



## Management Science

Publication details, including instructions for authors and subscription information:  
<http://pubsonline.informs.org>

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To cite this article:

Bibo Liu, Xuan Tian (2022) Do Venture Capital Investors Learn from Public Markets?. Management Science 68(10):7274-7297.  
<https://doi.org/10.1287/mnsc.2021.4201>

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# Do Venture Capital Investors Learn from Public Markets?

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Received: October 1, 2019

Revised: January 25, 2021; April 19, 2021

Accepted: April 3, 2021

Published Online in Articles in Advance:  
December 1, 2021

<https://doi.org/10.1287/mnsc.2021.4201>

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**Abstract.** We examine whether venture capitalists (VCs) learn information contained in public market stock prices. VCs are less likely to stage financings and send a signal to other VCs when stock prices are more informative. An instrumental variable approach suggests that the relation is likely causal. The start-up's initial public offering (IPO) prospectus is the plausible information contained in stock prices learned by VCs. The effect of VC learning on staging and sending a signal is more pronounced when collecting information is more costly and the information learned is more reliable. Evidence from a sample of VC investments confirms that they actively learn information from the public market. VCs' learning from the public market significantly affects their investments across start-up 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 has been thought.

**History:** Accepted by G. S. Manolopoulos, finance.

**Funding:** X. Tian was supported by the National Natural Science Foundation of China [Grants 71825002, 71790591, and 91746301] and the Beijing Outstanding Young Scientists Program [Grant BJJWZYJH 01201910003014].

**Supplemental Material:** The data files are available at <https://doi.org/10.1287/mnsc.2021.4201>.

**Keywords:** learning • venture capital • staging • syndication • price informativeness

## 1. Introduction

Do venture capitalists (VCs) 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 (Aldama 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 investments in start-up firms and even all the performance of these firms in the public market.

Second, there has been an intense debate on whether the stock market is just a side show or has real effects on economic activities. Starting from the pioneering work by Haek (1945), which posits that prices are a useful source of information, theories (Grossman and Silg 1980, Goldstein and Gembel 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; Focall and Frésard 2012, 2014; Frésard 2011; Dessain et al. 2019).<sup>1</sup> 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.<sup>2</sup>

In his 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 investments in start-up firms. It is possible that VCs learn from the public market to collect valuable information as private markets are subject to more informational environments than public markets. For example, VC investors could respond to favorable public market signals (provided by higher Tobin's  $Q$ ) by increasing investments (Gompers et al. 2008). Capital market conditions have a modest effect on VC investors' decisions on investments but a larger effect on the timing decision of exits according to a sample by Gompers et al. (2020). Another sample by Gompers et al. (2016) shows that private equity investments are more likely to

se comparable public companies as benchmarks when estimating the value, and capital market conditions are the largest concern when he 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, signaling and signaling, 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 strategy decisions in startup firms.

Second, on a larger extent, the VC setting allows us to disentangle active managerial learning from passive reflections of startup-specific information in stock prices, a major empirical challenge faced by studies focusing on managers of public firms. Because the information possessed by managers of public firms is not directly observable to economists, even if one observes a firm's security price information, it 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 that managers have already known about their investment opportunities. Our focus on VC investors alleviates this concern to a larger degree because startup firms founded 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 in 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 source, 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 strategy (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 even all borne 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.<sup>3</sup> To the extent that the more information 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 make the startup public is stronger, and the startup's IPO probability is higher. In addition, recent strong evidence by Gompers et al. (2020) shows that VC investors attach the capital market to determine their exit strategies. Based on the previous discussion, we argue that the information contained in the public market matters for VC investors and possibly that if VC investors are able to learn the information from information stock prices that their portfolio firms' IPO probabilities are higher, they adjust their investment strategies accordingly. In particular, we attempt to link VC investment strategies to stock price information of public firms in the same industry of the VC investors' portfolio firms.

