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Do Venture Capital Investors Learn from Public Markets?

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Abstract. We examine whether venture capital (VC) investors learn information contained in public market stock prices. VCs are less likely to stage finance startups and syndicate with other VCs when stock prices are more informative. An instrumental variable approach suggests that the relation is likely causal. The startup's initial public offering (IPO) prospect is the plausible information contained in stock prices learned by VCs. The effect of VC learning on staging and syndication is more pronounced when collecting information is more costly and the information learned is more reliable. Evidence from a survey of VC investors confirms that they actively learn information from the public market. VCs' learning from the public market significantly affects their investments across startup firms. Our paper sheds new light on the real effects of financial markets and suggests that the informational role of security prices is much broader than what we have thought.

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1. Introduction

Do venture capital (VC) investors learn valuable information contained in public market stock prices when making investment decisions? This is an important research question for at least two reasons. First, capital formation starts with the private market, which drives rapid developments in U.S. entrepreneurship, technological innovation, and economic growth in the past decades. Private capital formation also creates positive spillovers across industries (Aldatmaz and Brown 2020). However, studies on capital formation in the private market (e.g., the VC market) are limited, although numerous studies have explored how a variety of VC investors' characteristics, such as industry expertise, reputation, past experience, and network connections, affect their investment in startup firms and eventually the performance of these firms in the public market.

Second, there has been an intensive debate on whether the stock market is just a side show or has real effects on economic activities. Starting from the pioneering work by Hayek (1945), which posits that prices are a useful source of information, theories (Grossman and Stiglitz 1980, Goldstein and Guembel 2008) argue that, although individual market participants may be less informed than managers, financial markets as a whole have the ability to aggregate different pieces of information possessed by various market players and incorporate them into security prices. Although earlier studies, such as Morck et al. (1990), support the hypothesis that the stock market is just a side show, more recent work finds that managers of public firms learn from the public market and use the information contained in the stock price when they decide on firm policies (Luo 2005; Chen et al. 2007; Edmans et al. 2012; Foucault and Frésard 2012, 2014; Frésard 2011; Dessaint et al. 2019).[1] This literature, however, has mainly focused on learning by corporate managers of public firms and is largely silent on learning by private market players, for example, VC investors.[2]

In this paper, we attempt to fill in the gaps in the existing literature and explore whether VCs learn information from the public market when they decide on investment in startup firms. It is possible that VCs turn to the public market to collect valuable information as private markets are subject to worse informational environment than public markets. For example, VC investors could respond to favorable public market signals (proxied by higher Tobin's Q) by increasing investment (Gompers et al. 2008). Capital market cycles have a modest effect on VC investors' decisions on investment but a larger effect on the timing decision of exits according to a survey by Gompers et al. (2020). Another survey by Gompers et al. (2016) shows that private equity investors are very likely to use comparable public companies as benchmarks when estimating exit value, and capital market conditions are the largest concern when they determine the timing of exits.

Compared with the public market, VC provides an ideal research setting that offers several unique but important advantages. First, the VC setting allows us to directly observe the investment projects in question: the startup firms and their characteristics. This is an advantage that studies relying on public firms lack because researchers cannot directly observe the characteristics of investment projects undertaken by public firm managers. In addition, focusing on the VC market allows us to explore unique features of VC investment that are absent in the public market, that is, staging and syndication, which provides a variety of dimensions that allow us to better understand how the information learned from the public market prices affects VC investors' investment structure decisions in startup firms.

Second, to a larger extent, the VC setting allows us to disentangle active managerial learning from passive reflections of startup-specific information into stock prices, a major empirical challenge faced by studies focusing on managers of public firms. Because the information set possessed by managers of public firms is not directly observable to econometricians, even if one observes a firm's security price informativeness is positively related to its subsequent investment activities, it is difficult to disentangle whether it is managerial learning from stock prices or stock prices passively reflecting what managers have already known about their investment opportunities. Our focus on VC investors alleviates this concern to a larger degree because startup firms funded by VC investors are private companies whose shares are not publicly traded and, by definition, do not have a stock price. Hence, we conjecture that VC investors learn information from stock prices of public firms in the same industry of the startups because it is unlikely that startup-specific information known by VC investors is reflected into the stock prices of these public firms. Though we cannot completely rule out the possibility that some common macro or industry information is reflected in the stock prices, the concern that those prices being a passive reflection of startup-specific information is mitigated to a larger extent in the VC setting.

Third, the VC setting also allows us to better separate active managerial learning from a financing cash flow story, as startup firms (as opposed to public firms) cannot easily raise additional funds and increase investment simply in response of high stock prices of comparable public firms because of the lack of the access to the public market. In addition, this concern is also mitigated to some extent because we can observe the characteristics of VC investment and focus on the structure (rather than the amount) of VC investment, which is less directly linked to the financing channel.

We argue that VC investors actively gather information from the public market, and the information they collect is likely their startup firms' initial public offering (IPO) prospects. Chemmanur and Fulghieri (1999) develop a model on a startup's going public decision. In the model, when a startup decides whether to go public, it faces a tradeoff between enjoying a stronger bargaining power against many small investors from the public market (as opposed to a single private market investor) and bearing a higher cost of information production. This is because many investors produce duplicated information, and the information production cost is eventually born by the startup. Hence, the model suggests that when outsiders' cost of producing information about the startup in an industry is lower, the startup is more likely to go public.[3] To the extent that the more informative of the stock prices of public firms in an industry, the lower is the outsiders' cost of collecting information about the startup, the model of Chemmanur and Fulghieri (1999) implies that the entrepreneur's incentive to take the startup public is stronger, and the startup's IPO probability is higher. In addition, recent survey evidence by Gompers et al. (2020) shows that VC investors watch the capital market to determine their exit strategies. Based on the previous discussion, we argue that the information contained in the public markets matters for VC investors and postulate that if VC investors are able to learn the information from informative stock prices that their portfolio firms' IPO probabilities are higher, they adjust their investment structures accordingly. In particular, we attempt to link VC investment structures to stock price informativeness of public firms in the same industry of the VC investors' portfolio firms.

Specifically, the structure of VC investment in startup firms we focus on includes VC stage financing and syndication. VC staging is the stepwise infusion of capital from VC investors to startup firms. It is an effective tool used by VCs to mitigate information asymmetry and uncertainty associated with startup firms because it keeps an option of abandoning underperforming startups (Sahlman 1990, Gompers 1995). As argued in Tian (2011), however, stage financing is not a free lunch but costly. Potential costs associated with VC staging include negotiation and contracting costs in each round of financing, forgone economics of scale because of divided capital infusions, induced short-termist behavior on the part of entrepreneur, and underinvestment in early-stage startups. When public market prices are more informative, VC investors are more certain and optimistic about their startup firms' IPO prospects. As a result, they would stage finance less to reduce the cost of staging. We construct two measures to capture VC staging: the total number of financing rounds a startup firm receives from its VC investors and investment skewness (i.e., the percentage of investment amount a startup receives in the first round). If our learning hypothesis is supported, we expect to observe that VC investors tend to invest fewer financing rounds and invest more in the first round if the stock prices of public firms in the same industry are more informative.

Another investment feature we explore is VC syndication, which is an enduring and striking feature of the VC industry (Lerner 1994, Tian 2012, Bayar et al. 2020).[4] Besides risk sharing, a main and important motivation for VC investors to form syndicates to co-invest in a startup is to seek a second opinion from other VCs because of the high opaqueness nature of startup firms. However, syndication is costly as well, especially for lead VCs who are responsible for organizing the syndicate. First, co-investing in a startup means that the VC investor who first identifies the deal must share the returns with other VCs and cannot exclusively enjoy the reward if it turns out that the startup is a great success. Second, different types of VC investors (e.g., independent VCs, corporate VCs, bank-affiliated VCs, and government-sponsored VCs) could have different investment objectives and preferences, which might create conflicts among VCs within a syndicate and reduce the benefits of co-investing. Third, it could be time-consuming and difficult for VC investors to deal with problematic startup firms if there are multiple co-investing VCs, which increases communication costs and reduces investment efficiency. Hence, to reduce the costs associated with syndication, we expect that, if the stock prices of public firms in the same industry of their startup firms are more informative and the startup firms are more likely to go public, the risk-sharing and opinions from other VCs are less valuable. That is, VC investors are less likely to syndicate with other VCs and more likely to form a small syndicate.

Using a sample of 13,185 startup firms that receive VC financing between 1980 and 2012, our baseline results show that public market price informativeness is significantly correlated with VC investors' staging and syndication decisions. Specifically, when the stock prices of public firms in the same industry are more informative, VC investors finance a startup with a smaller number of financing rounds, with more money invested in the first round, and with fewer other VCs co-investing. Our finding is consistent with the learning hypothesis that VC investors learn valuable information from public market prices and respond by altering the structure of their investment in startup firms to reduce the costs associated with staging and syndication.

Although our research setting of VC markets significantly alleviates the concerns that stock prices are merely reflections of what VC investors have already known about the startup and firms are able to raise more funds for investment because of a high stock price, it is still possible that some unobservable factors in the VC investors' information set that affect both the structure of their investments in startups and stock price informativeness of public firms in the same industry drive the results. In other words, our findings are not driven by VC investors' learning from the public markets but by some unobservable omitted variables. To address this endogeneity concern, we construct two instrumental variables (IVs) and use a two-stage least squares (2SLS) approach for each of these two instruments in parallel tests.

Our first IV makes use of plausibly exogenous variation in stock price informativeness caused by mutual fund forced sales because of fund outflows. Because noisy trades by mutual funds could crowd out informed trades, more frequent forced sales lead to less informative stock prices. Specifically, our instrument is constructed as the frequency of mutual fund sales, as opposed to large selling events used in previous studies, such as Coval and Stafford (2007). It has very small impacts on the level of stock price and is unlikely to affect VC investment via the valuation channel, and we do not observe a significant relation between the instrument and industry valuation empirically. One concern, however, is that mutual fund managers could have the discretion in choosing the stocks to sell, which could reflect their information about the stocks and make the selling decisions endogenous. To mitigate this concern, following Edmans et al. (2012) and Dessaint et al. (2019), we use mutual fund hypothetical sales caused by large investor redemptions as a source of exogenous variation in stock price informativeness. Our 2SLS analysis of VC staging and syndication provides evidence that is consistent with the baseline results.

Our second instrument for stock price informativeness, in the spirit of the existing literature (Engelberg and Parsons 2011; Koudijs 2015, 2016), is based on the rationale that airport shutdowns because of extreme weathers or operational difficulties prevent financial analysts' timely on-site visits of the firms covered by them, which reduces these firms' stock price informativeness. The results using this alternative instrument are also consistent with our baseline findings. Overall, the 2SLS analyses suggest that there is likely a causal link between stock price informativeness and VC investment structure.

Next, to further strengthen the causal argument on VC learning, we undertake additional tests to explore the heterogeneous effects of public market price informativeness on VC investment structures. We first explore how the physical distance between VC investors and their startup firms alters our main results. The rationale behind this test is that geography matters in VC financing because close proximity reduces the cost of physically collecting information about the startups (Tian 2011). If information collection by VC investors becomes less costly, they may rely less on the information contained in public market prices to estimate the probability of going public. Hence, we expect the effect of stock price informativeness on the structure of VC financing to be less pronounced if the physical distance between VC investors and startup firms is short. Our results support this conjecture.

The second heterogeneous test explores how comparability of public firms within an industry alters our main results. We postulate that VC investors would find the information they could learn from stock prices is less reliable if public firms in the industry are less comparable to each other (i.e., firms in the industry are likely to have unique features). Hence, the effect of stock price informativeness on VC staging and syndication should be less pronounced in these industries. Using the industry research and development (R&D) expense ratio as a proxy for firm comparability, we find that VC staging and syndication is less sensitive to public stock price informativeness when the startups are from industries consisting of more heterogeneous firms.

