# Is the Stock Market Just a Side Show? Evidence from Venture Capital

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# Is the Stock Market Just a Side Show? Evidence form Venture Capital


## Abstract

We examine the real effects of financial markets from the perspective of venture capital (VC) investors. We postulate that VCs actively learn information contained in public markets when designing investment structure in their startup ventures. We find that, when public market prices are more informative, VCs are less likely to stage finance startup ventures and to syndicate with other VCs to save the costs associated with staging and syndication. This effect is more pronounced when VCs are lack of industry-specific expertise, VCs are physically distant from their ventures so that collecting soft information is costly, and their investments are less risky. Using exogenous events that unexpectedly alter financial analysts' and short sellers' ability to produce information, which makes public market prices less informative, we show that our results are unlikely driven by endogeneity. Our paper sheds new light on the real effects of financial markets by showing that private equity investors actively learn information from public equity markets.



Key words: Learning; Venture capital; Staging; Syndication; Price informativeness

JEL number: G24; G18; G14

## 1. INTRODUCTION

Is the stock market just a side show or does it have real effects on economic activities? Conventional wisdom believes that stock market security prices merely reflect expectations about future cash flows. However, a growing strand of literature in financial economics challenges this traditional view by both theoretically arguing for and empirically documenting evidence about the real effects of secondary stock markets on corporate decision making. Specifically, following the insightful work of Hayek (1945), which posits that prices are a useful source of information, recent theories (e.g., Grossman, 1976; Hellwig, 1980; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Goldstein and Guembel, 2008) argue that while 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. Consequently, managers of publicly traded firms can learn from the information in stock prices about the prospects of their own firms and use this information to guide their real investment decisions.[1]

While the above argument is very compelling, empirically testing the argument is challenging, because the information set possessed by managers of publicly traded firms is not observable to econometricians. As a result, 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. To alleviate this concern, in this paper, we focus on the investment decisions made by venture capital (VC) fund managers and examine whether VC fund managers learn from public market equity prices and use the information to guide their investment in startup companies.

Venture capital provides an ideal research setting that offers several unique but important advantages. First, startup ventures funded by VC investors are private companies whose shares are not publicly traded and do not have a stock price. Hence, it is unlikely that venture-specific information known by VC fund managers is reflected into the stock prices of public firms, even though the public firms are in the same industry as the startup venture. Hence, the concern that stock prices of public firms being a passive reflection is mitigated in the VC setting. Second, VC

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

fund managers have great incentives to learn from the public markets. VCs invest in early-stage startup ventures that have high growth potential but also substantial failure risk. VC industry is characterized as being full of information asymmetry between investors and entrepreneurs. Hence, before making investment decisions, VC fund managers have larger incentives to learn from the public market than public firm managers who possess more information and suffer from information asymmetry problems to a less extent. Finally, VC staging and syndication, unique features of VC investments compared to public firm investments, provide a variety of dimensions that allow us to better understand how precisely the information learnt from the public market affects VC fund managers' investment decisions in startup ventures.

To exploit the unique features of VC investment, we focus on VC stage financing and syndication in this paper. The staging of capital infusions by VC fund managers is the stepwise disbursement of capital from VC investors to startup ventures. It is an effective tool used by VCs to mitigate information asymmetry and uncertainty associated with startup ventures because it keeps a real option value of abandoning underperforming ventures (Sahlman, 1990; Gompers, 1995). However, as argued in Tian (2011), stage financing is not a free lunch but costly. Potential costs arising from VC staging include negotiation and contracting costs in each round of financing, forgone economics of scale due to divided capital infusions, induced short-termist behavior on the part of entrepreneur, and underinvestment in early-stage ventures. Hence, if pubic market prices are more informative so that VC fund managers can more effectively learn to guide their investment decisions, we expect that they will stage finance less to save the cost of staging. We develop three measures to capture VC staging: the number of rounds (i.e., the total number of financing rounds a startup venture receives from its VC investors), investment skewness (i.e., the amount an startup receives from the first round divided by total amount it receives across all financing rounds), and change in round amount (i.e., the difference in investment amount a venture receives from the current round and from the previous round). If our argument is supported, we expect to observe that VC fund managers tend to invest fewer rounds, invest more in the first round, and increase round amount if the stock prices of public firms in the same industry are more informative.

VC syndication is an enduring and striking feature of the VC industry (Lerner, 1994).[2] One main motivation for VCs to form syndicates to co-invest a startup is to seek a second opinion from other VCs (Lerner, 1994; Brander, Amit, and Antweiler, 2002) because of the high opaqueness nature of startup ventures. However, VC syndication is also very costly. First, co-investing a venture means that the VC who first identifies the deal has to share the returns with other VCs and cannot exclusively enjoy the reward if it turns out that the venture is a great success. Second, different types of VC investors (e.g., traditional 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 VCs to deal with problematic startups if there are multiple VC investors co-investing the venture, which increases communication costs and reduces investment efficiency. Hence, to avoid the costs associated with syndication, we expect that, if the stock prices of public firms in the same industry of their ventures are more informative, VCs are less likely to syndicate with other VCs and the syndicate size is more likely to be small.

Using a sample of 13,185 startup ventures that receive VC financing between 1980 and 2012, we find that public market price informativeness significantly affects the staging and syndication of VCs. Specifically, VC fund managers finance a venture with a smaller number of financing rounds, with more money invested in the first round, with more round amount, and with fewer other VCs co-investing if the stock prices of public firms in the same industry of the venture are more informative. Our finding is consistent with the hypothesis that VC fund managers learn from public market prices and respond by altering the structure of their investment in startup ventures to avoid the costs associated with staging and syndication.

Even though our research setting of VC markets significantly alleviates the concern that stock prices are merely reflections of what managers have already known about the investment opportunities instead of managers actively learning information from stock prices, it is still possible that some unobservable factors in the VC fund managers' information set that affect both the structure of their investments in startup ventures and industry stock price informativenss of publicly traded firms drive the results. In other words, our findings are not driven by VC fund

[2] 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.

managers' learning from the public markets but by omitted variables. To tackle this endogeneity concern, we use two different identification strategies.

Our first identification strategy is to construct an instrumental variable that captures exogenous reductions in stock price informativeness and to use the two-stage least squares (2SLS) analysis. Following the spirit of existing literature (Koudijs, 2014, 2015; Engelberg and Parsons, 2011), our instrument is based on the rationale that airport shutdowns due to 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 2SLS results are consistent with our OLS results and, more importantly, reveal the direction of potential bias if the omitted variable problem is not appropriately controlled for.

