn from the round amount of their most successful peers. One explanation is that investors are likely to rely on less costly anchors in less uncertain deals, but they focus on solid signals and close assessment of their riskier, i.e. younger, hi-tech, or no top auditor, portfolio companies.

6.3. Observational Learning and Economic Outcomes

So far, our empirical investigations have examined the effect of learning on the round amount. Yet, entrepreneurs and investors may learn from the value of their peers. Ewens et al. (2022) argue that determining startup value is a challenging research question and indicate that venture value depends on contract terms and negotiations between entrepreneurs and investors, as well as VC share ownership, governance, and the distribution among all concerned agents.

In Panel A of Table 10, we repeat our test of *Hypothesis 1* in Table 3 using venture value as a dependent variable. The results are consistent with our predictions. We find that the natural logarithm of a portfolio company's value is positively associated with the natural logarithm of the

Table 9. Learning from Peers and the Differential Effect of Firm Characteristics

Fixed effects regressions of the natural logarithm of the financing round amount of a portfolio company on the natural logarithm of round amount of its most successful peer, after controlling for the moderating effect of firm characteristics. Model (1) considers young (old) firms as those which age is lower or equal to (higher than) the highest quartile value, Model (2) divides the sample into portfolio companies that are part of the high- vs. low-technology industry, and Model (3) looks at companies with or without a top auditor. The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. The most successful peer is defined as the portfolio company with the highest financing round amount in the same 2-digit industry classification over the past year. All models have fixed industry and year effects and include all controls. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Dependent Variable: Ln(RdAmount)

	(1)	(2)	(3)
Young dummy	0.836**		
	0.111		
Ln Max Round Amount x Young	0.013		
	0.020		
Ln Max Round Amount x Old	0.130***		
	0.018		
Hi-tech dummy		0.238*	
		0.142	
Max Round Amount x Hi-tech		0.048*[a]	
		0.027	
Max Round Amount x Low-tech		0.091***[a]	
		0.016	
Top Auditor			0.029
			0.117
Max Round Amount x Top Auditor			0.092***a
			0.023
Max Round Amount x Non-Top Auditor			-0.065***a
			0.016
Controls	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	77,087	77,087	77,087
Adj. R-sq	0. 0.543	0. 0.542	0.599

a: the coefficients are significantly different at the 1% level.

value of its most successful peer. We define the most successful peer as the firm within the same 2-digit SIC with the highest venture value during the last year prior to the financing round date and use industry fixed effects to mitigate potential sector-specific valuation differences between companies. Despite the complexity of the determination of a venture value, our results confirm that firms learn from their peers while negotiating their value.

Finally, VC firms represent an asset class with a limited pre-set duration (Sahlman, 1990). They negotiate with a limited number of partners investing in their funds and manage initial investments, follow-on investments, and exits from portfolio companies over specific time horizons. Throughout their various financing rounds, portfolio companies work closely with their VC investors to resolve existing uncertainties, grow, and become profitable. These intermediate milestones accelerate a VC's successful exit through an initial public offering (IPO) or a trade sale, or even liquidation in the case of investment failure. Portfolio companies' learning from peers is thus expected to extend beyond the financing round and into ensuring a successful exit to the public market. Given the competitive advantage conferred by a public offering, Aghamolla and Thakor (2022) argue that privately held firms observe and learn from their close rivals. They find that the decision of a private firm to go public is affected by the IPO decisions of its competitors in the drug development industry. They conclude to the existence of IPO peer effects.

We explore whether portfolio companies learn from the exits of their most successful peers. Given that a successful exit through an IPO or a trade sale requires time and effort to review, run the required due diligence, and evaluate, we examine exits of most successful peers over a period of one year to three years.[12] If learning exists, we expect the probability of exit of a portfolio company to be higher following the exit of the most successful peer.

[12] In further robustness tests, we use the exit of the most successful peer during the past five years. Results support our main predictions (at the 1% level), and are available upon request.