We then directly test the implication of Chemmanur and Fulghieri (1999) on the IPO prospect information contained in public market stock prices. To examine this IPO prospect channel, we undertake two tests. First, we compare the effect of stock price informativeness of recently going-public firms to that of firms going public earlier on VC staging and syndication. Because the stock prices of recently going-public firms in the same industry should contain more relevant information on a startup's going-public prospect, we expect that VC investors are able to learn more valuable information from their stock prices and hence respond more by altering their investment structures. The evidence is consistent with our conjecture. Second, we examine how VC investors' past experience of bringing their startups public alters our main findings. We postulate that VC investors who have abundant experience of bringing their startups public in the past could learn valuable information from their own IPO experience and are better able to make appropriate judgement on their startups' IPO prospects. Hence, they rely less on the information contained in stock prices. As a result, these VC investors' staging and syndication decisions are less affected by public market price informativeness. We find evidence consistent with the conjecture.

Next, to confirm whether our findings are truly happening in the real business world, we undertake a survey to 5,004 VC practitioners residing in both North America and China to collect direct evidence on VC learning. We receive 200 responses, representing a response rate of 4%, which is comparable to similar studies. For example, Gompers et al. (2020) obtain a response rate of 4% for VCs from the VentureSource sample. A total of 170 (85%) of these respondents report that they turn to the public market when making investment decisions in startup firms. Among these 170 respondents, 140 (70%) suggest their learning purpose is to collect information about the IPO prospect of the startup firms. The survey evidence provides strong support for our learning hypothesis motivated by the IPO prospect channel.

Our analyses thus far focus on VC investors' decision on investment structures and suggest that they learn information on their portfolio firms' IPO prospects contained in public market stock prices and use it to determine staging and syndication. A natural question arises: What about their overall investment decisions? In other words, do VC investors react to signals contained in public market stock prices and allocate capital accordingly? Intuitively, if VC investors indeed learn information contained in public market stock prices, they should allocate capital across startups in response to public market signals. Moreover, the sensitivity of VC investment to public market signals should be larger if more information is contained in public market prices. In the final part of the paper, to test this conjecture, following Chen et al. (2007), we investigate the effect of price informativeness on the sensitivity of VC investment to a public market signal, Tobin's Q, at the industry level. We find that, when public market stock prices are more informative, the sensitivity of VC investment in an industry to public market signals is higher. The evidence suggests that VC investors make investment decisions and allocate capital more effectively after learning valuable information from the public market.

By exploiting the staging and syndication features of VC investment, our study complements Gompers (1995) and Tian (2011) on the determination of VC staging. They provide evidence that industry factors, such as R&D expenditure and asset tangibility, and the physical distance between VCs and startups affect VCs' stage financing. Our analysis shows that, besides these observable characteristics, more complicated information such as the IPO prospects contained in stock prices can also affect VC staging. More importantly, our study adds to Chen et al. (2007), Gompers et al. (2008), and Foucault and Frésard (2014) in the sense that VC investors actively collect information from the public market to make decisions on investment structures. This finding suggests an alternative learning mechanism through which VC investors optimize their investment structures, in addition to the amount of investments, according to the information they learn from the public market.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes sample selection and reports summary statistics. Section 4 presents the main results. Section 5 examines the information contained in stock prices. Section 6 presents survey evidence on VC investors' learning behavior. Section 7 reports VC overall investment results. Section 8 discusses alternative interpretations and caveats of the study and concludes the paper. Variable constructions and robustness tests are confined to the Appendix.

2. Relation to the Existing Literature

Our paper contributes to two strands of literature. First, it is related to the growing literature, both theoretical and empirical, that documents the real effects of financial markets. Starting from Hayek (1945), who argues that prices are a useful source of information, researchers (Grossman 1976, Hellwig 1980) realize that financial markets aggregate the information of many market participants who, although individually less informed, are collectively more informed than corporate decision makers. Dow and Gorton (1997), Subrahmanyam and Titman (1999), and Goldstein and Guembel (2008) show that decision makers use the new information learned from financial market prices to guide their real decisions.

Empirical studies provide evidence consistent with the learning channel through which financial markets affect firms' investment, financing, and governance practices. For example, Giammarino et al. (2004) find that information acquisition by the market influences managers' decisions on seasoned equity offerings. Luo (2005), in the merger and acquisition (M&A) setting, finds that managers learn new information from announcement returns of (M&A) deals and are more likely to withdraw a deal if its announcement return is low. Edmans et al. (2012) identify a negative, causal effect of a firm's share price on its likelihood of receiving a takeover bid and argue that this effect arises from a feedback learning channel. In a more general setting, Chen et al. (2007) find that the sensitivity of investment to stock price is stronger when there is more private information injected into the price during the trading process. Frésard (2012) shows that managers use the information they learn from the stock market when they decide on corporate cash savings. Foucault and Frésard (2014) further show that the sensitivity of investment to stock prices is higher for cross-listed firms in the United States. Both studies suggest that managers learn new information from the stock price and use it in their investment decisions. Foucault and Frésard (2012) find that firm managers learn from their product-market peers' stock prices when making investment decisions. Dessaint et al. (2019) show that even noise contained in stock prices of their peers has a ripple effect on a firm's investment. With respect to corporate governance, Ferreira et al. (2011) find that price informativeness and board independence are substitutes for public firms. All these studies suggest that managers or investors of public firms learn information from stock prices. Different from earlier studies, our paper focuses on a group of private investors, VCs, who are important promoters of entrepreneurship and innovation, and explore, for the first time in the literature, whether VC investors learn from public market stock prices when making investment decisions. Our findings suggest that the allocative role of security prices is much broader than what we have already known.

Our paper also contributes to the literature on VC investment (see Da Rin et al. 2013 for an excellent survey of the literature). This literature shows that VC investors' past experience, intensive monitoring, reputation, industry expertise, and network positions all affect their investment structures in terms of staging and syndication. Existing literature also explores the investment outcomes of VC financing to evaluate the effectiveness of various VC investment mechanisms. These studies conclude that VC investors generally create value for startup firms they invest in and promote technological innovation. Existing studies, however, have largely ignored a possible mechanism through which VC investors create value for their portfolio firms, that is, VC investors' active learning from public markets when making investment decisions. One exception is Gompers et al. (2008), who find VC investment reacts to public market signals, especially for those who have most industry experience. We push this inquiry one step further to explore how VC investors' reaction to public market signals depends on the informativeness of public market stock prices, which pins down a VC learning channel.

3. Data, Sample, and Variable Construction

3.1. Data and Sample Selection

We obtain data on VC investments in startup firms from the Thomson Reuters VentureXpert database. We include in our sample all U.S.-based startups with a complete VC financing history between 1980 and 2012, that is, startups receiving their first round of VC financing after 1980 and the last round before 2012. We classify startups that go public, are merged or acquired, are written off, or do not receive any VC financing within a 10-year span after the most recent round by 2012 as firms that have exited from VC financing and include them in our sample.[5] Finally we exclude observations with missing and inconsistent data, leaving 13,185 startup firms. To calculate the industry-level price informativeness measure and other control variables, we collect information on daily stock returns and annual financial data from the CRSP and Compustat databases, respectively. We use public firms traded on NYSE, NASDAQ, or AMEX with at least 50 trading days in a calendar year for calculations of stock price informativeness.

We follow the procedure from existing literature (Gompers 1995, Chemmanur et al. 2014, Gu et al. 2020) to match sample startup observations with public firms by the Standard Industrial Classification (SIC) system and dates of the first round of financing. In the matching procedure, we start with four-digit SIC industries. If there are fewer than four public firms in the four-digit SIC industry, we use three-digit SIC industries, and if there are fewer than four public firms in the three-digit SIC industries, we match startups with public firms in the same two-digit SIC industries instead. Next, we match each startup with the industry-level price informativeness for the calendar year before the first round of VC financing.

3.2. Variable Construction

3.2.1. VC Staging and Syndication Variables. We use four variables to capture VC investors' investment structures on their portfolio startups, that is, staging and syndication. Specifically, we use *N_round* and *Skewness* to capture VC investors' staging patterns. We define *N_round* as the total number of VC financing rounds a startup receives before the VC exits. *Skewness* is the investment amount put upfront by VC investors in the first round of financing, calculated as the amount a startup receives from round one divided by the total amount of VC financing across all financing rounds, multiplied by 100.

We use two other measures, *Syn* and *N_VC*, as the proxies for VC syndication. *Syn* is a syndication dummy that equals one if a startup is financed by more than one VC across rounds and zero otherwise. *N_VC* measures the size of the syndicate, that is, the number of VC investors in a syndicate co-investing in a startup firm. We provide detailed definitions of variables in Table A.1 in Appendix A.

3.2.2. Price Informativeness Variables. As suggested by Roll (1988) among a large body of literature, we use price nonsynchronicity (firm-specific return variation) as our price informativeness measure, which is mainly driven by private information. The proxy is widely used in many empirical studies, such as Durnev et al. (2004) and Chen et al. (2007) on corporate investment, Wurgler (2000) on capital allocation, and Chan and Chan (2014) on seasoned equity financing.

Specifically, we decompose the variation of stock returns into three components, a market-wide component, an industry-wide component, and a firm-specific component, by regressing daily stock returns on market and industry returns:

$$r_{i,j,t} = \beta_i + \beta_{i,m} r_{m,t} + \beta_{i,j} r_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,j,t}$ is the return of stock i from industry j at time t, and $r_{m,t}$ and $r_{j,t}$ are the market and industry j return at time t. We calculate the industry-level R^2, R_j^2, for industry j by averaging $R_{i,j}^2$ from Regression (1) across all firms in the industry. We then define the price nonsynchronicity measure $Info^{(j)}$ for industry j as

$$Info^{(j)} = ln\left(\frac{1 - R_j^2}{R_j^2}\right). \tag{2}$$

3.2.3. Control Variables. Following the literature on VC staging (Gompers 1995, Tian 2011, Tian et al. 2016), we control for a vector of startup-level and industry-level characteristics that may affect VC investors' decisions on staging and syndication in our analyses. Startup-level controls include *Ln_age,* the natural logarithm of startup age measured by the number of years since a startup's inception, and *Ln_amt1st*, the natural logarithm of the first-round investment amount. Industry-level controls include *Ind_Q*, the industry average of Tobin's *Q*; *Ind_ret*, the industry average of stock returns in excess of market returns; *Ind_RD*, the industry average of R&D expense ratio calculated as the R&D expenses divided by total assets; and *Ind_tangi*, the industry average of asset tangibility calculated as property, plant, and equipment divided by total assets.