Our second identification strategy relies on a regulatory change on short-selling constraints, Regulation SHO, that remove the uptick rule restriction for a randomly selected group of Russell 3000 firms (pilot firms). This sudden regulatory change provides a quasi-natural setting that alters short selling costs. To the extent that short sellers, a group of investors who actively collect various pieces of information about the firms, positively contribute to stock price informativeness, Regulation SHO makes stock prices of pilot firms more informative. We find generally consistent results, using the difference-in-differences (DiD) approach. Overall, our identification tests suggest that VC fund managers appear to learn from public market stock prices and respond by altering the structure of their investment in startup companies.

We next do additional tests to explore the heterogeneous effects of public market price informativeness on VC investment structure. We first explore how a VC's experience alters our baseline results. We distinguish a VC's industry-specific experience from its general experience. We posit that if a VC is more experienced in the venture's industry, it should rely less on the information contained in the public market. Hence, the effect of stock price informativeness on VC investment structure should be less pronounced when the VC is more experienced in the venture's industry. In contrast, a VC's general experience may not help it in specific industries to the same extent of its industry expertise. As a result, VCs with more general experience may still need to actively learn from public market prices. Consistent with our conjecture, our main results are more pronounced if the VCs are lack of industry experience but are largely unchanged if the VCs have more general experience.

The second heterogeneous test we perform explores how physical distance between VCs and their venture firms alters our main results. The rationale behind this test is that geography matters in VC financing because close proximity reduces a VC's monitoring cost (Lerner, 1995) and the cost of physically collecting information about the ventures. Tian (2011) further shows that VCs use less stage financing if they are located closer to their startup ventures because of reduced monitoring costs, which suggests intensive monitoring and staging are substitutes. If intensive monitoring and more information collection by VC fund managers become less costly due to close proximity, these VCs may rely less on the information contained in public market prices. Hence, we expect the effect of stock price informativeness on the structure of VC financing to be less pronounced if the physical distance between VCs and startup ventures is short. We find evidence that is consistent with this conjecture.

The last heterogeneous test explores how the riskiness of VCs' investment deals (startup ventures) alters our main results. We conjecture that when making investment in risky ventures, VC fund managers are more likely to stick to costly but powerful monitoring tools, such as staging and syndication, and rely less on learning from public market prices. This is because the consequence of inadequate monitoring would be much more severe if the venture is riskier. Hence, we posit that the effects of price informativeness on VC staging and syndication are less pronounced when ventures are riskier. Consistent with this conjecture, we find that VC staging and syndication is less sensitive to public stock price informativeness when the ventures are from more R&D intensive industries and in earlier stages.

In the final part of the paper, we explore a "bottom line" question: how do VCs' learning from public markets and investment structure decisions affect their investment outcomes? We find evidence that, while VC staging and syndication are positively associated with ventures' successful exit probability as documented in earlier studies, this association is stronger when public market prices are more informative. Hence, if VCs can learn information from public market prices more effectively, they are able to rely less on costly stage financing and syndication, which positively contributes to the success of their ventures.

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 addresses the endogeneity problem. Section 6 reports the heterogeneous effect and investment outcome results. Section 7 concludes.

## 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, documenting the real effects of financial markets. Starting from Hayek (1945), who argues that prices are a useful source of information, researchers (e.g., Grossman, 1976; Hellwig, 1980) realize that financial markets aggregate the information of many market participants who, though 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 learnt from financial market prices to guide their real decisions. Bond, Goldstein, and Prescott (2010) further argue that while it is important for managers to learn information from stock prices, they need to have some independent informational sources to achieve the desirable outcome.

Empirical studies provide evidence consistent with the learning channel through which financial markets affect firms' investment and financing activities. For example, Giammarino et al. (2004) find that information acquisition by the market influences managers' financial decisions in the SEO setting. Luo (2005), in the 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 lower. Kau, Linck, and Rubin (2008) further show that managers are more likely to listen to the market when more of their shares are held by large blockholders and when their CEOs have higher pay-performance sensitivities. Edmans, Goldstein, and Jiang (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, Goldstein, and Jiang (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, suggesting that managers learn new information from the price and use it in their investment decisions. In a related study, Durnev, Morck, and Yeung (2004) show that price informativeness is positively related to investment efficiency. All of these studies show 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, first time in the literature, whether VCs learn from public market prices when making investment decisions.

Our paper also contributes to the literature on venture capital investment. This literature shows that VCs' past experience, intensive monitoring, reputation, industry expertise, and network positions all affects their investment structure 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. Existing studies conclude that VC investors generally create value for startup ventures they invest in and promote technological innovation (See Da Rin, Hellmann, and Puri (2013) for an excellent survey of the literature). However, current studies have largely ignored a possible mechanism through which VC investors create value for their portfolio firms, i.e., VC investors' active learning from public markets when making investment decisions. Our paper attempts to fill in this void by providing empirical evidence that links VC learning and their investment structures and outcomes.

## 3. DATA, SAMPLE AND VARIABLE CONSTRUCTION

### *3.1 Data and sample selection*

We obtain data on round-level VC investments in startup companies from the Thomson Reuters VentureXpert database. We include in our sample all US-based ventures with a complete VC financing history between 1980 and 2012, that is, ventures receiving their first round of VC financing after 1980 and the last round before 2012. We classify ventures 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 exited from VC financing and include them in our sample.[3] Finally we exclude observations with missing and inconsistent data, leaving 13,185 ventures with 53,084 rounds of VC financing. To calculate the industry-level price informativeness measures and other control variables, we collect information on daily stock returns and annual financial data from CRSP and Compustat databases. 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 Gompers (1995)'s procedure to match sample venture observations with public firms by SIC industry classifications and round dates. 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,

[3] As noted by Tian (2011), in general VC industry requires investment liquidation within 10 years from the inception of the fund. Hence, venture 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.

we use there-digit SIC industries, and if there are fewer than four public firms in the three-digit SIC industries, we match ventures with public firms in the same two-digit SIC industries instead.