Specifically, the strategy of VC investment in startups focuses on includes VC stage financing and signaling. VC signaling 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 uncertain 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 because of the potential costs associated with VC signaling 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, the older stage

finance less to reduce the costs of signaling. We consider the measures to capture VC signaling: the total number of financing rounds a startup firm receives from its VC investors and investors' skepticism (i.e., the percentage of investors' amount a startup receives in the first round). If our learning hypothesis is supported, we expect to observe that VC investors end up in 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 investor feature we explore is VC signaling, which is an ending and signaling feature of the VC industry (Lerner 1994, Tian 2012, Baar et al. 2020).<sup>4</sup> 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 opacity nature of startup firms. However, signaling 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 investor 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 investors' efficiency. Hence, to reduce the costs associated with signaling, 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















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 is a causal link between public market price informativeness and VC investments.<sup>9</sup>

**4.2.2. Instrument Based on Airport Shutdowns.** To ensure the results documented previously are robust, besides *NMFHS*, we construct a second instrument

**Table 4.** Endogeneity Tests with an Alernaive IV

	First stage (1) <i>Info</i>	Second stage			
		(2) <i>N_round</i>	(3) <i>Skewness</i>	(4) <i>Prob. Syn</i>	(5) <i>N_VC</i>
<i>Shutdown</i>	−0.060*** (0.010)				
<i>Info</i>		−2.536* (1.517)	42.249** (15.810)	−0.369*** (0.105)	−1.131*** (0.419)
<i>Ind_Q</i>	−0.003*** (0.001)	−0.016*** (0.006)	0.241 (0.150)	−0.002** (0.001)	−0.020*** (0.007)
<i>Ind_ret</i>	−0.111*** (0.019)	−0.210 (0.199)	2.542 (2.226)	−0.024 (0.023)	−0.093 (0.167)
<i>Ind_RD</i>	1.658*** (0.110)	2.683 (2.520)	−68.310* (37.102)	0.677*** (0.184)	3.732*** (0.576)
<i>Ind_tangi</i>	1.334*** (0.284)	2.044 (2.300)	−46.332 (34.586)	0.441*** (0.125)	−1.028* (0.523)
<i>Ln_age</i>	−0.006* (0.003)	−0.318*** (0.038)	8.898*** (0.633)	−0.054*** (0.005)	−0.530*** (0.053)
<i>Ln_amt1st</i>	−0.002 (0.003)	−0.267*** (0.034)		0.017*** (0.003)	0.050** (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 aging and syndication. The instrumental variable is the natural logarithm of a average number of days when analysts having difficulties in paying on-site visits to public firms in the same industry as a sample of severe flight cancellations (defined as more than 20% of inbound and outbound flights are cancelled) caused by either operational conditions either in the airports closes or the firm's headquarters or closes or 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 airports 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 tests. This suggests that our analyses do not have a weak instrument problem. In the second-stage regressions reported in columns (2)–(5), the observed significant coefficients implies on the instrumented *Info* that signs consistent with those reported in Table 2.<sup>11</sup> Hence, using this alternative instrument, we continue to find a negative and causal link between stock price informativeness and VC aging and syndication.

### 4.3. Heterogeneity Tests

To further strengthen the causal link between VC learning and their investment strategies, we perform a battery of tests that explore the heterogeneous effects of public market price informativeness on VC aging 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 aging 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 aging and syndication is less pronounced if the VC is located close to the startup.

To test this conjecture, we estimate the following model:

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

where *Shortdist* is a dummy variable 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 instrument in the second-stage regressions. Table 5 reports the second-stage regression results. The coefficients estimates on the instrumented *Info* exhibit signs that are consistent with those observed in Table 3. The coefficients estimates on the key variable of interest, the instrumented *Info\*Shortdist*, are statistically significant

and exhibit signs opposite to those on the insured *Info* in the *N\_round*, *Skewness*, and *N\_VC* regressions. For example, in column (1), the positive and significant coefficients indicate on the insured *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 costs of staging and syndication. However, if the collected information is less reliable, VC investors would stick to the portfolio, 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 to that from industries in which private and public firms are similar in nature. Hence, we expect that the effect of public market price

information on VC staging and syndication is less pronounced in industries consisting of more heterogeneous firms.