3.3. Summary Statistics

Table 1 reports descriptive statistics on the characteristics of VC staging and syndication, startup firms, and their industries. Panel A shows that, in our sample, a median startup receives 3 rounds of financing from a syndicate consisting of four VC investors, with a total investment of $15.4 million. The money invested in the first round accounts for 37.5% of total VC investment. It has to wait for about 10 months for the next round of VC financing of $3.9 million. Panel B shows that the median startup is two years old and at the early stage of its life cycle when it receives the first round of VC financing of $3.5 million. Panel C shows the startup operates in the industry with an average Tobin's *Q* of 6.4, an average R&D ratio of 10.3%, and an average asset tangibility ratio of 21.2%. Public firms in these industries have an average market capitalization of $3.4 billion. The mean and median values of the industry-level price nonsynchronicity measure

Table 1. Summary Statistics

Variable	Mean	P25	Median	P75	Standard deviation
Panel A: VC staging and syndication					
No. of financing rounds	3.82	2.00	3.00	5.00	2.93
Skewness	49.66	10.51	37.50	100.00	40.20
Syndication	0.83	1.00	1.00	1.00	0.37
No. of VC investors	4.86	2.00	4.00	6.00	4.07
Interround duration (months)	14.90	5.06	9.83	17.16	19.76
Funding amount per round (mil.)	12.25	1.04	3.93	10.00	67.21
Total funding across rounds (mil.)	38.38	5.00	15.39	39.50	98.63
Panel B: Startup firms					
Early stage at round 1	0.57	0.00	1.00	1.00	0.50
Investment amount at round 1 (mil.)	11.53	1.25	3.50	9.00	28.81
Firm age at round 1	7.08	1.00	2.00	6.00	12.41
Panel C: Benchmark Industries (one year before round 1)					
Price nonsynchronicity	2.22	1.79	2.24	2.68	0.70
Amihud illiquidity ratio (×1,000)	0.007	0.001	0.002	0.006	0.013
Tobin's Q	6.39	4.04	5.45	7.19	4.44
R&D/assets (%)	10.26	3.44	8.70	15.69	8.41
Asset tangibility (%)	21.19	12.28	17.07	26.03	13.06
Market cap (billions)	3.43	0.50	1.29	2.50	6.32

Notes. This table reports summary statistics on VC staging and syndication, startup firms, and their industries. The sample consists of 13,185 startup firms completing VC financing between 1980 and 2012.

before the first VC financing round are 2.2 and 2.2, respectively, with the standard deviation of 0.7.

4. Main Results

In this section, we test our conjecture on VC learning from stock prices in the public market. We attempt to address endogeneity concerns by constructing IVs for stock price informativeness and using the 2SLS approach. We then undertake heterogeneity tests to further strengthen our causal arguments.

4.1. Baseline Regression Results

To assess the effect of public market price informativeness on VC staging and syndication, we estimate the following model

$$Y_i^{(j,t)} = a + bInfo^{(j,t-1)} + cControls_i + \varepsilon_i, \qquad (3)$$

where $Y_i^{(j,t)}$ is VC investors' staging and syndication variables described in Section 3.2.1 for startup i in industry j that are determined at year t, including the total number of financing rounds (*N_round*), the skewness of round investments (*Skewness*), the syndication dummy (*Syn*), and the number of VCs in the syndicate (*N_VC*). The first two variables capture VC stage financing, and the last two variables measure VC syndication. $Info^{(j,t\text{-}1)}$ is the price nonsynchronicity measure for industry j at year $t-1$. The vector $\boldsymbol{Controls_i}$ contains startup-level characteristics (calculated with startup information) and industry-level characteristics (calculated with information from industry j) that could affect VC staging and syndication as discussed in Section 3.2.3. In the *Skewness* regressions, as *Ln_amt1st* may overlap with the dependent variable mechanically, we exclude this variable from the regressions. We estimate *Info* using stock returns during the calendar year before the first round of VC financing and calculate the industry-level control variables with information as of the end of that year. We control for the first VC investment year-quarter fixed effects, lead VC fixed effects, industry fixed effects, and state fixed effects in regressions to absorb any influence varying only with year-quarter, lead VC, industry, and firm location in *N_round*, *Skewness*, and *N_VC* regressions.[6] We include year-quarter, industry, and state fixed effects in the *Syn* regression. We run ordinary least squares (OLS) regressions to estimate Equation (3) when *N_round*, *Skewness*, and *N_VC* are the dependent variable and run the Probit regression when *Syn* is the dependent variable.

Table 2 reports the baseline regression results regarding the effect of public market price informativeness on VC staging and syndication. For simplicity, we omit startup, industry, and year indicators i, j, and t when presenting results. Our VC learning hypothesis argues that, when stock prices are more informative, VC investors are better able to collect valuable information about the IPO prospects of their portfolio startup firms from the public market, so they can stage finance startups less to reduce the cost of staging (Sahlman 1990, Gompers 1995). They are also less likely to invite other VCs to form a syndicate to seek the

Table 2. Effect of Price Informativeness on VC Staging and Syndication

	(1) *N_round*	(2) *Skewness*	(3) *Prob. Syn*	(4) *N_VC*
Info	−0.207***	3.632***	−0.016*	−0.458***
	(0.034)	(0.930)	(0.010)	(0.043)
Ind_Q	−0.009*	0.176*	−0.001	−0.005
	(0.005)	(0.092)	(0.001)	(0.006)
Ind_ret	0.098	−1.531	0.021	0.042
	(0.112)	(1.978)	(0.014)	(0.134)
Ind_RD	1.057***	−32.948***	−0.004	3.467***
	(0.378)	(6.754)	(0.080)	(0.506)
Ind_tangi	−0.116	8.442*	0.168*	−0.332
	(0.286)	(4.979)	(0.089)	(0.371)
Ln_age	−0.354***	8.291***	−0.053***	−0.639***
	(0.040)	(0.687)	(0.005)	(0.089)
Ln_amt1st	−0.233***		0.023***	0.175***
	(0.019)		(0.002)	(0.046)
Lead VC fixed effects	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	13,185	10,312	13,185	13,185

Notes. This table reports the baseline regression results on the effect of stock price informativeness in the public market on VC staging and syndication. The sample consists of 13,185 startups completing VC financing between 1980 and 2012. Dependent variables are the total number of VC financing rounds a startup receives, the skewness of VC investments, the syndication dummy, and the number of VC firms in the syndicate. The independent variable, stock price informativeness, is defined as $ln((1-R^2)/R^2)$, where R^2 is the industry average of R-squared obtained by regressing daily stock returns on market and industry returns. See Appendix A for definitions of variables. Marginal effects are reported for the Syn regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

second opinions, which allows them to enjoy the returns exclusively (Lerner 1994).

We observe results that are consistent with the learning hypothesis. The coefficient estimates on *Info* are negative and significant at the 1% level in column (1) and positive and significant at the 1% level in column (2). That is, more informative public market stock prices in the same industry of the startups are associated with fewer financing rounds and more funding upfront in the first round by VC investors. In columns (3) and (4), the coefficient estimates on *Info* are negative and significant at the 10% and 1% level, respectively, suggesting that more informative public stock prices are related to less intensive syndication by VC investors.

In these regressions, we include industry Tobin's *Q* to control for the potential valuation or price-level effect on VC staging and syndication. Gompers (1995) and Tian (2011) include a similar proxy, market-to-book ratio, in their analyses on VC financing rounds. The coefficient estimates on Tobin's *Q* are negative and significant in column (1) and positive and significant in column (2), suggesting that startup firms in high-growth industries with higher valuation receiving fewer financing rounds. We also consider the influences of recent price movements by including industry stock returns *Ind_ret* in regressions, which has no significant effect on VC staging and syndication. In addition, we find that VC investors of startups in more R&D intensive industries rely more on staging and syndication. Results on other control variables show that younger startups tend to receive a larger number of VC financing rounds and a smaller first round amount. These startups are also more likely to be financed by VC syndicates and by a larger syndicate.

4.2. Identification

The baseline results are consistent with the hypothesis that VC investors actively learn from public market stock prices when making investment structure decisions in their startups to reduce the associated cost. The documented relation, however, could be subject to endogeneity although our setting significantly alleviates the concern that stock prices are merely reflections of what VC investors have already known. For example, there may exist some omitted variables that affect public market price informativeness and VC staging and syndication decisions simultaneously, which could bias the coefficient estimate on price informativeness and makes the interpretations of our findings difficult. In this section, we construct two IVs for public market price informativeness and use the 2SLS approach to address above concerns.

4.2.1. Instrument Based on Mutual Fund Forced Sales. Our first instrument for public market price informativeness, *NMFHS*, is defined as the industry average frequency of mutual fund forced sales because of fund outflows experienced by a firm across the year.

The basic idea is that many small sales cause significant price variations and crowd out informed traders, but they have tiny impacts on price levels. The existing literature has shown that large forced sales by mutual funds can cause significant variations in stock prices (Coval and Stafford 2007). One issue, however, is that mutual fund managers may have the discretion in choosing the stocks to sell, which reflects their information about the stocks and makes the selling decisions endogenous. To mitigate this concern, following Edmans et al. (2012) and Dessaint et al. (2019), we use mutual fund hypothetical sales caused by large investor redemptions as an exogenous source of variation in stock price informativeness.

Specifically, to construct the industry-level instrument, we first identify all nonspecialized U.S. mutual funds subject to large outflows (net inflow ≤ −5% of total net assets) during a quarter using the CRSP survivor-bias-free mutual fund database. We next combine the outflow information with the mutual fund shareholding data at the end of the previous quarter from the CDA Spectrum/Thomson database to estimate whether a stock is subject to mutual fund hypothetical sales. The assumption is that, if a mutual fund experiences a large outflow, it will liquidate the stocks it is holding proportionally. This action results in variation in the stock's price that is unrelated to firm fundamentals. For each stock, we then count the number of fund-quarters that is subject to hypothetical sales in a year. Apparently, the stock's price is noisier if there are more selling events that carry no information. We then average the number of mutual fund hypothetical sales across stocks in an industry to obtain the industry-level instrument, *NMFHS*. We discuss more on the instrument construction in Appendix B.1.

The previous rationale suggests that the instrument should be negatively related to stock price informativeness, because frequent mutual fund forced sales could introduce many noisy trades without any fundamental information and crowd out private information-based trades. In unreported tests, we find that this instrument is significantly and negatively correlated with the probability of informed trading (*PIN*). Thus, our proposed instrument satisfies the relevance condition of the IV approach.

Meanwhile, it is reasonable to believe that mutual fund hypothetical sales because of extreme mutual fund outflows are exogenous to VCs' investment decisions, because the noises created by these sales are unrelated to the fundamentals of the public firms, the startups, and VC investors' private information about their investments. Hence, our proposed instrument is likely to affect a VC's staging and syndication decision only through its effect on the informativeness of public market prices.

One possibility, however, is that the instrument may affect VC staging and syndication decisions through the level of industry valuations, since mutual fund sales could suppress share prices, according to the literature. We can rule out this possibility to a large extent because we find that the frequency of mutual fund sales could not cause large price shocks. In untabulated analyses, we find that (1) the correlation between price levels, proxied by Tobin's *Q*, and *NMFHS* is low, only −0.003 at the industry level; and (2) the prices of stocks ranking in the top (largest) quintile by *NMFHS* rise slightly by 0.9% in a one-year horizon (see Appendix B.1 for more details). These observations suggest that our instrument mainly captures short-run variation in stock prices rather than large and permanent price pressures.[7] To further eliminate the effect of (changes in) price levels, we include price levels (*Ind_Q*) and industry stock returns (*Ind_ret*) in all regressions. It is hence reasonable to believe that, in our setting, the instrument *NMFHS* is unlikely to affect VC investors' staging and syndication decisions through changes in price levels. Overall, this IV reasonably satisfies the exclusion restriction.[8]

We report the 2SLS regression results in Table 3. Column (1) reports the first-stage regression results with public market price informativeness, *Info*, as the dependent variable. The main independent variable of interest is our instrumental variable, *NMFHS.* We include all control variables from the baseline regressions reported in Table 2 in the first-stage regressions. As we observe, the coefficient estimate on the instrument is negative and significant at the 1% level, which suggests that the noisy trading by mutual funds with large outflows decreases stock price informativeness. The instrument is highly correlated with the endogenous right-hand side variable, *Info*, with a t statistic of 10.6 in the first stage. The corresponding F statistic of the first-stage regression is 111.4, which is much larger than the critical values from the Stock and Yogo (2005) weak instrument test. Combining these two statistics, we can rule out the possibility that when minimizing the valuation effect of forced sales in constructing *NMFHS*, its influence on stock price informativeness is not weakened unintentionally. That is, our analysis does not appear to have the weak instrument problem.