### *3.2 Variable Construction*

#### *3.2.1 VC staging and syndication variables*

Following existing literature, we use five variables to capture VC fund managers' investment structure on their portfolio ventures, i.e., staging and syndication (Gompers, 1995; Lerner, 1994). Specifically, we use *N_round*, *Skewness*, and *ΔR_amount* to capture a VC's staging patterns. We define *N_round* as the total number of VC financing rounds a venture receives before it exits. *Skewness* is the investment amount put upfront by VC investors in the first round of financing, calculated as the amount a venture receives from round one divided by the total amount of VC financing across all financing rounds. *ΔR_amount* is the increase in round amount from the previous to the current round, calculated as the natural logarithm difference between the current round and the previous round.

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 venture is financed by a VC syndicate and zero otherwise. *N_VC* measures the size of the syndication, i.e., the number of VC investors in a syndicate co-investing in a startup venture. We provide detailed definitions of variables in Appendix A.

#### *3.2.2 Price informativeness variables*

As suggested by Roll (1988) among a large body of theoretical and empirical literature, we use price nonsynchronicity (firm-specific return variation) as our main price informativeness measure, which is mainly driven by private information. The proxy is widely used in many empirical studies, such as Durnev, Morck, and Yeung (2004) and Chen, Goldstein, and Jiang (2007) on corporate investments, 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:

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

where $r_{i,j,t}$ is the return of firm *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 define the price nonsynchronicity measure $Info_{i,j}$ for firm *i* from industry *j* as

$$Info_{i,j} = ln(\frac{1 - R_{i,j}^2}{R_{i,j}^2}) \quad (2)$$

where $R_{i,j}^2$ is the R-squared from Regression (1). We then calculate the industry-level price nonsyncronicity measure $Info_j$ by averaging $Info_{i,j}$ across all firms in industry *j*.

### *3.2.3 Control variables*

Following the VC literature we control for a vector of venture-level and industry-level characteristics in our analysis that may affect VC fund managers' decisions on staging and syndication. Firm-level controls include the natural logarithm value of venture age, *Ln_age*, defined as the number of years since the venture's inception; an early stage dummy, *Early_dum*, that equals one if the venture is in its seed/startup or early stage, and zero if the venture is in the expansion, late, or buyout/acquisition stage as recorded in the VentureXpert database; *Ln_amt1st*, the natural logarithm value of the first round investment amount; an IPO dummy, *IPO_dum*, that equals one if the firm goes public and zero otherwise; and an acquisition dummy, *Acq_dum*, that equals one if the venture firm is acquired by another firm and zero otherwise. Industry-level controls include the industry average of Tobin's Q, *Ind_Q*; R&D expense ratio, *Ind_RD*, calculated as the R&D expenses divided by total assets; and asset tangibility, *Ind_tangi*, calculated as property, plant, and equipment divided by total assets.

### *3.3 Summary statistics*

Table 1 reports descriptive statistics of the characteristics of VC staging and syndication, startup firms and their industries. Panel A shows that in our sample, a median venture receives 3 rounds of financing from a syndicate consisting of 4 VC investors, with a total investment of $15.4 million. It has to wait for another 9.8 months for the next round of VC financing of $3.9 million. Panel B shows that the median venture is 2 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 venture 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%. These industries have an average market capitalization of $3.4 billion.

The mean and median values of the industry-level price nonsynchronicity measure prior to the first VC financing round are 2.2 and 2.2, respectively, with the standard deviation being 0.7.

## 4. EMPIRICAL RESULTS

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

$$Y_{i,j} = a + bInfo_j + cControls + \varepsilon \qquad (3)$$

where $Y_{i,j}$ is VC fund managers' staging and syndication variables described in Section 3.2.1 for venture *i* in industry *j*, including the total number of financing rounds (*N_round*), the skewness of round investments (*Skewness*), the change in round amount (*ΔR_amount*), the syndication dummy (*Syn*), and the number of VCs in the syndicate (*N_VC*). These five variables collectively describe how VC fund managers optimize the structure of their investments in the venture to alleviate information asymmetry and venture uncertainty problems, and how they organize VC syndication for the second opinions. $Info_j$ is the average price nonsynchronicity measure for industry *j*. The vector *Controls* contains venture-level and industry-level characteristics that may affect VC staging and syndication as discussed in Section 3.2.3. We control for the first VC investment year fixed effects, lead VC fixed effects, industry fixed effects, and state fixed effects in regressions to absorb any influence varying only with year, lead VC, industry and firm location.[4] In the *Skewness* regression, we also include round number fixed effects to address the concern that the *skewness* measure is negatively related to the number of financing rounds by construction.

We run OLS regressions to estimate equation (3) for *N_round*, *Skewness*, *ΔR_amount*, and *N_VC*, and run Probit regressions for *Syn*. In venture-level analyses of *N_round*, *Skewness*, *Syn*, and *N_VC*, we estimate *Info* and control variables within/at the end of the calendar year prior to the first round of VC financing. In the round-level analysis of *ΔR_amount*, we estimate variables within/at the end of the calendar year of the previous round of financing.

[4] We follow the following steps to determine the lead VC for the venture if a syndication is formed (*N_VC* > 1): 1) we identify the VC making the largest investment amount across all financing rounds for the venture; 2) if the lead VC is not determined in Step 1 due to missing or equal total amounts, we then choose the VC participating in the largest number of rounds for the venture; 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.

Table 2 reports the baseline regression results on the effects of public price informativeness on VC staging and syndication. Our VC learning hypothesis argues that, when stock prices are more informative, VC fund managers are able to collect more information about the industry of their portfolio firms from the public market, so they rely less on costly staging to mitigate information asymmetry and venture uncertainty problems (Sahlman, 1990; Gompers, 1995). They are also less likely to invite other VCs to form a syndicate to seek the second opinions, which allows them to enjoy the returns exclusively (Lerner, 1994; Brander, Amit, and Antweiler, 2002).

We observe findings that are consistent with the learning hypothesis. The coefficient estimates of *Info* are significant in columns (1) – (3), suggesting that with more informative public market prices in the same industry of the ventures, VCs tend to invest a fewer number of financing rounds, invest more funding upfront in the first round, and increase investment amount in the current round compared to the previous round. In columns (4) and (5), the coefficient estimates of *Info* are negative and significant at the 5% or 1% level, suggesting that with more informative public market prices, VC fund managers are more reluctant to syndicating with other VCs.