We use the industry R&D expenditure ratio as a proxy for the comparability of firms within an industry. R&D intensive industries are characterized by more investments 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 assess the effect of industry comparability on VC learning. The interaction term is



Table 7. Round-Level Evidence

	Baseline regressions		IV regressions: Second stage	
	(1) <i>R_amount</i>	(2) <i>Duration</i>	(3) <i>R_amount</i>	(4) <i>Duration</i>
<i>Info</i>	−0.0003 (0.028)	3.080*** (0.400)		
<i>Info</i>			0.652*** (0.206)	47.028*** (3.308)
<i>Ind_Q</i>	0.003 (0.003)	−0.073*** (0.021)	0.000 (0.003)	−0.258*** (0.041)
<i>Ind_ret</i>	−0.003 (0.032)	−0.936*** (0.324)	−0.155*** (0.056)	−9.575*** (0.925)
<i>Ind_RD</i>	0.599** (0.265)	−9.388*** (3.267)	−0.103 (0.332)	−50.312*** (6.969)
<i>Ind_tangi</i>	−0.133 (0.389)	62.270*** (5.655)	−0.578 (0.419)	35.914*** (8.716)
<i>Ln_age</i>	−0.291*** (0.033)	−29.542*** (0.778)	−0.274*** (0.035)	−26.669*** (0.958)
<i>Lag_amt</i>	0.003 (0.009)		0.003 (0.009)	
<i>Lag_duration</i>		−0.189*** (0.017)		−0.167*** (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 information in the public market on VC round amounts and durations. The sample consists of 31,219 VC follow-on investments made 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 sample level.

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

We propose that a plausible piece of valuable information contained in public market stock prices that VC investors actually learn is the IPO prospects of their startup firms. According to the model of Chemmanur and Flghieri (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 even all borne 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 exercises that explore how IPO-related variables affect our main results.

We first use the IPO prospect channel by comparing the effect of stock price informativeness of recent going-public firms on VC staging and syndication of those firms going public earlier. Because the prices of

recent 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-examine our main specification in Equation (3) in the 2SLS framework using NMFHS as the instrument in subsamples. In the *Recent* subsample, *Info* is estimated in the stock returns of firms in the same industry of the startup in 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 in the stock returns of firms in 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 coefficients are on the instrumented *Info* between the 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

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 recent going-public firms when determining the investment returns in their portfolio firms.

Our second lesson 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 less 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.











Table A.1. (Con in ed)

Variable name	Defini ion
<i>R_amount</i>	The na ral logari hm of he dollar amo n of a ro nd in ho sands.
<i>Duration</i>	The d ra ion in mon hs from a f nding da e o he ne f nding da e.
<i>Info</i>	The ind s r p blic marke s ock price nons nchronici meas re, defined as $\ln((1 - R^2)/R^2)$ . $R^2$ is he ind s r average of $R$ -sq ared ob ained b regressing dail s ock re rns on marke and ind s r re rns.
<i>PIN<sub>DY</sub></i>	The ind s r average of probabili of informa ion-based rading, as defined in D are and Yong (2009).
<i>Ind_Q</i>	The ind s r average of Tobin's $Q$ , calc la ed as he marke val e of eq i pl s long-erm liabili , divided b oal asse s pl s long-erm liabili .
<i>Ind_ret</i>	The ind s r average of s ock re rns in e cess of marke re rns.
<i>Ind_RD</i>	The ind s r average of R&D e penses ra io, calc la ed as he R&D e penses divided b oal asse s.
<i>Ind_tangi</i>	The ind s r average of he asse angibili ra io, calc la ed as proper , plan and eq ipmen divided b oal asse s.
<i>Ln_age</i>	The na ral logari hm val e of s ar p age, defined as he n mber of ears since he s ar p's incep ion.
<i>Ln_amt1st</i>	The na ral logari hm val e of he firs ro nd in ves men amo n in ho sand dollars.
<i>Amihud<sub>x1000</sub></i>	The ind s r average of he Amih d (2002) illiq idi ra io, m l iplied b 1,000.
<i>NMFHS</i>	The ind s r average of he n mber of m al f nd h po he ical sales.
<i>MFHS</i>	The ind s r average of he magni de of m al f nd h po he ical sales.
<i>Shutdown</i>	The na ral logari hm of average da s in a ear hen here are severe fligh cancella ions ei her in he airpor s closes o he firm's headq ar ers or closes o he offices of he financial anal s covering he firm.
<i>IPOexp</i>	A d mm variable ha eq als one if he s ar p's lead VC ranks in he op half b he n mber of IPOs in he same o-digi SIC ind s r from 1962 o he da e of he firs ro nd of financing, and ero o her ise.
<i>Shortdist</i>	A d mm variable ha eq als one if he s ar p and i s leading VC are in he same s a e, and ero o her ise.
<i>HRD</i>	A R&D e pense d mm variable ha eq als one if he R&D spending in a s ar p's ind s r ranks in he op half among all ind s ries, and ero o her ise.
<i>N_VCstartup</i>	The oal n mber of in ves men ro nds made b all ne VC-s ar p pairs in an ind s r .
<i>N_startup</i>	The n mber of ne s ar ps financed b VCs in an ind s r .
<i>N_ttlround</i>	The n mber of in ves men ro nds made b all VCs in an ind s r .
<i>Ind_std</i>	The ind s r average of s ock re rns andard devia ion.