Columns (2)–(5) report the second-stage regression results with *N_round*, *skewness*, *Syn*, and *N_VC* as dependent variables, respectively. The signs of the coefficient estimates on the instrumented *Info* are consistent with those obtained from the OLS regressions and are significant at the 1% or 5% levels. The economic effect of public market price informativeness on VC staging and syndication is also sizable. For example, with a one standard deviation increase in the instrumented *Info*, VC investors reduce the number of investment rounds by 0.11, which is a 2.9% decrease from the mean number of financing rounds. Meanwhile, with a one standard deviation increase in the instrumented *Info*, VC investors invest 2.1% (i.e., \$0.8

Table 3. Endogeneity Tests with the IV Approach

	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)
	Info	*N_round*	*Skewness*	*Prob. Syn*	*N_VC*
NMFHS	−0.016***				
	(0.002)				
$\widehat{Info}$		−0.192**	4.922**	−0.101***	−0.469***
		(0.090)	(1.840)	(0.032)	(0.103)
Ind_Q	−0.007***	−0.010*	0.198**	−0.001	−0.005
	(0.002)	(0.005)	(0.090)	(0.001)	(0.006)
Ind_ret	−0.301***	0.125	−1.285	0.005	0.059
	(0.031)	(0.119)	(1.837)	(0.014)	(0.117)
Ind_RD	0.165	1.106**	−33.884***	0.151	3.402***
	(0.124)	(0.419)	(7.107)	(0.093)	(0.525)
Ind_tangi	−0.522***	−0.034	9.579*	0.197**	−0.523
	(0.098)	(0.272)	(4.873)	(0.080)	(0.360)
Ln_age	−0.000	−0.351***	8.255***	−0.053***	−0.618***
	(0.004)	(0.039)	(0.695)	(0.005)	(0.082)
Ln_amt1st	−0.005	−0.237***		0.022***	0.160***
	(0.005)	(0.018)		(0.002)	(0.045)
Lead VC fixed effects	Yes	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,998	11,998	9,223	11,998	11,998

Notes. This table reports the 2SLS instrumental variable regression results on the effect of stock price informativeness in the public market on VC staging and syndication. The instrumental variable is the industry average of the number of mutual fund hypothetical sales. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

million) more in the first round and decrease their probability of forming a syndicate to finance a startup by 5.8%. The size of the syndicate drops by 0.3 VCs, which is 5.5% of the mean syndicate size. These findings suggest that there likely exists a causal link between public market price informativeness and VC investment structure.[9]

4.2.2. Instrument Based on Airport Shutdowns. To ensure the results we documented previously are robust, besides *NMFHS*, we construct a second instrument based on airport shutdowns to address the endogeneity concern. Specifically, we define the instrument, *Shutdown*, as the natural logarithm of average days in a year when there are severe flight cancellations either in the airports closest to the firm's headquarters or closest to the offices of the financial analysts covering the firm, which prevents financial analysts from visiting the firms. We define severe flight cancellations as the situation when more than 20% of inbound and outbound flights of local airports are cancelled because of weather, airline operations, air traffic, or security reasons. We discuss details on constructing *Shutdown* in Appendix B.2.

Shutdowns of airports because of extreme weather conditions or operational difficulties make the analysts' on-site visits to the firm difficult. Because financial analysts are active information producers and can incorporate the information to stock prices (Brennan et al. 1993, Brennan and Subrahmanyam 1995, Hong et al. 2000, Bradley et al. 2014, Cheng et al. 2016), this interruption on the analysts' visits to the firm could significantly reduce the firm's stock price informativeness.[10] Hence, this instrument should satisfy the relevance requirement of the IV approach.

It is reasonable to believe that flight cancellations between public firms and their analysts because of extreme weather conditions or operational difficulties are exogenous to the investment decisions of VC investors. In other words, our instrument affects a VC's staging and syndication decision only through its effect on the informativeness of public market prices. That is, our instrument reasonably satisfies the exclusion restriction. This *Shutdown* instrument shares the same spirit of Koudijs (2015, 2016) in which boats arrive with information in the 18th century, and bad weather causes exogenous reductions in information arrival, and Engelberg and Parsons (2011), in which bad weather prevents the delivery of print media, which, in turn, affects local trading. It is also in the same spirit of Bernstein et al. (2016) in which new airline routes opening increases VC monitoring.

We report the 2SLS regression results in Table 4. The coefficient estimate on *Shutdown* is negative and significant

Table 4. Endogeneity Tests with an Alternative IV

	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)
	Info	*N_round*	*Skewness*	*Prob. Syn*	*N_VC*
Shutdown	−0.060***				
	(0.010)				
$\widehat{Info}$		−2.536*	42.249**	−0.369***	−1.131***
		(1.517)	(15.810)	(0.105)	(0.419)
Ind_Q	−0.003***	−0.016***	0.241	−0.002**	−0.020***
	(0.001)	(0.006)	(0.150)	(0.001)	(0.007)
Ind_ret	−0.111***	−0.210	2.542	−0.024	−0.093
	(0.019)	(0.199)	(2.226)	(0.023)	(0.167)
Ind_RD	1.658***	2.683	−68.310*	0.677***	3.732***
	(0.110)	(2.520)	(37.102)	(0.184)	(0.576)
Ind_tangi	1.334***	2.044	−46.332	0.441***	−1.028*
	(0.284)	(2.300)	(34.586)	(0.125)	(0.523)
Ln_age	−0.006*	−0.318***	8.898***	−0.054***	−0.530***
	(0.003)	(0.038)	(0.633)	(0.005)	(0.053)
Ln_amt1st	−0.002	−0.267***		0.017***	0.050**
	(0.003)	(0.034)		(0.003)	(0.022)
Lead VC fixed effects	Yes	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10,326	10,326	7,876	10,326	10,326

Notes. This table reports the 2SLS instrumental variable regression results on the effect of stock price informativeness in the public market on VC staging and syndication. The instrumental variable is the natural logarithm of average number of days when analysts having difficulties in paying on-site visits to public firms in the same industry of a startup due to severe flight cancellations (defined as more than 20% of inbound and outbound flights are cancelled) caused by weather or operational conditions either in the airports closest to the firm's headquarters or closest to the analysts' offices. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

at the 1% level in the first stage, suggesting that airport shutdowns significantly reduce price informativeness. The *t* statistic is 6.2, and the *F* statistic is 38.3, which is much larger than the critical values from the Stock and Yogo (2005) weak instrument test. This suggests that our analyses do not have weak instrument problem. In the second-stage regressions reported in columns (2)–(5), we observe significant coefficient estimates on the instrumented *Info* with signs consistent with those reported in Table 2.[11] Hence, using this alternative instrument, we continue to find a negative and causal link between stock price informativeness and VC staging and syndication.

4.3. Heterogeneity Tests

To further strengthen the causal link between VC learning and their investment structures, we perform a few tests that explore the heterogeneous effects of public market price informativeness on VC staging and syndication in the 2SLS framework, using *NMFHS* as the instrument.

4.3.1. Geographical Distance. Tian (2011) finds that VC investors located farther away from the startup firms tend to rely more heavily on staging because close proximity makes it less costly for them to visit the startups to directly collect information and monitor them. Similarly, if a VC investor is located far away from its startup firms, it would be more costly for the VC to physically visit the distant startups to collect information than learning information from the public market. Hence, the VC should rely more on the information she learns from the public market. Based on this rationale, we expect that the effect of public market price informativeness on VC staging and syndication is less pronounced if the VC is located close to the startup.

To test this conjecture, we estimate the following model:

$$Y_i^{(j,t)} = a + bInfo^{(j,t-1)} * Shortdist_i + cInfo^{(j,t-1)} + dShortdist_i + eControls_i + \varepsilon_i \quad (4)$$

where *Shortdist* is a dummy that equals one if the startup and its leading VC are in the same state and zero otherwise. The key variable of interest is the interaction term between *Info* and *Shortdist*.

We use *NMFHS* and *NMFHS*Shortdist* as the instruments to undertake 2SLS regressions. Table 5 reports the second-stage regression results. The coefficient estimates on the instrumented *Info* exhibit signs that are consistent with those observed in Table 3. The coefficient estimates on the key variable of interest, the instrumented *Info*Shortdist*, are statistically significant

Table 5. Effects of VC-Startup Distance

	(1) *N_round*	(2) *Skewness*	(3) *Prob. Syn*	(4) *N_VC*
$Info * \widehat{Shortdist}$	0.264*	−4.901***	0.002	0.323***
	(0.152)	(1.585)	(0.006)	(0.111)
$\widehat{Info}$	−0.247**	5.510**	−0.112***	−0.548***
	(0.115)	(2.538)	(0.033)	(0.116)
Shortdist	−0.712**	9.906***	0.029**	−0.977***
	(0.334)	(3.500)	(0.015)	(0.249)
Ind_Q	−0.009*	0.171*	−0.001	−0.004
	(0.005)	(0.092)	(0.001)	(0.006)
Ind_ret	0.139	−1.435	−0.002	0.043
	(0.127)	(2.380)	(0.012)	(0.125)
Ind_RD	1.032**	−32.574***	0.161	3.349***
	(0.438)	(7.452)	(0.099)	(0.550)
Ind_tangi	−0.043	10.221*	0.188**	−0.583*
	(0.274)	(5.182)	(0.078)	(0.340)
Ln_age	−0.359***	8.450***	−0.050***	−0.632***
	(0.041)	(0.729)	(0.004)	(0.083)
Ln_amt1st	−0.239***		0.022***	0.169***
	(0.018)		(0.002)	(0.046)
Lead VC fixed effects	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	11,848	9,077	11,848	11,848

Notes. This table reports the 2SLS regression results on the effects of VC-startup distance on the relationship between stock price informativeness and VC staging and syndication. VC-startup distance is measured by a dummy variable that equals one if the VC and startup are in the same state, and zero otherwise. The *NMFHS* instrument, and the same set of control variables and fixed effects in Table 3 are used. The second-stage regression results are reported. See Appendix A for definitions of variables. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

and exhibit signs opposite to those on the instrumented *Info* in the *N_round*, *Skewness*, and *N_VC* regressions. For example, in column (1), the positive and significant coefficient estimate on the instrumented *Info*Shortdist* suggests that VC investors located close to their startups rely less on the information they learn from public market stock prices when making staging decisions. Overall, we find consistent evidence that the effect of VC learning from the public market on staging and syndication is less pronounced if they are located closer to their startups and hence have a lower cost of collecting information by visiting their portfolio firms.

4.3.2. Firm Comparability. Our learning hypothesis suggests that VC investors learn actively from public market stock prices to reduce costly staging and syndication. However, if the collected information is less reliable, VC investors would stick to the powerful, although expensive, staging and syndication tools. Specifically, in an industry with low comparability among firms, VC investors should find that information they learn from stock prices of public firms is less useful and reliable compared with that from industries in which private and public firms are similar in nature. Hence, we expect that the effect of public market price informativeness on VC staging and syndication is less pronounced in industries consisting of more heterogeneous firms.