In above regressions we include industry Tobin's Q to control for potential valuation effects on VC staging and syndication, as previous studies show that the industry valuation affects investments and takeovers, among other corporate policies (e.g., Foucault and Frésard, 2012, 2014). The coefficient estimates of industry Tobin's Q are not significant once the public market price informativenss variable is included, suggesting that VC staging and syndication are not driven by the valuation effect. In addition, we find that VC fund managers investing in ventures in more R&D intensive industries rely more on staging and syndication, consistent with Gompers (1995) and Tian (2011). Results on other control variables show that younger ventures at early stages tend to receive a larger number of VC financing rounds and a smaller first round but larger follow-on round investment amount. These ventures are also more likely to be financed by VC syndicates (as opposite to individual VCs) and by a larger VC syndicate.

## 5. IDENTIFICATION

The baseline results are consistent with the hypothesis that VCs actively learn from public market prices before making decisions on investment structure and syndication to save the cost associated with them. However, the documented relation could be spurious and subject to endogeneity concerns. For example, there may exit some omitted variables that affect both public market price informativeness and VC staging and syndication decisions simultaneously, which could bias the coefficient estimate of public market price informativeness and makes the interpretations of our findings difficult. In this section, we address the endogeneity concern with two identification attempts. First, we construct an instrument variable (IV) for public market price informativeness and use the two-stage least squares (2SLS) approach. Second, we utilize a quasi-natural experiment, Regulation SHO, in which a regulatory shift alters stock price informativeness that is likely exogenous to VCs' staging and syndication decisions.

*5.1 The instrumental variable approach*

Our instrument for public market price informativeness, *Ln_canc_days*, is based on the rationale that financial analysts, an important public market player, are active information producers who collect information about the firms' fundamental value. The information gathered by financial analysts is reflected in the firms' current stock prices (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Brennan and Subrahmanyam, 1995; Hong, Lim, and Stein, 2000; Bradley et al., 2014).[5] Hence, events that prevent financial analysts actively produce information about the firms should reduce the firms' stock price informativeness. The event we consider is airport shutdowns.

Shutdowns of airports that are close to either the public firm or the analyst due to extreme weather conditions or operational difficulties make the analyst's on-site visit to the firm difficult. This interruption on the analyst's visit to the firm significantly reduces her ability to produce accurate information about the firm she covers and hence reduces the firm's stock price informativeness. Our proposed instrument should satisfy the relevance requirement of the IV approach. Our instrument  shares the same sprits of Koudijs (2014, 2015), in which boats arrive with information in 18$^{th}$ century and bad weather cause exogenous reductions in information arrival, and Engelberg and Parsons (2011), in which bad weathers prevent the delivery of print media, which, in turn, affects local trading.

Based on the above discussion, we construct the instrument as the natural logarithm of average days in a year when there are severe flight cancellations either in the airports closest to the

[5] Consistent with this rational, recent studies (e.g., Kelly and Ljungqvist, 2012; Hong and Kacperczyk, 2010; Derrien and Kecskes, 2013; He and Tian, 2013; Chen, Harford, and Lin, 2015) find that an exogenous loss in one analyst leads to various consequences on stock prices, liquidity, and firm investment and financing decisions.

firm's headquarter or closest to the offices of the analysts covering the firm, which prevents financial analysts from visiting the firms they cover. 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 operation, air traffic, or security reasons.[6] We provide more variable construction details in Appendix B.

It is reasonable to believe that flight cancellations due to extreme weather conditions or operational difficulty reasons between public firms and their analysts are exogenous to the investment decisions of VCs who invest in the startup venture in the same industry of the affected public firms. In other words, our instrument affects a VC's staging and syndication decision only through its effect on the informativeness of public market prices. Hence, our instrument variable reasonably satisfies the exclusion restriction.

We report the 2SLS regression results in Table 3. Columns (1), (3), (5) and (7) report 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, *Ln_canc_days*. We include all control variables in the OLS regressions reported in Table 2 in the first-stage regressions. As we observe, the coefficient estimates of the instrument are negative and significant at the 1% level across all regressions. The results suggest that flight cancellations that prevent analysts from visiting covered firms lead to a decrease in stock price informativeness, which is consistent with our intuition for constructing the instrument. The *t*-statistics for the instrument variable are 8.5, 6.2, 16.0, and 9.8 in columns (1), (3), (5) and (7), respectively. Based on the rule-of-thumb diagnostics suggested by Staiger and Stock (1997), our instrument is highly correlated with the endogenous right-hand side variable, *Info*, in the second stage and hence does not appear to suffer from weak instrument problem.

Columns (2), (4), (6), (8), and (9) report the second-stage regression results with *N_round*, *skewness*, *ΔR_amount*, *Syn*, and *N_VC* as the dependent variable, respectively, and the predicted values of public market price informativeness variable as the independent variable. The coefficient estimates of instrumented *Info* are consistent with those obtained from the OLS regressions and support our hypothesis. The economic effect of public market price informativenss on VC staging and syndication is also sizable. For example, with one standard deviation increase in instrumented

[6] In untabulated analyses, we use an alternative cutoff, 30%, to define severe flight cancellations for robustness checks, and obtain qualitatively similar results.

*Info*, VCs reduce the number of investment rounds by 0.6, which is a 16.7% decrease from the mean number of financing rounds. Meanwhile, with one standard deviation increase in instrumented *Info,* VCs invest 5.9% (i.e., $2.3 million) more in the first round relative to later rounds, and increase round investment amount by 57.1% (i.e., $4.6 million) compared to the previous round, decrease their probability of forming a syndicate to finance a venture by 7.6%. If a syndicate is formed, the size of the syndicate drops by 0.6 VCs with one standard deviation increase in instrumented *Info*.

Comparing results obtained from the OLS regressions (Table 2) with those obtained from the 2SLS regressions (Table 3), we observe that the magnitudes of coefficient estimates obtained from the 2SLS regressions are larger than their counterparts in the OLS regressions, though they have consistent signs and are all statistically significant. This finding suggests that the coefficient estimates are biased towards zero in OLS regressions due to endogeneity in public market price informativeness. In other words, omitted variables are likely to simultaneously make VC staging and syndication more desirable and public market stock price less informative. An industry's opaqueness could be an example of an omitted variable. For example, VCs investing in a startup venture that is in a more opaque industry may choose to stage and syndicate more to mitigate information asymmetry and venture uncertainty problems. Meanwhile, precisely because of the opaqueness of the industry, information about firms in this industry cannot be easily understood by investors and hence stock prices are less informative. Hence, the negative correlations caused by the omitted variable is the main driving force that biases the coefficient estimates of stock price informativeness toward to zero. With the instrumental variable approach, we are able to clean up the correlation between public market price informativeness and the residuals in the structural equation. Hence, the endogeneity of public market price informativeness is removed and we observe the coefficients with larger magnitudes (i.e., become more positive and more negative compared to those obtained from the OLS regressions).