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

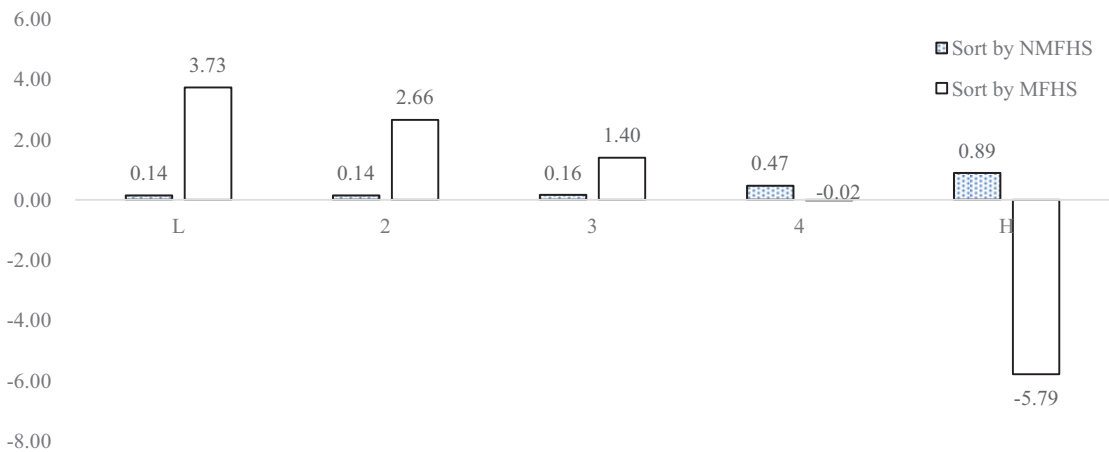
B.1. Mutual Fund Hypothetical Sales Instrument

We follo he proced res proposed b Edmans e al. (2012) and Dessain e al. (2019) o cons r c he freq enc -based

*NMFHS* ins r men based on ind s r -level m al f nd h -po he ical sales. For he convenience on comparing he *NMFHS* ins r men ih he ins r men sed b Edmans e al. (2012) and Dessain e al. (2019), e also describe he proced res o es ima e heir in ensi -based pro , *MFHS*.

Firs , in each q arer  $t$ , e es ima e he ne inflo b each nonspecialized U.S. m al f nd i sing he CRSP

Figure B.1. (Color online) Freq enc and In ensi of M al F nd H po he ical Re rns and S ock Re rns



Notes. This fig re plo s he average c m lai e abnormal re rns (CARs) for s ocks sor ed b he freq enc of m al f nd h po he ical sales (*NMFHS*) and he magni de of hese sales (*MFHS*). The ann al *MFHS* meas re is calc la ed sing he me hod s gges ed b Edmans e al. (2012) and Dessain e al. (2019). Ann al CARs in percen age are es ima ed b s b rac ing he CRSP eq al- eigh ed inde re rns from s ock re rns from 1979 o 2011. S ocks are sor ed in o q in iles based on he absol e val e of *NMFMS* (*MFHS*), and he mean CAR for each q in ile is plo ed.

is a prior-bias-free method database:

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

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

Next, we set quarterly market shareholding data from CDA Spectrum/Thomson to estimate the normalized hypothetical sales of stock  $m$  from a market 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 the 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 market sales for stock  $m$  are calculated by aggregating quarterly sales from the  $P$  market 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 in which 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 market 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 market fund hypothetical sales in our sample portfolios based on these 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 market 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 a smaller impact on price levels.