We use the industry R&D expense ratio as a proxy for the comparability of firms within an industry. R&D intensive industries are characterized by more investment in innovation, technologies, and intangible assets, making it harder to compare one firm with another. We define an intensive R&D dummy, *HRD*, which equals one if the R&D spending in a startup's industry is in the top half among all industries, and zero otherwise. We then estimate Equation (4) with the key variable of interest replaced with the interaction term between *Info* and *HRD* to test the effect of industry comparability on VC learning. The instruments we used in the 2SLS analysis are *NMFHS* and *NMFHS*HRD*.

Table 6 reports the second-stage regression results. The coefficient estimates on the main variable of interest, the instrumented *Info *HRD*, are with signs opposite to those of coefficient estimates on the instrumented *Info* in *N_round*, *Syn*, and *N_VC* regressions. These estimates are significant at the 5% or 1% levels. The results suggest that the effect of public market price informativeness on staging and syndication is more pronounced for startups in industries with high comparability.

Table 6. Effects of Industry Comparability

	(1) *N_round*	(2) *Skewness*	(3) *Prob. Syn*	(4) *N_VC*
$\widehat{Info*HRD}$	0.290**	0.350	0.053**	0.796***
	(0.137)	(2.320)	(0.022)	(0.208)
$\widehat{Info}$	−0.218**	4.545**	−0.120***	−0.581***
	(0.088)	(1.827)	(0.032)	(0.071)
HRD	−0.438	−4.985	−0.097*	−1.248**
	(0.318)	(5.511)	(0.054)	(0.486)
Ind_Q	−0.009*	0.151*	−0.001	−0.003
	(0.005)	(0.083)	(0.001)	(0.006)
Ind_ret	0.142	−1.378	0.000	0.077
	(0.125)	(1.812)	(0.013)	(0.133)
Ind_tangi	0.078	12.343**	0.170*	−0.397
	(0.286)	(4.849)	(0.103)	(0.343)
Ln_age	−0.354***	8.248***	−0.054***	−0.627***
	(0.038)	(0.692)	(0.005)	(0.083)
Ln_amt1st	−0.237***		0.023***	0.163***
	(0.018)		(0.002)	(0.046)
Lead VC fixed effects	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	11,998	9,223	11,998	11,998

Notes. This table reports the 2SLS regression results on the effects of industry comparability on the relationship between stock price informativeness and VC staging and syndication. Industry comparability is measured by a dummy variable that equals one if the industry R&D expense ranks in the top half, and zero otherwise. The *NMFHS* instrument, and the same set of control variables and fixed effects in Table 3 are used. The second-stage regression results are reported. See Appendix A for definitions of variables. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4. Additional Tests

4.4.1. Round-Level Evidence on VC Staging. We use round-level data to further test the effect of price informativeness on VC staging. Similar to Gompers (1995) and Tian (2011), we consider two outcome variables: round amount (*R_amount*) and round duration (*Duration*). Our prior is, conditional on that VC investors have invested in a startup firm, if they can collect information from the public market, they are likely to reduce costly staging in subsequent investments by (1) increasing duration between rounds and (2) increasing round amounts. Combining (1) and (2), they can use fewer financing rounds to invest the same amount in a startup firm.

Specifically, we define *R_amount* as the natural logarithm of the financing amount of a round in thousands dollars and count the months from a funding date to the next funding date to calculate *Duration*. Columns (3) and (4) in Table 7 report the second-stage 2SLS regression results using *NMFHS* as the instrument. The coefficient estimates on the instrumented *Info* are positive and significant. In summary, our results from the round-level analysis supports the notion that VC investors respond to more informative stock prices in the public market by increasing round amounts and lengthening the duration between two successive rounds.

4.4.2. Additional Robustness Tests. We perform a number of additional analyses to check the robustness of our main findings and report the results in Appendix C. All these robustness tests are undertaken in the 2SLS framework using *NMFHS* as the instrument as discussed in Section 4.2.

Specifically, we (1) use the *PIN* measure as an alternative informativeness proxy (Easley et al. 1996, Duarte and Yong 2009); (2) calculate *Info* with a 250-day horizon; and (3) including the Amihud (2002) illiquidity ratio in our main specification to control for the liquidity effect. Results reported in Table C.1 suggest that our main findings stay qualitatively unchanged in the previous robustness tests.

5. Why Would Informative Public Markets Matter?

We have shown that VC investors adjust their investment structures in startup firms based on the information they learn from public market stock prices. In this section, we attempt to answer a deeper question: what is the underlying economic mechanism of our main finding? In other words, what is the information contained in stock prices VC investors are learning and hence why would informative public markets matter?

Table 7. Round-Level Evidence

	Baseline regressions		IV regressions: Second stage	
	(1) *R_amount*	(2) *Duration*	(3) *R_amount*	(4) *Duration*
Info	−0.0003	3.080***		
	(0.028)	(0.400)		
$\widehat{Info}$			0.652***	47.028***
			(0.206)	(3.308)
Ind_Q	0.003	−0.073***	0.000	−0.258***
	(0.003)	(0.021)	(0.003)	(0.041)
Ind_ret	−0.003	−0.936***	−0.155***	−9.575***
	(0.032)	(0.324)	(0.056)	(0.925)
Ind_RD	0.599**	−9.388***	−0.103	−50.312***
	(0.265)	(3.267)	(0.332)	(6.969)
Ind_tangi	−0.133	62.270***	−0.578	35.914***
	(0.389)	(5.655)	(0.419)	(8.716)
Ln_age	−0.291***	−29.542***	−0.274***	−26.669***
	(0.033)	(0.778)	(0.035)	(0.958)
Lag_ramt	0.003		0.003	
	(0.009)		(0.009)	
Lag_duration		−0.189***		−0.167***
		(0.017)		(0.018)
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	28,754	24,971	28,699	24,921

Notes. This table reports the 2SLS regression results on the effects of stock price informativeness in the public market on VC round amounts and durations. The sample consists of 31,219 VC follow-on investment rounds between 1980 and 2012. The independent variables are the natural logarithm of the dollar amount of a round in thousands, and the duration in months from a funding date to the next funding date. The *NMFHS* instrument is used in IV regressions. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the startup level.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

We postulate that a plausible piece of valuable information contained in public market stock prices that VC investors actively learn is the IPO prospects of their startup firms. According to the model of Chemmanur and Fulghieri (1999) on a startup's going-public decision, when a startup decides to go public, it faces a tradeoff between enjoying a stronger bargaining power against many small investors from the public market (as opposed to a single private market investor) and bearing a higher cost of information production (because many investors produce duplicated information and the information production cost is eventually born by the startup). Hence, when stock prices are more informative in the public market and outsiders' cost of producing information about the startup in an industry is lower, the startup is more likely to go public.

Specifically, in our empirical setting, *Info* measures the volume of information outsiders can obtain from the public market, and hence captures a startup's IPO prospect. To examine the IPO prospect channel, we undertake two tests that explore how IPO-related variation alters our main results.

We first test the IPO prospect channel by comparing the effect of stock price informativeness of recently going-public firms on VC staging and syndication to that of firms going public earlier. Because the prices of recently going-public firms in the same industry contain more relevant information on the going-public prospect, we expect that VC investors respond more to the informativeness of these firms' stock prices when determining staging and syndication.

Specifically, we re-estimate our main specification in Equation (3) with the 2SLS framework using *NMFHS* as the instrument in two subsamples. In the *Recent* subsample, *Info* is estimated with stock returns of firms in the same industry of the startup with a listing history ranking in the bottom quartile (i.e., the most recent listings) among all public firms. In the *Distant* subsample, *Info* is estimated with stock returns of firms with a listing history ranking in the top quartile (i.e., the most distant listings). Table 8 reports the second-stage regression results. In general, we observe a negative and significant relation between the instrumented *Info* and VC staging (*N_round* and *Skewness*) and syndication (*Syn* and *N_VC*) in the *Recent* subsample and no such effect in the *Distant* subsample. The differences in the coefficient estimates on the instrumented *Info* between the two subsamples are statistically significant at the 1% level in the *N_round*, *Skewness*, and *N_VC* regressions. In *Syn* regressions, although the difference is not significant, the magnitude of the estimate in the *Recent* subsample is around

Table 8. VC Learning from Recently Going-Public Firms

	N_round		*Skewness*		*Prob. Syn*		*N_VC*	
	(1) Recent	(2) Distant	(3) Recent	(4) Distant	(5) Recent	(6) Distant	(7) Recent	(8) Distant
$\widehat{Info}$	−0.273***	0.011	4.160***	−0.480	−0.031*	−0.003	−0.286***	0.046
	(0.072)	(0.051)	(0.879)	(0.818)	(0.017)	(0.016)	(0.072)	(0.069)
Ind_Q	−0.020***	−0.016**	0.262***	0.198**	−0.002**	−0.002*	−0.019***	−0.014***
	(0.007)	(0.006)	(0.093)	(0.081)	(0.001)	(0.001)	(0.007)	(0.004)
Ind_ret	0.169	0.217	−1.946	−4.700*	0.031**	0.034*	0.272*	0.375**
	(0.114)	(0.136)	(1.910)	(2.370)	(0.015)	(0.019)	(0.152)	(0.185)
Ind_RD	1.068***	0.915**	−32.153***	−32.867***	0.193**	0.187*	3.313***	3.263***
	(0.368)	(0.425)	(6.683)	(8.525)	(0.088)	(0.113)	(0.375)	(0.470)
Ind_tangi	−0.095	−0.047	8.335	5.295	0.214	0.106	−0.220	−0.015
	(0.394)	(0.421)	(7.878)	(8.345)	(0.152)	(0.132)	(0.439)	(0.480)
Ln_age	−0.352***	−0.366***	9.055***	9.307***	−0.061***	−0.061***	−0.584***	−0.593***
	(0.030)	(0.024)	(0.558)	(0.473)	(0.005)	(0.005)	(0.073)	(0.061)
Ln_amt1st	−0.264***	−0.252***			0.021***	0.023***	0.085**	0.087**
	(0.020)	(0.022)			(0.003)	(0.003)	(0.040)	(0.039)
Lead VC fixed effects	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diff.in $\widehat{Info}$	−0.284***		4.640***		−0.028		−0.332***	
Observations	8,994	8,554	6,853	6,522	8,994	8,554	8,994	8,554

Notes. This table reports the 2SLS regression results on the effect of stock price informativeness of firms going public recently and firms going public earlier. In the *Recent* (*Distant*) regressions, the informativeness measure is calculated using stock returns of firms with a listing history ranking in the bottom (top) quartile. The *NMFHS* instrument, and the same set of control variables and fixed effects in Table 3 are used. The second-stage regression results are reported. The Wald chi-square testing results are reported for the difference in coefficient estimates on $\widehat{Info}$. See Appendix A for variable definitions. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

10 times of that in the *Distant* subsample. The result of this analysis is consistent with our prior that VC investors are learning information on IPO prospects from recently going-public firms when determining the investment structures in their portfolio firms.

Our second test on the IPO prospect channel is based on the conjecture that there is a substitution between VC investors' own IPO experience and the information they could learn from the public market. The rationale is that, if VC investors are learning information about the IPO prospects of their startup firms from public market stock prices in the same industry as we proposed, VC investors with lots of experience in IPOs could have other information resources and hence rely less on the information extracted from the public market. Put differently, with abundant prior IPO experience, VC investors have more information sources other than the public market on the IPO prospects of their portfolio firms and may be able to use related information more effectively. Hence, their investment decisions should rely less on the information learnt from the public market.