### *5.2 The natural experiment approach*

Our second identification strategy exploits the information production role played by short sellers and uses a quasi-natural experiment, Regulation SHO, that alters short sellers' behavior and hence affects public price informativeness exogenously. Short selling has been largely constrained in the U.S. historically. For example, the uptick rule that was established in 1935 prohibits short sales when stock prices are declining, which imposes a significant cost on short sellers. In 2004, the SEC announced that 968 firms from the Russell 3000 Index were selected in a pilot program, for which the uptick rule and other price restrictions are exempted. However, the uptick rule remained in effect for the remaining Russell 3000 firms (Grullon, Michenaud, and Weston, 2015; He and Tian, 2015). These pilot firms were randomly selected by the SEC. Specifically, the regulator ranked Russell 3000 stocks listed on NYSE, NASDAQ, and AMEX by daily volume, and then picked one firm from every three firms into the pilot program. The exemption of the uptick rule for pilot stocks was in effect on May 2, 2005, and the regulator lifted the restrictions for the remaining stocks on August, 2007.

Short sellers are informed traders and important information contributors to the stock market (e.g., Miller, 1977; Diamond and Verrecchia, 1987; Boehmer, Jones and Zhang, 2008; Boehmer and Wu, 2013). Hence, after short-selling constraints are removed, short selling activities are largely enhanced and stock prices become more informative, as shown in Massa, Zhang and Zhang (2015). Therefore, the Regulation SHO provides a nice quasi-natural experiment setting that allows us to explore the effect of public market price informativeness on VC staging and syndication.

The SHO pilot program provides two regulatory events that generate likely exogenous variation in stock price informativeness. The first event is in 2005 when the uptick rule was removed for pilot stocks. As a result, price informativeness of pilot stocks increases relative to that of non-pilot stocks. If our hypothesis is supported, we expect to observe a decrease in VC staging and syndication for startup ventures in the same industries of pilot stocks. The second event is the removal of the uptick rule for all stocks in 2007. Hence, price informativeness of non-pilot stocks increases compared to that of pilot stocks. We hence expect to observe a larger decrease in VC staging and syndication for startup ventures in the same industries of the pilot stocks after the pilot program was in effect and the difference in VC staging and syndication becomes insignificant after the uptick rule was removed for all stocks in 2007. We implement the DiD approach and estimate the following model:

$$\begin{aligned} Y = a + bTreat * During + cTreat * Post + dDuring + ePost \\ + fControls + \varepsilon \end{aligned} \tag{4}$$

where $Y$ is VC staging and syndication variables at either venture- or round-level. The treatment group dummy, *Treat*, equals one if at least one of the largest 3 public firms in the same industry of the startup venture is in the pilot group and zero otherwise. *During* takes the value of one if the observation is from November 2, 2005 to August 7, 2007, in which the stocks of pilot firms become more informative than those of non-pilot firms due to Regulation SHO, and zero otherwise. Note that the removal of the uptick rule for the pilot stocks was in effect in May 2, 2005. We choose November 2, which is 6 months after the removal date, as the beginning of the event period to allow enough time for short sellers to enter the market and affect stock price informativeness. *Post* takes the value of one if the observation is from August 7, 2007 to the end of 2012 in which the difference in price informativeness between pilot and non-pilot firms vanishes due to the removal of the uptick rule for all stocks. *Controls* contains a vector of control variables that is the same as in the baseline regressions.

At the venture-level analyses, we restrict our DiD tests in a sample that contains 1,737 startup ventures from industries with at least 15 ventures receiving the first round of financing both during the event period and in either the pre- or post-event period. At the round-level analysis, we require sample ventures to have at least one round both within and outside the event period, leaving 4,487 rounds of VC financing.

Table 4 reports the DiD test results with *N_rounds*, *Skewness*, *R_amount*, *Syn*, and *N_VC* as the dependent variable. The coefficient estimates of the interaction term *Treat*During*, the DiD estimators, exhibit signs that are consistent with our hypothesis and are statistically significant in four out of five regressions. Column (1) suggests that, during the SHO pilot program period, VC fund managers on average invest 0.7 fewer financing rounds for the ventures that are in the industries containing pilot stocks (and hence their stock prices become more informative) than those that are in the industries not containing pilot stocks. In column (3), we define the dependent variable, *R_amount*, as the natural logarithm of differences between the current round amount and the financing amount at round one. The result suggests that VC fund managers invest 10.1% ($e^{0.096}$-1) more in rounds for ventures from industries containing pilot stocks during the pilot program period. Columns (4) and (5) suggest that syndication probability and VC syndicate size for ventures that are in the industries containing pilot firms drop by 4.6% and 0.8, respectively.

The coefficient estimates of *Treat*Post* is statistically insignificant, suggesting that there exists a reverting pattern in VC staging and syndication because of the removal of the uptick rule for all stocks when differences in stock price informativeness between pilot and non-pilot firms disappear. This observation is consistent with earlier findings, e.g., Fang, Huang, and Karpoff

(2015) who find that a similar reverting pattern in earnings management (the key outcome variable in their setting) after the removal of the uptick rule for all stocks.

We perform a number of additional analyses to check the robustness of our main findings and obtain consistent results. We report the results in Appendix C.

## 6. HETEROGENEITY AND INVESTMENT OUTCOMES

In this section, we perform additional tests that explore heterogeneous effects of public market price informativeness and the consequences of VC learning in the 2SLS framework with the instrument constructed in Section 5.1.

### *6.1 VC experience and learning*

Our findings so far suggest that VC fund managers rely less on staging and syndication to mitigate information asymmetry and venture uncertainty problems if they are able to learn more from public market prices in the same industries of their portfolio firms. In this section, we further explore how VC fund managers' past investment experience alter the effect of price informativeness on their staging and syndication decisions. We distinguish a VC's industry-specific and general experience and expect them to have different effects on how VCs learn from stock prices. Specifically, we estimate the following model:

$$Y_{i,j} = a + bInfo_j * Exp + cInfo_j + dExp + eControls + \varepsilon \qquad (5)$$

In table 5, we report the second-stage regression results estimating equation (5). The key variable of interest is the interaction terms between the industry price informativeness measure and VC experience measures. We first examine how VC industry-specific experience alters our main results and report the results in Panel A. We capture a VC's industry-specific experience by constructing a dummy variable, $Exp\_exit_{ind}$, that equals one if the venture's lead VC firm is ranked in the top quintile in terms of the number of successful exits in the same 3-digit SIC industry of the venture since 1962 and zero otherwise. We define a successful exit if a venture either goes public or is acquired, following existing VC literature. In the same spirit, we construct an alternative VC industry-specific experience dummy, $Exp\_IPO_{ind}$, that equals one if the venture's lead VC firm is ranked in the top quintile in terms of the number of IPOs in the same 3-digit SIC industry of the venture since 1962 and zero otherwise.