Table 10. Observational Learning and Economic Outcomes

Peer effects in the context of firm value and successful exit. Panel A (Models (1) and (2)) displays results of fixed effects regressions of the natural logarithm of firm value on the natural logarithm of the firm value of the most successful peer. Panel B reports results of the hazard rate model of the exit probability of a portfolio company on the exit of its most successful peer over the past year (Models (3)) and three years (Model (4)). The sample consists of 192,775 observations representing firm financing rounds between 1980 and 2018 in the United States. All models have fixed industry and year effects. Standard errors are in italics. *N* is the number of observations. All variables are defined in the Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	Panel A. Learning from Peers Using Firm Value		*Panel B. Learning from Peers and Successful Exit*	
Dependent Variable:	Ln(Firm Value)		(Prob. of Exit = 1) using Successful Exits	
			Over the last 1 Year	Over the last 3 Years
	(1)	(2)	(3)	(4)
Ln Max Firm Value	0.105***	0.094***		
	0.013	*0.014*		
Peer Exit			0.312***	0.355***
			0.028	*0.029*
Lagged Exit			0.071*	0.052
			0.038	*0.038*
CG Index		0.047***	-0.128***	-0.136***
		0.013	*0.017*	*0.017*
VC Reputation		0.005***	0.004***	0.004***
		0.001	*0.001*	*0.001*
Top Auditor		0.125***	0.638***	0.603***
		0.020	*0.035*	*0.034*
Stage Number		0.540***	0.028	0.035**
		0.011	*0.018*	*0.018*
Firm Age		0.007***	-0.004***	-0.004***
		0.001	*0.001*	*0.001*
VC Syndicate Size		0.088***	-0.017***	-0.018***
		0.003	*0.005*	*0.005*
Prior Investment		0.001***	-0.001***	-0.001***
		0.000	*0.000*	*0.000*
HH Index		0.000	0.000***	0.000***
		0.000	*0.000*	*0.000*
Industry Sales Growth		0.002***	0.002***	0.002***
		0.001	*0.001*	*0.001*
Industry R&D		-0.047	-0.136***	-0.125***
		0.029	*0.037*	*0.036*
Industry ROA		-0.006*	0.018***	0.017***
		0.003	*0.003*	*0.003*
Industry CapEx		0.196	2.609***	2.656***
		0.264	*0.199*	*0.200*
Hot Market		0.064	1.010***	1.037***
		0.046	*0.036*	*0.035*
Cold Market		0.000	2.719***	2.785***
		0.000	*0.451*	*0.451*

Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	17,553	11,540	5,570	5,833
Adj. R-sq	0.19	0.444		
Pseudo R2			0.025	0.026

Panel B of Table 10 tests this prediction using the probability of exit as dependent variable. Model (1) uses the exit of the most successful peer in the previous year as main explanatory variable, while Model (2) uses the most successful peer's exit in the past three years as main variable of interest. Both models confirm our predictions and show a positive and significant association between the probability of a portfolio company's successful exit and that of its most successful peer ($p < 0.01$). This suggests that learning from peers goes beyond the negotiation of funding amounts in the VC market.

Our results also indicate that the probability of a successful exit is positively and significantly associated with *VC Reputation*, the presence of a *Top Auditor*, *Industry ROA*, *Industry CapEx*, and both hot and cold market dummies ($p < 0.01$). However, it is significantly negatively related to corporate governance, *Firm Age*, *Industry R&D*, the number of prior VC investments, and the size of the VC syndicate ($p < 0.01$).

7. Conclusion

To the best of our knowledge, this is the first paper to examine the role of learning from peers in the private capital market and its impact on the fundraising ability of startup companies. We find that portfolio companies, usually with limited age and experience, observe and learn from their most successful peers, i.e., comparable firms with the highest round amount during the prior year that could be used as an anchor when negotiating their own financing round amount.

We also document that the presence of conversational learning channels, i.e. through common directors or common VC investors with the most successful peer, helps increase the round amount. The number of common directors or common VCs further mediates the observational learning process through which a portfolio company learns from its peers and positively affects its round amount. However, the effect of conversational channels seems to be less economically significant for learning from peers than observational channels. Our results remain robust using an entropy balancing approach.

Moreover, we find that observational learning is affected by market conditions. Specifically, we find that the round amount is lower in hot market periods, which are likely to be more competitive than normal or cold periods. However, the round amount is more significantly associated with the one of most successful peer during hot markets, suggesting the latter is likely used as a low-cost available anchor information.

Portfolio companies looking to raise a higher round amount are likely to learn about the investment appetite of VC investors from their observations of and conversations with their peers. Specifically, portfolio companies converse with their peers through the presence of common directors or common VC investors, which allows for knowledge spillover and the transfer of valuable information in the fundraising process and enhances their ability to negotiate a higher round amount. Learning from peers thus represents a new channel which supports firms' access to financing and enhances their ability to grow and compete, and this is more significant in hot periods.

In further investigation, we show that similarity in VC reputation strengthens the positive association between the round amount of a portfolio company and the one of its most successful peer. This suggests that VC reputation similarity strengthens observational learning across portfolio companies. Moreover, we explore whether learning from peers helps ensure a portfolio company's successful exit to the public market. Although exit probabilities can be influenced by numerous factors, and investors may have different exit strategies, we find that the probability of a successful exit is positively associated with the exit of the most successful peer in the past one to three years.