To test this conjecture, we estimate Equation (4) with the key variable of interest replaced with *IPOexp*, which captures the VC investors' industry IPO experience, measured by a dummy variable that equals one if a startup's lead VC is ranked in the top half by the number of IPOs it backs in the same two-digit SIC industry from 1962 to the date of the first round of financing and zero otherwise.[12]

In Table 9, we report the second-stage regression results. The instruments we used in the 2SLS analysis are *NMFHS* and *NMFHS*IPOexp*. The coefficient estimates on the instrumented *Info* exhibit signs that are consistent with those observed in Table 3. The key variable of interest is the interaction terms between the industry price informativeness measure and the VC IPO experience measure, *Info*IPOexp*. This interaction term has significant and positive coefficient estimates in regressions with *N_round* and *N_VC* being the dependent variable and has a negative and significant coefficient estimate in the regression with *Skewness* being the dependent variable. The evidence suggests that the effect of price informativeness on VC staging and syndication is mitigated if the VC investor has more prior IPO experience in the same two-digit SIC industry. Our findings appear to suggest that a VC investor's industry IPO experience and her learning from public market stock prices are substitutes, which provides suggestive evidence that the information VC investors

Table 9. IPO Experience and VC Learning

	(1) *N_round*	(2) *Skewness*	(3) *Prob. Syn*	(4) *N_VC*
$Info*\widehat{IPOexp}$	0.420**	−7.075*	−0.017	0.684***
	(0.208)	(3.729)	(0.018)	(0.146)
$\widehat{Info}$	−0.347***	7.022***	−0.131***	−0.736***
	(0.126)	(2.015)	(0.032)	(0.107)
IPOexp	−1.024**	16.475**	0.084**	−1.405***
	(0.450)	(8.117)	(0.039)	(0.326)
Ind_Q	−0.010**	0.206**	−0.001	−0.007
	(0.005)	(0.091)	(0.001)	(0.006)
Ind_ret	0.147	−1.935	0.001	0.089
	(0.121)	(2.158)	(0.013)	(0.122)
Ind_RD	0.979**	−30.469***	0.209**	3.048***
	(0.397)	(6.704)	(0.106)	(0.528)
Ind_tangi	−0.088	10.023*	0.207**	−0.558
	(0.270)	(5.074)	(0.087)	(0.351)
Ln_age	−0.358***	8.370***	−0.053***	−0.626***
	(0.041)	(0.734)	(0.005)	(0.082)
Ln_amt1st	−0.237***		0.020***	0.159***
	(0.018)		(0.002)	(0.045)
Lead VC fixed effects	Yes	Yes	No	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	11,998	9,223	11,998	11,998

Notes. This table reports the 2SLS regression results on the effect of VC IPO experience on the relation between stock price informativeness and VC staging and syndication.VC IPO experience is measured by a dummy variable that equals one if the startup's lead VC ranks in the top half by the number of IPOs in the same two-digit SIC industry from 1962 to the date of the first round of financing and zero otherwise. The *NMFHS* instrument, and the same set of control variables and fixed effects in Table 3 are used. The second-stage regression results are reported. See Appendix A for definitions of variables. Marginal effects are reported for the *Syn* regressions. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the state level.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

learn from the stock prices of public firms in the same industry is likely the IPO prospects of their portfolio firms.

6. Survey Evidence on VC Learning

To further examine whether VC investors indeed rely on public market information when making investment decisions, we undertake a survey study among VC practitioners residing in both North America and China. Specifically, we ask these VC practitioners two questions: (1) in general, whether they watch the stock prices in the public market when making investments; and (2) if so, the underlying reasons for which they watch the stock prices. Questions in the survey include the following:

(1) Do you watch the stock price of public firms in the same industry when making investment decisions in a startup firm? (Select one answer)

A. Yes

B. No

(2) If A is chosen in Question 1: Which of the following are the purposes that you watch the stock prices of public firms in the same industry when making investment decisions in a startup firm? (Select all that apply)

A. To collect information about the IPO prospect of the startup firm

B. To collect information about the probability that the startup firm is acquired by another firm

C. To estimate valuation of the startup firm

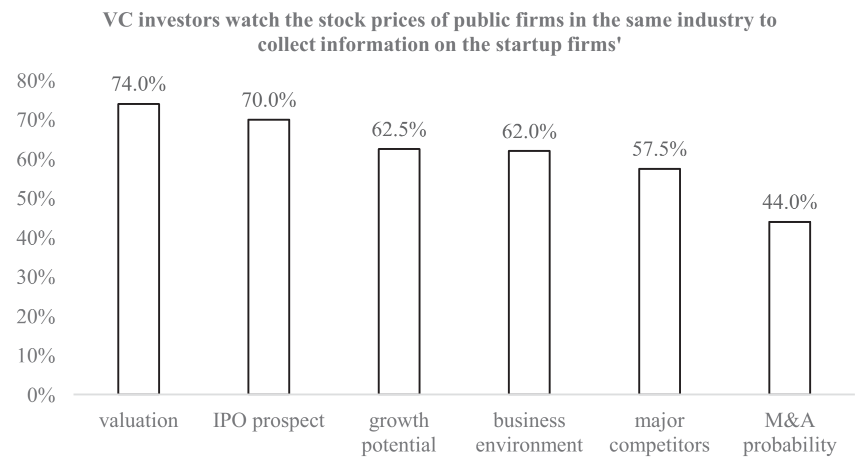
D. To evaluate the growth potential of the startup firm

E. To collect information about major competitors of the startup firm

F. To evaluate the business environment of the startup firm

We distributed the questionnaire to 5,004 VC practitioners via email on March 31, 2021, and received 200 responses within one week, which represents a response rate of 4%. The response rate is comparable to similar studies. For example, Gompers et al. (2020) obtain a response rate of 4% for VCs from the VentureSource sample. A total of 170 (85%) of the 200 VC respondents choose "Yes" in the first question and report that they turn to the public market when making decisions on investments in startup firms. This observation suggests VC investors' learning from the public market is prevalent across markets and hence provides direct support to our hypothesis. The second question attempts to collect VC practitioners' opinions

Figure 1. Response to the Survey Question on the Purposes of Watching Stock Prices of Public Firms



Notes. This figure plots the frequency of the purposes chosen by the 170 VC investors watching the stock prices of public firms in the same industry when making investments in a startup firm. Respondents are allowed to make multiple choices of reasons. The data are collected from a survey covering 5,004 VC investors residing in both North America and China. The total number of responses is 200.

on the purposes of watch stock prices, and Figure 1 summarizes the responses. Among the 170 VC practitioners who watch the public market when making investments in startup firms, 140 (70%) suggest their purpose is to collect information about the IPO prospect of the startup firms. It is among the most important reasons for which these VC investors watch the stock prices, ranking only after collecting valuation information (74%). Our finding from responses to the second question echoes the IPO prospect channel we documented in detail in Section 5. Other plausible reasons why VC investors watch the public market include collecting information about the startup firms' growth potential (63%), business environment (62%), and competitors (58%).

In summary, our survey evidence suggests that it is a common practice for VC investors to turn to the public market for information collection when making investments in startup firms. One important piece of information they collect is the IPO prospect of the startup firm. Thus, our learning hypothesis, motivated by the IPO prospect channel, is also supported by survey evidence from the field.

7. VC Investments Across Startups

Our results thus far suggest that VC investors learn information contained in public market stock prices and use it to adjust their investment structures in their portfolio firms. In this section, we push the inquiry one step further and explore how VC investors react to signals contained in public market stock prices when allocating capital across startup firms.

Intuitively, if VC investors indeed learn information contained in public market stock prices, they should allocate capital across startup firms in response to public market signals. That is, the sensitivity of VC investment to public market signals should be larger if more information is contained in public market stock prices and the IPO prospect is better.[13] To test our conjecture, we examine the effect of price informativeness on the sensitivity of VC investment to a public market signal, Tobin's Q, at the industry level. Specifically, we estimate the following model at the industry level:

$$VCinv_{i,t} = a_i + b_t + cInd\_Q_{i,t-1} + dInfo_{i,t-1} + eInd\_Q_{i,t-1} * Info_{i,t-1} + fVCinv_{i,t-1} + gControls_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $VCinv_{i,t}$ is the total VC investment in industry i at year t. We calculate three proxies for total VC investment. The first proxy, $N\_VCstartup_{i,t}$, is defined as the total number of investment rounds made by all new VC-startup pairs in industry i at year t. Following Gompers et al. (2008), this proxy captures the first-time investment by VC investors in a startup firm. Follow-on investments are excluded because the main interest is on new capital formation. Our second proxy, $N\_startup_{i,t}$, focuses on new capital formation as well and is defined as the number of new startups financed by VC investors in industry i at year t. The last proxy, $N\_ttlround_{i,t}$, is defined as the number of rounds made by all VC investors. The independent variables include $Ind\_Q_{i,t\text{-}1}$, the average Tobin's Q for industry i at year $t-1$, and $Info_{i,t\text{-}1}$, the average price informativeness measure for industry i at year $t-1$. We also control for industry asset tangibility, R&D expenditure, industry stock return and volatility, lagged VC industry investment, and year and industry fixed effects in the regressions.

Table 10 reports the results on VC learning and their overall investment. Column (1) shows that, when an industry has more investment opportunities, there would be more new VC-startup pairs in the industry, which is

Table 10. VC Learning and Capital Allocation Across Industries

	N_VCstartup		*N_startup*		*N_ttlround*	
Industry VC investment	(1)	(2)	(3)	(4)	(5)	(6)
*Ind_Q * Info*		0.029*		0.008*		0.014*
		(0.018)		(0.005)		(0.007)
Ind_Q	0.038*	−0.019	0.002	−0.014	0.006	−0.021
	(0.021)	(0.040)	(0.005)	(0.009)	(0.008)	(0.017)
Info	0.975	0.845	0.406**	0.368**	0.627**	0.566*
	(0.716)	(0.676)	(0.195)	(0.185)	(0.315)	(0.315)
Ind_tangi	−1.624	−1.662	−0.058	−0.069	−0.009	−0.026
	(1.376)	(1.381)	(0.319)	(0.322)	(0.462)	(0.463)
Ind_RD	16.108**	15.916**	2.971**	2.915**	9.292**	9.201**
	(7.954)	(7.953)	(1.461)	(1.473)	(4.455)	(4.465)
Ind_ret	0.061**	0.061**	0.012**	0.012**	0.025**	0.025**
	(0.024)	(0.024)	(0.005)	(0.005)	(0.011)	(0.011)
Ind_std	−90.462	−90.828	−23.849*	−23.955*	−51.062*	−51.234*
	(59.385)	(59.508)	(13.318)	(13.354)	(27.492)	(27.500)
Lagged Ind. VC Inv.	0.780***	0.780***	0.849***	0.849***	0.943***	0.943***
	(0.014)	(0.014)	(0.029)	(0.029)	(0.016)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,920	17,920	17,920	17,920	17,920	17,920

Notes. This table reports the OLS regression results on the effect of stock price informativeness in the public market on the relation between VC investment and public market valuation at the industry level. Dependent variables include the total number of investment rounds made by all new VC-startup pairs in an industry; the number of new startups financed by VCs in an industry; and the number of investment rounds made by all VCs in an industry. Other variables are defined as in Table 2 and calculated with data from the year prior to VC investments. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering at the industry level.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

consistent with the findings of Gompers et al. (2008). In column (2), the coefficient estimate on our main variable of interest, *Ind_Q*Info*, is positive and statistically significant. This finding suggests that the sensitivity of VC investment to industry investment opportunities is positive and significant when stock prices are more informative and startups are more likely to go public, which indicates that VC investors can effectively learn information contained in the prices. Columns (4) and (6) report the results on the effect of VC learning on *N_startup* and *N_ttlround*, respectively. The coefficient estimates on the interaction term, *Ind_Q*Info*, are also positive and significant in these two regressions, which is consistent with our finding with *N_VCstartup* and supports the learning hypothesis.