The coefficient estimates of *Info* exhibit signs that are consistent with those observed in the 2SLS regressions as reported in Table 3. The key variable of interest, the interaction terms between stock price informativeness and a VC's industry-specific expertise, have significant and positive coefficient estimates in regressions with *N_round*, *Syn* and *N_VC* being the dependent variable, respectively, and have negative and significant estimates in regressions 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 has more industry-specific experience. We observe a similar finding when the alternative VC industry-specific measure, $Exp\_IPO_{ind}$, is used. Our findings appear to suggest that a VC's industry-specific experience and her learning from public market prices are substitutes. If a VC fund managers know more about the industry from her own past experience, she relies less on the information contained in public market prices when making investment structure decisions.

In Panel B, we consider a VC's general experience and construct a variable that captures it, i.e., a dummy variable, $Exp\_exit_{gen}$, that equals one if the lead VC firm is ranked in the top quintile in terms of the number of successful exits since 1962 and zero otherwise. Similarly, we construct the dummy variable, $Exp\_IPO_{gen}$, that is based on the number of IPOs since 1962. The coefficient estimates of *Info* exhibit signs that are consistent with those observed in the 2SLS regressions. The key variable of interest, the interaction term between stock price informativeness and a VC's general expertise, are generally not significant except for columns (1) and (2), suggesting that a VC's general experience does not appear to affect her learning from stock prices when making investment decisions.

Our evidence on how a VC's industry and general experience affect her learning from stock prices suggests that the VC's industry-specific experience are more relevant than her general experience when the VC learns information from public market prices. As a result, VCs rely less on the information contained in public market prices when making staging and syndication decisions if they have more industry-specific experience than the scenario if they have more general experience in the VC industry.

*6.2 Geography and learning*

Tian (2011) argues that VC staging and monitoring are substitutes and finds that VCs located farther away from the entrepreneurial firms tend to rely more heavily on staging because it is more costly for them to effectively monitor the ventures. Similarly, if a VC firm is located far away from its startup ventures, it is less costly for the VC to learn from public markets than physically visiting the distant ventures. Hence, we expect the effect of public market price informativeness on VC staging and syndication is more pronounced if the VC is physically more distant from the startup venture.

To test this conjecture, we estimate equation (5) with the key variable of interest replaced with the interaction term between *Info* and distance measures. We construct two distance measures. The first measure, *Samezip*, is a dummy variable that equals one if a venture and its lead VC firm share the same zip code and zero otherwise. The second distance measure, *Distant*, is a dummy variable that equals one if the geographical distance between a venture and its lead VC is in the top decile (the longest decile) among all venture-VC pair distances and zero otherwise. We report the results in Table 6.

The coefficient estimates of *Info* exhibit signs that are consistent with those observed in the 2SLS regressions. The key variable of interest, the interaction term between distance variables and *Info*, are statistically significant in some specifications. For example, in column (2), the negative and significant coefficient estimate of *Distant***Info* suggest that VC fund managers located far away from their ventures rely more on information they could learn from public market prices when making staging decisions. In column (3), the coefficient estimates of *Samezip***Info* is negative and significant at the 1% level, suggesting that the effect of public market price informativeness on a VC's propensity to invest more heavily in the first round is largely mitigated if the VC and the startup venture are in the same zip code area.

Overall, we find some evidence that VCs located farther away from ventures (and hence have a higher cost of collecting information about the venture and monitoring the venture) rely more on active learning from public market prices when making staging and syndication decisions.

*6.3 Investment riskiness and learning*

Our learning hypothesis suggests that VC fund managers learn actively from public market price to reduce costly staging and syndication. An underlying assumption is that the monitoring mechanisms and learning from public prices are substitutes. If learning becomes less reliable because the information and undertainty problems on their investments are severe and the ventures are very risky, VC fund managers would stick to the powerful, though expensive, staging and syndication tools. Hence, we expect that the effect of public market price informativeness on VC staging and syndication is less pronounced when the ventures are more risky.

To test this conjecture, we estimate equation (5) with the key variable of interest replaced with the interaction term between *Info* and two venture riskiness measures, respectively. The first measure, *Intensive*, is a dummy that equals one if the R&D spending in a venture's industry ranks in the top tercile of all industries and zero otherwise. The second riskiness measure, *Early_dum*, is a dummy variable that equals one if a venture is in its seed/startup or early stage when receiving the first/previous round of VC financing and zero otherwise. Our prior is that venture startups in early stages and from R&D-intensive industries are riskier investments for VC fund managers. Hence, VCs rely less on learning from public stock prices when making their staging and syndication decisions.

Panel A of Table 7 reports the results with R&D intensity as the riskiness measure. The coefficient estimates of *Info* exhibit signs that are consistent with those observed in the 2SLS regressions in Table 3. The main variable of interest, the interaction term between *Info* and *Intensive*, are significant in four out of five columns, suggesting that the effect of public market price informativeness on staging and syndication is significantly mitigated for ventures from R&D intensive industries. Panel B reports the results with *Info*Early_dum* as the main variable of interest. We obtain significant coefficient estimates in three out of five regressions, which suggests that the price informativeness effect is less pronounced for ventures at their early stages when they receive the first round financing.

*6.4 Evidence on economic consequences*

Our last set of tests tries to answer a "bottom line" question: how do VCs' learning from public markets and investment structure decisions affect their investment outcomes? If VCs learn valuable information from public market prices and make optimal decisions on staging and syndication, we expect to observe that their investments are able to enjoy better outcomes. We measure investment outcomes by constructing a successful exit dummy that equals one if the venture either goes public (IPO) or is acquired by another company and zero otherwise. We test our conjecture by dividing our sample into a high-informativeness subsample and a low-price informativeness subsample, and estimating the following model using Probit regressions:

$$Succexit = a + bInvStructure + cControls + \varepsilon \quad (6)$$

where *InvStructure* represents for VC investment structure variables, i.e., *N_Round*, *Skewness*, *Syn*, and *N_VC*. The high-informativeness subsample contains ventures in industries with average price nonsynchronicity ranking in the top decile (the highest decile) among all industries; and the low-informativeventures subsample contains ventures in industries with average price nonsynchronicity ranking in the bottom decile.