## B.2. Airport Shutdown Instrument

We follow the following steps to construct our instrumental variable, *Shutdown*, the natural logarithm value of annual flight cancellations:

(1) We download the airline on-time performance data from the website of Bureau of Transportation Statistics, U.S. Department of Transportation.<sup>15</sup> The database 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, the label has data as an flight-cancellation day has previous analysis.

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Table C.1. Robustness Checks

	(1) <i>N_round</i>	(2) <i>Skewness</i>	(3) <i>Prob. Syn</i>	(4) <i>N_VC</i>
Panel A: Use <i>PIN</i> as an informationness measure				
<i>PIN</i>	−5.480** (2.650)	152.495** (61.532)	−1.596*** (0.542)	−13.999*** (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				
<i>Info</i> <sub>250</sub>	−0.202** (0.098)	6.308*** (2.337)	−0.126*** (0.041)	−0.547*** (0.146)
Controls and fixed effects				
Observations	11,998	9,223	11,998	11,998
Panel C: Control for liquidity effects				
<i>Info</i>	−0.154** (0.076)	4.783*** (1.787)	−0.129*** (0.042)	−0.426*** (0.113)
<i>Amihud</i> <sub>x1000</sub>	−2.868 (3.066)	78.594** (33.678)	0.397 (0.285)	−2.545 (3.015)
Controls and fixed effects	Yes	Yes	Yes	Yes
Observations	11,998	9,223	11,998	11,998

Notes: All the robustness checks for the return stock price measures in the public market VC's aging and the sample consists of 13,185 startups completed financing in 1980 and 2012. The NM's ratio is the same set of control variables defined in Table 3. The second-stage regression is also reported. Panel A reports results for the modified *PIN* defined in Dar and Yong (2009) as the price information measure. Panel B reports results for the modified *PIN* defined in Dar and Yong (2009) as the price information measure. Panel C reports results for the Amihud (2002) illiquidity ratio. All the regression results are adjusted for the standard errors. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A of Table C.1 reports the second-stage regression results using Equation (3) with *PIN*<sub>DT</sub> as an alternative price informationness measure. The coefficients estimates on the first round *PIN*<sub>DT</sub> exhibit consistent signs with those reported in Table 3 and are statistically significant in all columns, suggesting that more information in public stock prices leads to less VC's aging and standardization. In the reported 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 informationness 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 consider the price informationness 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

Evidence suggests that besides stock price informationness, 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 acquisitions (Roosenboom et al. 2014). In addition, as argued by

Dar and Yong (2009) and Lai et al. (2014), the widely used *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 more clearly.

Panel C of Table C.1 reports the regression results using 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 informationness effect across all regressions.

Endnotes

- <sup>1</sup> Bond et al. (2012) provide an excellent survey on theoretical and empirical studies that examine the effect of financial markets on the real economy.
- <sup>2</sup> Some exceptions are Focall and Frésard (2014) who show private firms learn product market strategies from peer firms' stock prices and Yan (2020) who finds U.K. private firms react to noises in public market stock prices.
- <sup>3</sup> 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 liquidity shocks trading in the public market.
- <sup>4</sup> Tian (2012) finds that 70% of entrepreneurs are financed by VC's indicating that consists of a more VC-intensive environment. While, 88% of VC-backed firms have gone public during the same period receiving financing from VC's indicating.

<sup>5</sup> As noted by Tian and Wang (2014), in general VC investors require information in 10 years from the inception of the fund. Hence, startups that failed to receive an follow-on VC investment within 10 years after the first round are likely to be written off by VCs and have completed VC financing.

<sup>6</sup> We follow the following steps to determine the lead VC for a startup if a syndicate is formed ( $N_{VC} > 1$ ): (1) 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 ownership 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 investment in an 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.