In this section, we find that, when public market stock prices are informative, VC investors respond to improved investment opportunities in an industry by increasing their investment in the industry as the IPO probability is higher. That is, VC investors not only use the information they learn from the public market to optimize their investment structures in startup firms but also to make investment decisions and allocate capital across startup firms accordingly.

8. Discussion and Conclusion

In this paper, we have examined the real effects of financial markets from the perspective of VC investors. When public market stock prices are more informative, suggesting a higher probability of going-public, VC investors are less likely to stage finance startup firms and to syndicate with other VCs, which reduce the costs associated with staging and syndication. Using exogenous variation in price informativeness generated by mutual fund forced sales because of fund outflows and airport shutdowns, we show that our main findings are likely causal. We further verify that IPO prospects of their portfolio firms are likely the valuable information contained in stock prices learned by VC investors when they decide on their investment structures. We also find that VCs' learning from the public market significantly affects their capital allocation across startup firms. Our paper sheds new light on the real effects of financial markets by showing that private equity investors actively learn information from the public equity market. Overall, our findings suggest that the informational role of security prices is much broader than what we have already thought.

Although our results are consistent with VCs' active learning from the public market, an alternative interpretation of our findings is that it could be driven by entrepreneur learning. Specifically, one could argue that entrepreneurs learn from the public market, and they may over-react to investor sentiment reflected in the public market. VC investors use staging to prevent entrepreneurs being too sensitive to public market sentiment. Hence, when stock prices are more informative, entrepreneur learning reduces their overreaction to public market sentiment and the need for VCs to stage is less. Although this argument seems appealing, in reality, entrepreneurs play very limited roles in the venture capital market. Competition among entrepreneurs for VC funding is very fierce, for example, on average 1 of 100 business proposals submitted by entrepreneurs could be funded by VC investors. As a result, VC investors play dominating roles during the processes of project selection, investment contracting, capital infusions, and exit decisions. We therefore believe that, compared with the entrepreneur learning argument, our results are most likely driven by VC learning.

Another concern is that our results on staging may be driven by entrepreneurs' greater bargaining power in hot markets. When the supply of private capital is high and entrepreneurs have a lot of bargaining power against VC investors, there is going to be less staging used by VCs. To rule out this alternative interpretation, we first include year-quarter fixed effects in all our analyses, which absorb the influences of private capital market conditions. We also control for Tobin' Q at the industry level (a proxy for public market conditions and price levels) and recent stock returns, which in turn could affect private capital supply. Second, we directly test whether VC investors stage less in hot markets by regressing our staging variables on the overall supply of venture capital proxied by the amount of VC fundraising and the number of newly established VC funds in each year.[14] Unreported results suggest that VC investors stage more in periods when they raise more money and establish more funds, which contradicts with the "hot market" interpretation of our results. One plausible reason of this observation is that hot markets are associated with both higher capital supply and investment risk. Though entrepreneurs are more likely to receive investments, VC investors need to monitor their investments more intensively. Therefore, we believe that our findings are more likely to be driven by the learning channel we proposed.

We also note that, although we argue that IPO prospects of their startups are one piece of the valuable information learned by VCs to guide their staging and syndication decisions (i.e., the IPO prospect channel), VC investors could learn a variety of information from the public market stock prices. For example, in the same spirit as the adverse selection model of Ferreira et al. (2011) that price informativeness and board independence are substitutes, informative prices could facilitate better monitoring on startup firms. That is, VC investors may learn the information from the public market to decide the optimal level of monitoring through staging and syndication (see Gompers (1995) and Tian (2011, 2012) on how VC investors monitor startups by staging and syndication). Our survey among VC investors also points out other valuable information (e.g., valuation, business environment, competitors) can be learned from the public market. Given the information set possessed by VC investors is not observable to researchers, our current tests cannot rule out the possibility that VC investors learn other pieces of valuable information from the public market that guide their investment structure decisions. We provide suggestive evidence and point out one most plausible and testable channel. Exploring other plausible channels through which VC learning affects their investment decision calls for future research when more relevant data become available.

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Appendix A. Variable Definitions

In *N_round*, *Skewness*, *Syn* and *N_VC* regressions, we calculate variables using data from the calendar year prior to the first round of VC financing. In *R_amount* and *Duration* regressions, we use variables calculated using data from the calendar year of the previous round of VC financing.

Table A.1. Variables

Variable name	Definition
N_Round	The total number of VC financing rounds a startup receives.
Skewness	The amount a startup receives from round one divided by total amount of VC financing across all financing rounds, multiplied by 100.
Syn	A dummy that equals one if a startup is financed by more than one VC across all rounds and zero otherwise.
N_VC	The number of VC investors in a syndicate co-investing in a startup.

Table A.1. (Continued)

Variable name	Definition
R_amount	The natural logarithm of the dollar amount of a round in thousands.
Duration	The duration in months from a funding date to the next funding date.
Info	The industry public market stock price nonsynchronicity measure, defined as $\ln((1-R^2)/R^2)$. R^2 is the industry average of *R*-squared obtained by regressing daily stock returns on market and industry returns.
PIN_{DY}	The industry average of probability of information-based trading, as defined in Duarte and Yong (2009).
Ind_Q	The industry average of Tobin's *Q*, calculated as the market value of equity plus long-term liability, divided by total assets plus long-term liability.
Ind_ret	The industry average of stock returns in excess of market returns.
Ind_RD	The industry average of R&D expenses ratio, calculated as the R&D expenses divided by total assets.
Ind_tangi	The industry average of the asset tangibility ratio, calculated as property, plant and equipment divided by total assets.
Ln_age	The natural logarithm value of startup age, defined as the number of years since the startup's inception.
Ln_amt1st	The natural logarithm value of the first round investment amount in thousand dollars.
$Amihud_{x1000}$	The industry average of the Amihud (2002) illiquidity ratio, multiplied by 1,000.
NMFHS	The industry average of the number of mutual fund hypothetical sales.
MFHS	The industry average of the magnitude of mutual fund hypothetical sales.
Shutdown	The natural logarithm of average days in a year when there are severe flight cancellations either in the airports closest to the firm's headquarters or closest to the offices of the financial analysts covering the firm.
IPOexp	A dummy variable that equals one if the startup's lead VC ranks in the top half by the number of IPOs in the same two-digit SIC industry from 1962 to the date of the first round of financing, and zero otherwise.
Shortdist	A dummy variable that equals one if the startup and its leading VC are in the same state, and zero otherwise.
HRD	A R&D expense dummy variable that equals one if the R&D spending in a startup's industry ranks in the top half among all industries, and zero otherwise.
N_VCstartup	The total number of investment rounds made by all new VC-startup pairs in an industry.
N_startup	The number of new startups financed by VCs in an industry.
N_ttlround	The number of investment rounds made by all VCs in an industry.
Ind_std	The industry average of stock return standard deviation.

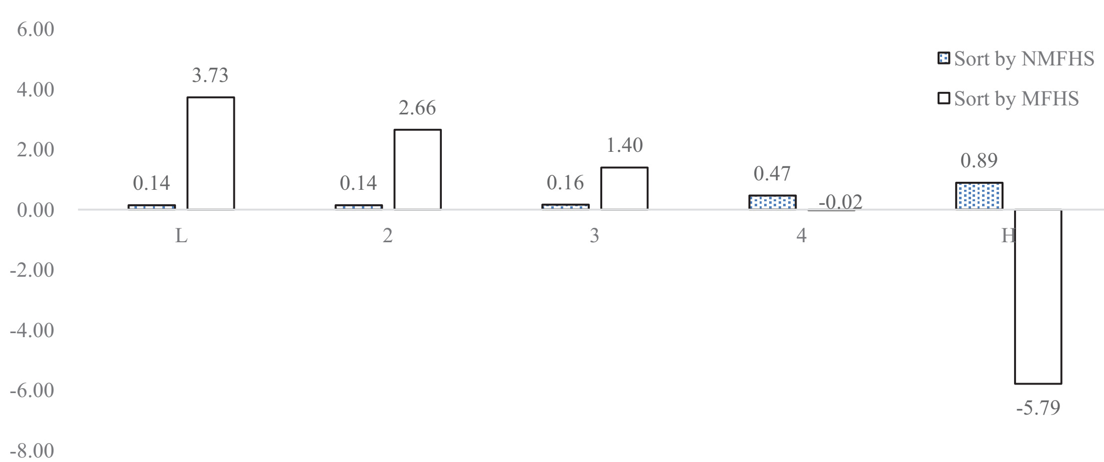
Appendix B. Data and Procedures for IV Construction and Additional Endogeneity Tests

B.1. Mutual Fund Hypothetical Sales Instrument

We follow the procedures proposed by Edmans et al. (2012) and Dessaint et al. (2019) to construct the frequency-based *NMFHS* instrument based on industry-level mutual fund hypothetical sales. For the convenience on comparing the *NMFHS* instrument with the instrument used by Edmans et al. (2012) and Dessaint et al. (2019), we also describe the procedures to estimate their intensity-based proxy, *MFHS*.

First, in each quarter *t*, we estimate the net inflow by each nonspecialized U.S. mutual fund *i* using the CRSP

Figure B.1. (Color online) Frequency and Intensity of Mutual Fund Hypothetical Returns and Stock Returns



Notes. This figure plots the average cumulative abnormal returns (CARs) for stocks sorted by the frequency of mutual fund hypothetical sales (*NMFHS*) and the magnitude of these sales (*MFHS*). The annual *MFHS* measure is calculated using the method suggested by Edmans et al. (2012) and Dessaint et al. (2019). Annual CARs in percentage are estimated by subtracting the CRSP equal-weighted index returns from stock returns from 1979 to 2011. Stocks are sorted into quintiles based on the absolute value of *NMFMS* (*MFHS*), and the mean CAR for each quintile is plotted.

survivor-bias-free mutual fund database:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + Return_{i,t})}{TNA_{i,t-1}}.$$

Because mutual fund shares could be offered in different classes, we estimate the fund-level total net asset, $TNA_{i,t}$, by aggregating class-level total net asset, $TNA_{k,t}$, across share classes k, and calculate fund-level gross returns, $Return_{i,t}$, as the value-weighted returns.

Next, we use quarterly mutual fund shareholding data from CDA Spectrum/Thomson to estimate the normalized hypothetical sales of stock m from a mutual fund p that experienced an extreme fund outflow ($Flow \leq -0.05$) in quarter t:

$$MFHS_{m,p,t} = \frac{Flow_{p,t}^{\leq -0.05} * Shares_{m,p,t-1} * PRC_{m,t-1}}{Vol_{m,t}}$$

where $Flow_{p,t}^{\leq -0.05}$ is the net inflow of fund p in quarter t; $Shares_{m,p,t-1}$ is the number of stock m held by fund p at the end of quarter $t-1$; $PRC_{m,t-1}$ is the closing price of stock m at last quarter end; and $Vol_{m,t}$ is the dollar trading volume for stock m in quarter t.

Third, in a given year, the frequency and intensity of hypothetical mutual fund sales for stock m are calculated by aggregating quarterly sales from the P mutual funds that held the stock and experienced an extreme outflow during the quarter:

$$NMFHS_m = \sum_{t=1}^{4} \sum_{p=1}^{P} I_{MFHS_{m,p,t}<0},$$

$$MFHS_m = \sum_{t=1}^{4} \sum_{p=1}^{P} MFHS_{m,p,t},$$

where t corresponds to the four quarters in the year; and $I_{MFHS_{m,p,t}<0}$ is an indicator variable that equals one if $MFHS_{m,p,t} < 0$ and zero otherwise. By construction, $NMFHS_m$ counts the number of fund-quarters with mutual fund hypothetical sales of stock m caused by extreme fund outflows across the year, and $MFHS_m$ measures the aggregate size of these sales.