Table 8 reports the regression results on the effects of VC staging and syndication on the probability of successful exits across subsamples with different levels of price informativeness. We first explore the effects of VC staging and syndication in the full sample. Results in columns (1) and (4) of Panel A suggest that VC staging is positively associated to the likelihood of successful exits. The coefficient estimate of *N_round* in column (1) is positive and that of *Skewness* in column (4) is negative. Both coefficient estimates are significant at the 1% level, suggesting that a larger number of financing rounds and smaller investment amount upfront are positively associated with a higher probability of successful exits. In columns (1) and (4) of Panel B, the coefficient estimates of *Syn* and *N_VC* in the full sample are both positive and significant, suggesting that VC syndication is positively related to successful exits, consistent with the findings reported in Tian (2012).

In subsample tests, we find that there is a significant and positive effect of VC staging on exit outcomes, both economically and statistically, for ventures in industries with more informative stocks in the public market, as shown in column (2) of Panel A. In contrast, column (3) reports that there is no such effect for ventures from low-informativeness industries. The difference is significant at the 1% level.[7] We observe similar patterns for the coefficient estimates of *Skewness* across two subsamples, for which the magnitude of the estimate is significantly larger for ventures from more informative industries than those from less informative industries and the difference is significant at the 1% level, as reported in columns (5) and (6) of Panel A. These findings suggest that VC staging is more effective when VC fund managers are able to learn more information from the public market prices.

[7] Assuming equal disturbance variances for the Probit models in the high- and low-informativeness subsamples, we use a Wald chi-square test for the significance of the difference between coefficient estimates of the staging and syndication variables.

Panel B reports subsample results on VC syndication. Similarly, we find that the effects of syndication on ventures' successful exits are stronger in the high-informativeness subsample. The difference is significant at the 1% level for *Syn*, the syndication dummy, suggesting VC syndication are more powerful when VC fund managers could learn information from public stock prices more effectively.

In this subsection, we find that the positive effect of VC staging and syndication on a venture's successful exit probability is more pronounced when the public market prices are more informative. Hence, if VCs are able to learn information from public stock prices more effectively, tools used by VC investors (i.e., staging and syndication) are more powerful when contributing the success of their ventures.

## 7. CONCLUSION

In this paper, we have examined the real effects of financial markets from the perspective of VC investors, an important market player that promotes entrepreneurship. We postulate that VCs actively learn information contained in public market prices when making investment decisions. When public market prices are more informative, VCs are less likely to stage finance startup ventures and to syndicate with other VCs to save the costs associated with staging and syndication. This effect is more pronounced when VCs are lack of industry-specific expertise, VCs are physically distant from their ventures so that collecting soft information is costly, and their investments are less risky. Using exogenous events that unexpectedly alter financial analysts' and short sellers' ability to produce information, which makes public market prices less informative, we show that our results are unlikely driven by endogeneity concerns. Our paper sheds new light on the real effects of financial markets by showing that private equity investors actively learn information from public equity markets

## REFERENCES


Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which shorts are informed? *Journal of Finance* 63, 491–527.

Boehmer, Ekkehart, and Juan Julie Wu, 2013, Short selling and the price discovery process, *Review of Financial Studies* 26, 287–322.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *Annual Review of Financial Economics* 4, 339–360.

Bond, Philip, Itay Goldstein, and Edward S. Prescott, 2010, Market-based corrective actions, *Review of Financial Studies* 23, 781-820

Bradley, Daniel, Jonathan Clarke, Suzanne Lee, and Chayawat Ornthanalai, 2014, Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays, *Journal of Finance* 69, 645–673.

Brander, James A., Raphael Amit, and Werner Antweiler, 2002, Venture-capital syndication: Improved venture selection vs. the value-added hypothesis, *Journal of Economics Management Strategy* 11, 423–452.

Brennan, Michael J., Narasimhan Jegadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799-824.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 3, 361-381.

Chan, Kalok, and Yue-Cheong Chan, 2014, Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offerings, *Journal of Financial Economics* 114, 36–53.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619–650.

Chen, Tao, Jarrad Harford, and Chen Lin, 2015, Do analysts matter for governance? Evidence from natural experiments, *Journal of Financial Economics* 115, 383-410

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.

Da Rin, Marco, Thomas Hellmann, and Manju Puri, 2013, A survey of venture capital research. in: George Constantinides, Milton Harris, and René Stulz (eds.) Handbook of the Economics of Finance 2.

Derrien, Francois, and Ambrus Kecskes, 2013, The real effects of financial shocks: Evidence from exogenous changes in analyst coverage, *Journal of Finance* 68, 1407-1440

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection? *Journal of Finance* 52, 1087–1129.

Duarte, Jefferson, and Lance Yong, 2009, Why is *PIN* priced? *Journal of Financial Economics* 91, 119-138.

Durnev, Art, Randall Morck, and Bernard Yeung, 2004, Value-enhancing capital budgeting and firm-specific stock return variation, *Journal of Finance* 59, 65-105.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1996, Cream-skimming or profit-sharing? The curious role of purchased order flow, *Journal of Finance* 51, 811–833.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1997a, One day in the life of a very common stock, *Review of Financial Studies* 10, 805–835.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1997b, The information content of the trading process, *Journal of Empirical Finance* 4, 159–186.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is Information risk a determinant of asset returns? *Journal of Finance* 57, 2185–2221.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The causal impact of media in financial markets, *Journal of Finance* 66, 67–97.

Fang, Vivian W., Xuan Tian, and Sheri Tice, 2014, Does stock liquidity enhance or impede firm innovation? *Journal of Finance* 69, 2085–2125.

Foucault, Thierry, and Laurent Frésard, 2012, Cross-listing, investment sensitivity to stock price, and the learning hypothesis, *Review of Financial Studies* 25, 3305–3350.

Foucault, Thierry, and Laurent Frésard, 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554–577.

Giammarino, Ronald, Robert Heinkel, Burton Hollifield, and Kai Li, 2004, Corporate decisions, information and prices: Do managers move prices or do prices move managers? *Economic Notes* 33, 83-110.

Goldstein, Itay, and Alexander Guembel, 2008, Manipulation and the allocational role of prices, *Review of Economic Studies* 75, 133–164.