<sup>7</sup> Edmans et al. (2012) and Dessain et al. (2019) document that the relationship between the initial sales and the long-lasting downward price pressure. In Figure B.1, we follow their methods to calculate the magnitude of the initial sales, *MFHS* (see Appendix B.1 for the calculation) and find a similar price drop of 5.8% for the *MFHS* stocks during the year of sales. However, unlike *MFHS*, which is defined as the total dollar volume of the initial sales, our frequency-based indicator *NMFHS* are unrelated to large price drops because of the following. (1) The previous results are obtained from stocks experiencing the *MFHS* ranking in the lowest decile (the largest total sale 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 in the *MFHS*. (2) *NMFHS* 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 the event, flows, and *MFHS* depends on how many shares are held by these funds. Thus, these measures are not necessarily highly correlated. Using stock-level data, we find the correlation is only -0.026 in our sample period.

<sup>8</sup> In the reported analysis, the drop in 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 indicator *NMFHS* (the indicator) eliminates the price-level effect. The results are qualitatively the same.

<sup>9</sup> In these cases, the incremental information is across all the noise caused by the initial forced sales. This does not contradict the other main hypothesis because VC investors could reduce signaling and syndication (by mistake) as they observe larger price non-synchronicity and believe that the IPO probability of their startups is higher.

<sup>10</sup> Consistent with his rationale, recent studies (Hong and Kacperczyk 2010, Kell and Ljungqvist 2012, He and Tian 2013, Chen et al. 2015) find that an exogenous loss in one analysis leads to various consequences on stock prices, liquidity, and firms' investment and financing decisions.

<sup>11</sup> In the natural experimental setting, we see an alternative cutoff, 30%, to define severe flight cancellations or conscription *Shutdown* for robustness checks. We obtain qualitatively similar results.

<sup>12</sup> We include *Info* in the VC investors' IPO experience in regressions to test the effect of experience on learning. In contrast, when including the VC investors learn from recent listings or historical listings, we calculate *Info* in the returns of recent (removed) listed stocks and estimate Equation (3).

<sup>13</sup> 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. Fomatal and Frésard (2014) study the sensitivity of corporate investment to peer firms' valuation.

<sup>14</sup> 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) to replace *Info* in fundraising proxies and drop the year-quarter fixed effects.

<sup>15</sup> See [https://www.fama.org/Downloads/SelectFields.aspx?TableID=236&DB\\_ShortName=On-Time](https://www.fama.org/Downloads/SelectFields.aspx?TableID=236&DB_ShortName=On-Time).

## References

- Aldamale, S., Brown, G.W. (2020) Private equity in the global economy: Evidence on industry spillovers, *J. Corporate Finance*, 60.
- Amihud, Y. (2002) Illiquidity and stock returns: Cross-section and time-series effects, *J. Financial Markets* 5(1):31–56.
- Baron, O., Chemmanur, T., Tian, X. (2020) Peer monitoring, syndication, and the dynamics of venture capital investments: Theory and evidence, *J. Financial Quantitative Analysis*, 55(6):1875–1914.
- Bernstein, S., Giroud, X., Townsend, R.R. (2016) The impact of venture capital monitoring, *J. Finance* 71(4):1591–1622.
- Bond, P., Edmans, A., Goldstein, I. (2012) The real effects of financial markets, *Annu. Rev. Financial Economics*, 4(1):339–360.
- Bradley, D., Clarke, J., Lee, S., Ornathalai, C. (2014) Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delay, *J. Finance* 69(2):645–673.
- Brennan, M.J., Sraha, A. (1995) Investment analysis and price formation in securities markets, *J. Financial Economics*, 38(3):361–381.
- Brennan, M.J., Jegadeesh, N., Srinivasan, B. (1993) Investment analysis and the adjustment of stock prices to common information, *Rev. Financial Studies*, 6(4):799–824.
- Chan, K., Chan, Y.-C. (2014) Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offerings, *J. Financial Economics*, 114(1):36–53.
- Chemmanur, T.J., Fich, P. (1999) A theory of going-public decision, *Rev. Financial Studies*, 12(2):249–279.
- Chemmanur, T.J., Lofskin, E., Tian, X. (2014) Corporate venture capital, value creation, and innovation, *Rev. Financial Studies*, 27(8):2434–2473.
- Chemmanur, T.J., He, J., He, S., Nand, D. (2018) Product market characteristics and the choice between IPOs and acquisitions, *J. Financial Quantitative Analysis*, 53(2):681–721.
- Chen, Q., Goldstein, I., Jiang, W. (2007) Price informativeness and investment sensitivity to stock price, *Rev. Financial Studies*, 20(3):619–650.
- Chen, T., Harford, J., Lin, C. (2015) Do analysts matter for governance? Evidence from natural experiments, *J. Financial Economics*, 115(2):383–410.
- Cheng, Q., Dechow, D., Wang, X., Wang, Y. (2016) Seeing is believing: Analysts' corporate securities, *Rev. Accounting Studies*, 21(4):1245–1286.
- Coval, J., Stafford, E. (2007) Asset fire sales (and purchases) in equity markets, *J. Financial Economics*, 86(2):479–512.
- Da Rin, M., Hellmann, T., Puri, M. (2013) A survey of venture capital research. Constantinides, G., Harris, M., Sarno, L., eds. *Handbook of the Economics of Finance*, vol. 2 (Elsevier, North Holland), 573–648.
- Dessain, O., Fomatal, T., Frésard, L., Marra, A. (2019) Noise stock prices and corporate investment, *Rev. Financial Studies*, 32(7):2625–2672.
- Dooley, J., Gordon, G. (1997) Stock market efficiency and economic efficiency: Is there a connection? *J. Finance* 52(3):1087–1129.
- Daraj, J., Yong, L. (2009) What is PIN priced? *J. Financial Economics*, 91(2):119–138.
- Dme, A., Morck, R., Yeung, B. (2004) Value-enhancing capital budgeting and firm-specific stock return variation, *J. Finance*, 59(1):65–105.