Finally, we average $NMFHS_m$ and $MFHS_m$ across firms in an industry to calculate the corresponding industry-level mutual fund hypothetical sales measures *NMFHS* and *MFHS* for the year.

To compare the impacts of *NMFHS* and *MFHS* on stock price levels, we sort all stocks that are affected by mutual fund hypothetical sales into quintile portfolios based on these two measures and calculate the annual average cumulative abnormal returns (CARs) for each portfolio. CARs are estimated by subtracting the CRSP equal-weighted index returns from stock returns. For the stocks that are affected by mutual fund sales, prices increase slightly by 0.36%. As shown in Figure B.1, the prices of stocks ranking in the top quintile among all affected stocks (experiencing the largest *MFHS*) drop by 5.79%, which is consistent with findings in the literature. In contrast, the price increase for stocks ranking in the top quintile by *NMFHS* is only 0.89%, and more trivial in other quintiles, suggesting the frequency-based instrument is likely to have very small impacts on price levels.

B.2. Airport Shutdown Instrument

We follow the following steps to construct our instrumental variable, *Shutdown*, the natural logarithm value of annul flight-cancellation-days:

(1) We download the airline on-time performance data from the website of Bureau of Transportation Statistics, U.S. Department of Transportation.[15] The data set contains information on flight delays, cancellations, and diversions because of weather, air traffic, security, and airline reasons for 14 U.S. airlines that have at least 1% of total domestic scheduled-service passenger revenues since 1988. For each airport, if at least 20% of inbound and outbound flights in one day are cancelled because of the reasons mentioned previously, we label that day as an flight-cancellation day that prevent analysts' on-site visits.

(2) We assign each firm and following analysts the closest commercial airports from their offices, in which the firm-airport and analyst-airport geographical distances are calculated by the great circle distance formula:

$$\begin{aligned} Distance = 3963 * arccos(&\sin(latitude1)\sin(latitude2) \\ &+ \cos(latitude1)\cos(latitude2) \\ &\cos(longitude1 - longitude2)) \end{aligned}$$

with hand-collected analyst office zip codes data, firm headquarters zip codes information from Compustat, geological coordinates information for zip codes from CivicSpace U.S. ZIP Code Database (http://www.boutell.com/zipcodes/), and airport coordinate information from OpenFlights.org (http://openflights.org/data.html). The analysts following the public firms are obtained from the IBES data set.

(3) After merging firm and analyst airport data from Step 2 with airport flight-cancellation data from Step 1, we count the number of flight-cancellation days in each calendar year for each public firm-analyst pair. Last, the number of flight-cancellation days are averaged across analysts following the firm to compute firm-level annual cancellation days and then averaged across firms and taken natural logarithm of to compute the industry-level annual flight-cancellation-days, *Shutdown*.

Appendix C. Additional Robustness Checks

We perform a number of additional analyses to check the robustness of our results in this section. All these robustness check tests are undertaken in the 2SLS framework using *NMFHS* as the instrument as discussed in Section 4.2.

C.1. An Alternative Proxy for Price Informativeness

The probability of information-based trading, *PIN*, proposed by Easley et al. (1996) is a widely used price informativeness proxy in the literature (Chen et al. 2007). The *PIN* measure captures the probability of informed trading in a stock. Hence, a higher *PIN* suggests that stock prices incorporate more private information and stock prices are more informative. Duarte and Yong (2009) further decompose the original *PIN* measure into an asymmetric information component and an illiquidity component and develop a modified PIN_{DY} measure for the asymmetric information component.

Table C.1. Robustness Checks

	(1) *N_round*	(2) *Skewness*	(3) *Prob. Syn*	(4) *N_VC*
Panel A: Use PIN as an informativeness measure				
$\widehat{PIN_{DY}}$	−5.480**	152.495**	−1.596***	−13.999***
	(2.650)	(61.532)	(0.542)	(3.753)
Controls and fixed effects	Yes	Yes	Yes	Yes
Observations	10,916	8,320	10,916	10,916
Panel B: Use a 250-day measurement horizon				
$\widehat{Info_{250}}$	−0.202**	6.308***	−0.126***	−0.547***
	(0.098)	(2.337)	(0.041)	(0.146)
Controls and fixed effects	Yes	Yes	Yes	Yes
Observations	11,998	9,223	11,998	11,998
Panel C: Control for liquidity effects				
$\widehat{Info}$	−0.154**	4.783***	−0.129***	−0.426***
	(0.076)	(1.787)	(0.042)	(0.113)
$Amihud_{x1000}$	−2.868	78.594**	0.397	−2.545
	(3.066)	(33.678)	(0.285)	(3.015)
Controls and fixed effects	Yes	Yes	Yes	Yes
Observations	11,998	9,223	11,998	11,998

Notes. This table reports robustness checks for the results on the effects of stock price informativeness in the public market on VC staging and syndication. The sample consists of 13,185 startups completing VC financing between 1980 and 2012. The *NMFHS* instrument and the same set of control variables and fixed effects in Table 3 are used. The second-stage regression results are reported. Panel A reports results with the modified *PIN* defined in Duarte and Yong (2009) as the price informativeness measure. Panel B reports results with the stock price nonsynchronicity measure calculated with returns during the 250 days before the first round of VC financing. Panel C reports results with the Amihud (2002) illiquidity measure controlled. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity and clustering.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A of Table C.1 reports the second-stage regression results estimating Equation (3) with PIN_{DY} as an alternative price informativeness measure. The coefficient estimates on instrumented PIN_{DY} exhibit consistent signs with those reported in Table 3 and are statistically significant in all columns, suggesting that more informative public stock prices lead to less VC staging and syndication. In unreported analyses, we use the original *PIN* measure as defined in Easley et al. (2002) and obtain similar results.

C.2. Alternative Measurement Horizon for Price Nonsynchronicity

In the previous analysis, our main price informativeness measure is calculated using stock price information in the calendar year prior to the first VC financing round. To check whether our results are sensitive to the horizon of this measure, we construct the price informativeness measure using an alternative measurement horizon, that is, 250 trading days before the first round of VC financing. Panel B of Table C.1 reports the results using this alternative measurement horizon. The results are qualitatively the same as in Table 3.

C.3. Controlling for the Liquidity Effect

Exiting literature suggests that besides stock price informativeness, stock liquidity plays important roles and has real effects on firms such as on shareholder activism (Norli et al. 2015), innovation (Fang et al. 2014), and takeovers (Roosenboom et al. 2014). In addition, as argued by Duarte and Yong (2009) and Lai et al. (2014), the widely tested *PIN* measure defined by Easley et al. (2002) is potentially a liquidity measure rather than an information measure. To address these concerns, we directly control for a well-received liquidity proxy, the Amihud (2002) illiquidity ratio, to distinguish between the liquidity effect and the information effect we meant to examine.

Panel C of Table C.1 reports the regression results estimating Equation (3) with the Amihud (2002) illiquidity ratio included. The evidence shows that our main results are robust after controlling for the liquidity effect. We still observe a significant price informativeness effect across all regressions.

Endnotes

[1] Bond et al. (2012) provide an excellent survey on theoretical and empirical studies that examine the effects of financial markets on the real economy.

[2] Some exceptions are Foucault and Frésard (2014) who show private firms learn product market strategy from peer firms' stock prices and Yan (2020) who finds U.K. private firms react to noises in public market stock prices.

[3] Consistent with the theory's prediction, Chemmanur et al. (2018) find that entrepreneurs are more likely to take private firms public in industries with lower information asymmetry and more liquid stocks trading in the public market.

[4] Tian (2012) finds that 70% of entrepreneurial firms are financed by VC syndicates that consist of two or more VC investors between 1980 and 2005. Meanwhile, 88% of VC-backed firms that go public during the same period receive financing from VC syndicates.

[5] As noted by Tian and Wang (2014), in general VC industry requires investment liquidation within 10 years from the inception of the fund. Hence, startup firms failed to receive any follow-on VC investments within 10 years after the very last round are likely to be written off by VCs and have completed VC financing.

[6] We follow the following steps to determine the lead VC for a startup if a syndicate is formed (*N_VC* > 1): (1) we identify the VC making the largest investment amount across all financing rounds for the startup; (2) if the lead VC is not determined in Step 1 because of missing or equal total amounts, we choose the VC participating in the largest number of rounds for the startup; (3) if the lead VC is not determined in Step 2, we choose the VC with the most rounds of investments in any firm since 1962; and (4) if the lead VC is still not determined in Step 3, we choose the VC with the longest investment history.

[7] Edmans et al. (2012) and Dessaint et al. (2019) document that extreme mutual fund hypothetical sales induce long-lasting downward price pressure. In Figure B.1, we follow their methods to calculate the magnitude of mutual fund hypothetical sales, *MFHS* (see Appendix B.1 for the calculations) and find a similar price drop of 5.8% for extreme *MFHS* stocks during the year of sales. However, unlike *MFHS*, which is defined as the total dollar volume of mutual fund hypothetical sales, our frequency-based instrument *NMFHS* are unrelated to large price drops because of the following. (1) The previous results are obtained from stocks experiencing extreme *MFHS* ranking in the lowest decile (the largest total size of sales) and hence exposed to the largest negative shocks. In contrast, in our sample period, the stocks affected by *MFHS* have a moderate average annual market-adjusted return of 0.36% in the full sample. Our analysis is based on the full sample of stocks rather than those stocks with extreme *MFHS*. (2) *NMFMS* only accounts for the total number of sales, which may differ significantly from the number of shares sold captured by *MFHS*. The reason is *NMFHS* depends on the number of funds holding the stock experiencing extreme outflows, and *MFHS* depends on how many shares are held by these funds. Thus, these two measures are not necessarily highly correlated. Using stock-year level data, we find the correlation is only −0.026 in our sample period.

[8] In unreported analysis, we drop stocks for which the historical correlation between *NMFHS* and the absolute value of *MFHS* is in the top quintile among all stocks when calculating the industry average of *NMFHS* (the instrument) to eliminate the price-level effect. The results are qualitatively the same.

[9] In these tests, the incremental information is actually the noises caused by mutual fund forced sales. This does not contradict with our main hypothesis because VC investors could reduce staging and syndication (by mistake) as they observe larger price nonsynchronicity and believe that the IPO probability of their startup firms are higher.

[10] Consistent with this rationale, recent studies (Hong and Kacperczyk 2010, Kelly and Ljungqvist, 2012, He and Tian 2013, Chen et al. 2015) find that an exogenous loss in one analyst leads to various consequences on stock prices, liquidity, and firms' investment and financing decisions.

[11] In untabulated analyses, we use an alternative cutoff, 30%, to define severe flight cancellations to construct *Shutdown* for robustness checks. We obtain qualitatively similar results.

[12] We interact *Info* with VC investors' IPO experience in regressions to test the effect of experience on learning. In contrast, when testing whether VC investors learn from recent listings or historical listings, we calculate *Info* with the returns of recently (remotely) listed stocks and estimate Equation (3).

[13] Gompers et al. (2008) find that VCs with industry experience increase their investment in an industry when public market signals become favorable. In terms of corporate investment, Chen et al. (2007) show that price informativeness has a positive effect on the investment-price sensitivity of public firms. Foucault and Frésard (2014) study the sensitivity of corporate investment to peer firms' valuation.

[14] The data on VC fundraising is from Preqin, and the sample period is restricted to 2000–2012 because of data availability. We use a specification similar to Equation (3) but replace *Info* with fundraising proxies and drop the year-quarter fixed effects.

[15] See http://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time.

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