VC markets play a central role in financing innovation and supporting increased productivity and employment which otherwise would not be possible through the traditional banking system and debt capital markets. Therefore, understanding the factors contributing to successful fundraising in private capital markets is essential to promoting economic growth and, as a consequence, the stability of these markets and of the financial system as a whole.

To shed further light on the dynamics in VC funding markets, this study could be extended with a more detailed analysis of private information acquired during the learning process. Small firms preparing to go public could also benefit from a more detailed examination of the impact of corporate governance, involving, for example, more fine-grained, hand-collected information on governance mechanisms and/or on the human capital of board members. Additionally, data on common directors is limited due the Clayton Act rules, and therefore extending this study outside the US where these rules are not in place could give further insight into the role of conversational learning.

Finally, future research could examine whether portfolio companies that learn from their peers are able to better compete in their product market. Learning from peers may thus extend to investment choices that are similar to those of their peers, as well as to whether portfolio companies use funding amounts to differentiate themselves from others and, if so, whether this practice impacts their survival.

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Appendix A – Variables definition

Round and Portfolio Company-level variables

Round Amount$_{i,t}$	The round amount of portfolio company (i) at time (t). All empirical tests use the natural logarithm of the amount of money raised by the portfolio company in the current round.
Most Successful Peer Maximum Round Amount$_{j,t-1}$	The round amount of the portfolio company (j) with the highest round amount (most successful peer) during the last year prior to the financing round date (t-1). A peer company is defined as being classified within the same 2-digit SIC. All empirical tests use the natural logarithm of the amount of money raised by the most successful peer in the industry of the portfolio company over the previous year.
Number of Common Directors	The Number of common directors between a portfolio company and its most successful peer.
Number of Common VCs	The Number of common VCs between a portfolio company and its most successful peer.
CG Index	The Corporate Governance Index, a composite score ranging from 0 to 4, which includes the following four board-of-director variables: size, proportion of independent members, proportion of women, and proportion of doctoral degree holders. We assign a score of one for each variable whenever it is higher than the median value over the entire observation period, and zero otherwise.
Firm Age	The age of the portfolio company at the time of the financing round.
Stage Number	The stage of the financing round, a scale variable that summarizes the four main funding stages of a portfolio company: 1 for seed funding, 2 for early stage, 3 for expansion, and 4 for later stage and other bridge or mezzanine funding stages prior to exit.
Top Auditor	A dummy variable which is equal to one if the portfolio company has one of the big four external auditors, zero otherwise.
Prior Investment	The total amount invested in previous rounds in USD millions.
Firm Exit	A dummy that takes the value of one if the portfolio company has had an IPO or merger, zero otherwise.
Peer Exit	A dummy that takes the value of one if the most successful peer in the industry in the previous year had an IPO or merger, zero otherwise.

Industry-level variables

Industry Average RoA	The 2-digit SIC industry average return on assets.

Industry Average Capex	The 2-digit SIC industry average capital expenditures
Industry Average R&D	The 2-digit SIC industry research and development
Industry Average Sales Growth	The 2-digit SIC industry sales growth over a three-year period prior to the financing round date
HH Index	The Herfindahl-Hirschman index representing industry concentration by revenue.
Market Conditions	
Hot Market	An indicator that takes the value of 1 if the moving average of quarterly financing rounds is 50% above the historic average of all financing rounds across all previous quarters.
Cold Market	An indicator that takes the value of 1 if the moving average of quarterly financing rounds is 50% below the historic average of all financing rounds across all previous quarters.
VC characteristics	
VC Reputation	A time-variant equally-weighted average composite index of VC reputation-related criteria ranging from 0 (lowest) to 100 (highest). VC reputation index is calculated as in Lee et al. (2011) using six measures with rating from 0 to 100 for each criterion: the average of the total amount of funds under management by the VC over the previous five years, the average of the number of investment funds under management by the VC in the previous five years, the number of companies the VC invested in over the previous five years, the total amount of funds the VC invested in companies over the previous five years, the number of companies taken public in the previous five years, and the VC age at the current round. These measures are transformed into z-scores for standardization, and then summed up and normalized to form the final VC reputation index.
VC Similarity	A VC similarity score calculated by adding up dummies to six sub-similarity categories based on the previously mentioned criteria in Lee et al. (2011) VC reputation index. All six criteria's dummies are then summed up to constitute the similarity index. The index can range from 0 to 6, with higher values indicating higher similarity between the portfolio company and the most successful peer in the industry in the previous year.
VC Syndicate Size	The number of VC firms within the VC syndicate.