- Easley D, Hvidkjaer S, O'Hara M (2002) Is information risk a determinant of asset returns? *J. Finance* 57(5):2185–2221.
- Easley D, Kiefer NM, O'Hara M (1996) Cream-skimming or profit-sharing? The critical role of purchased order flow. *J. Finance* 51(3):811–833.
- Edmans A, Goldstein I, Jiang W (2012) The real effects of financial markets: The impact of prices on takeover offers. *J. Finance* 67(3):933–971.
- Engelberg JE, Parsons CA (2011) The causal impact of media in financial markets. *J. Finance* 66(1):67–97.
- Fang VW, Tian X, Tice S (2014) Does stock liquidity enhance or impede firm innovation? *J. Finance* 69(5):2085–2125.
- Ferreira D, Ferreira MA, Raposo CC (2011) Board structure and price informativeness. *J. Financial Econom.* 99(3):523–545.
- Focall T, Frésard L (2012) Cross-listing, investor sensitivity to stock price, and the learning hypothesis. *Rev. Financial Stud.* 25(11):3305–3350.
- Focall T, Frésard L (2014) Learning from peers' stock prices and corporate investors. *J. Financial Econom.* 111(3):554–577.
- Frésard L (2012) Cash savings and stock price informativeness. *Rev. Finance* 16(4):985–1012.
- Giammarino R, Heinkel R, Hollifield B, Li K (2004) Corporate decisions, information and prices: Do managers move prices or do prices move managers? *Econom. Notes* 33(1):83–110.
- Goldstein I, Gompers P (2008) Manipulation and the allocational role of prices. *Rev. Econom. Stud.* 75(1):133–164.
- Gompers P (1995) Optimal investor monitoring and the pricing of venture capital. *J. Finance* 50(5):1461–1489.
- Gompers P, Kaplan SN, Mohan V (2016) What do private equity firms really do? *J. Financial Econom.* 121(3):449–476.
- Gompers P, Gornall W, Kaplan SN, Siegel IA (2020) How do venture capitalists make decisions? *J. Financial Econom.* 135(1):169–190.
- Gompers P, Kohner A, Lerner J, Scharfstein D (2008) Venture capitalists' roles: The impact of public markets. *J. Financial Econom.* 87(1):1–23.
- Grossman S (1976) On the efficiency of competitive stock markets where traders have diverse information. *J. Finance* 31(2):573–585.
- Grossman S, Stiglitz J (1980) On the impossibility of informationally efficient