Gompers, Paul A., 1995, Optimal investment, monitoring, and the staging of venture capital, *Journal of Finance* 50, 1461–1489.

Grossman, Sanford, 1976, On the efficiency of competitive stock markets where trades have diverse information, *Journal of Finance* 31, 573–585.

Grullon, Gustavo, Sébastien Michenaud, and James P. Weston, 2015, The real effects of short-selling constraints, *Review of Financial Studies* 28, 1737–1767.

Hayek, F. A., 1945, The use of knowledge in society, *American Economic Review* 35, 519-530.

He, Jie, and Xuan, Tian, 2013, The dark side of analyst coverage: The case of innovation, *Journal of Financial Economics* 109, 856-878.

He, Jie, and Xuan, Tian, 2015, SHO time for innovation: The real effects of short sellers, *Working paper*, University of Georgia.

Hellwig, Martin F., 1980, On the aggregation of information in competitive markets, *Journal of Economic Theory* 22, 477–498.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *The Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Kau, James B., James S. Linck, and Paul H. Rubin, 2008, Do managers listen to the market? *Journal of Corporate Finance* 14, 347-362

Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25, 1366–1413.

Koudijs, Peter A. E., 2014, Those who know most: Insider trading in 18th c. Amsterdam, *Journal of Political Economy*, forthcoming.

Koudijs, Peter A. E., 2015, The boats that did not sail: Asset price volatility in a natural experiment, *Journal of Finance*, forthcoming.

Lai, Sandy, Lilian Ng, and Bohui Zhang, 2014, Does *PIN* affect equity prices around the world? *Journal of Financial Economics* 114, 178–195.

Lerner, Joshua, 1994, The syndication of venture capital investments, *Financial Management* 23, 16–27.

Lerner, Joshua, 1995, Venture capitalists and the oversight of private firms, *Journal of finance* 50, 301–318.

Luo, Yuanzhi, 2005, Do insiders learn from outsiders? Evidence from mergers and acquisitions, *Journal of Finance* 60, 1951-1982

Massa, Massimo, Bohui Zhang, and Hong Zhang, 2015, The invisible hand of short selling: Does short selling discipline earnings management? *Review of Financial Studies* 28, 1701-1736.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.

Norli, Oyvind, Charlotte Ostergaard, and Ibolya Schindele, 2015, Liquidity and shareholder activism, *Review of Financial Studies* 28, 486–520.

Roll, Richard, 1988, $R^2$, *Journal of Finance* 43, 541–566.

Roosenboom, Peter, Frederik P. Schlingemann, and Manuel Vasconcelos, 2014, Does stock liquidity affect incentives to monitor? Evidence from corporate takeovers, *Review of Financial Studies* 27, 2392–2433.

Sahlman, William A., 1990, The structure and governance of venture-capital organizations, *Journal of Financial Economics* 27, 473–521.

Staiger, Douglas, and James H. Stock, 1997, Instrumental variables regression with weak instruments, *Econometrica* 65, 557-586.

Subrahmanyam, Avanidhar, and Sheridan Titman, 1999, The going public decision and the development of financial markets, *Journal of Finance* 54, 1045–1082.

Tian, Xuan, 2011, The causes and consequences of venture capital stage financing, *Journal of Financial Economics* 101, 132–159.

Tian, Xuan, 2012. The role of venture capital syndication in value creation for entrepreneurial firms. *Review of Finance* 16, 245-283.

Vega, Clara, 2006, Stock price reaction to public and private information, *Journal of Financial Economics* 82, 103–133.

Wurgler, Jeffrey, 2000, Financial markets and the allocation of capital, *Journal of Financial Economics* 58, 187–214.

**Table 1**
Summary statistics.
This table reports summary statistics for VC staging and syndication, startup firms and their industries. The sample consists of 13,185 venture firms completing 53,084 rounds of VC financing between 1980 and 2012. See Appendix A for definitions of variables.

| Variable | Mean | P25 | Median | P75 | STD |
|---|---|---|---|---|---|
| *Panel A: VC staging and syndication* | | | | | |
| # of financing rounds | 3.82 | 2.00 | 3.00 | 5.00 | 2.93 |
| # of VC investors | 4.86 | 2.00 | 4.00 | 6.00 | 4.07 |
| Inter-round 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 one | 0.57 | 0.00 | 1.00 | 1.00 | 0.50 |
| Inv. amount at round one (mil.) | 11.53 | 1.25 | 3.50 | 9.00 | 28.81 |
| Firm age at round one | 7.08 | 1.00 | 2.00 | 6.00 | 12.41 |
| *Panel C: Benchmark Industries (1-year prior to round one)* | | | | | |
| Price nonsynchronicity | 2.22 | 1.79 | 2.24 | 2.68 | 0.70 |
| Amihud illiquidity ratio (x1000) | 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 |

**Table 2**
The effects of public market price informativeness on VC staging and syndication.
This table reports the baseline regression results on the effects of stock price informativeness of public firms in the same industry of a venture on VC staging and syndication. The sample consists of 13,185 ventures completing 53,084 rounds of VC financing between 1980 and 2012. Dependent variables are the total number of VC financing rounds a venture receives, the skewness of VC investments, the increase in round amount, the syndication dummy, and the number of VC firms in the syndicate. The independent variable, stock price nonsynchronicity, is defined as $\ln(R^2/(1-R^2))$, where $R^2$ is obtained by regressing daily stock returns on market and industry returns. The informativeness measure and other industry-level controls are calculated using information within/at the end of the calendar year prior to the first round of VC financing for models in Column (1), (2), (4) and (5), and within/at the end of the calendar year of the previous round for the model in Column (3). Marginal effects and Pseudo $R^2$ are reported for Probit regression (4), otherwise OLS coefficients and adjusted $R^2$ are reported. 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.

| | *N_round* (1) | *Skewness* (2) | *ΔR_amount* (3) | *Prob. Syn* (4) | *N_VC* (5) |
|---|---|---|---|---|---|
| *Info* | -0.147** | 0.719** | 0.065*** | -0.014** | -0.337*** |
| | (0.060) | (0.288) | (0.023) | (0.007) | (0.087) |
| *Ind_Q* | -0.007 | -0.004 | 0.001 | -0.000 | -0.002 |
| | (0.006) | (0.064) | (0.002) | (0.001) | (0.009) |
| *Ind_RD* | 0.386 | -4.186 | 0.054 | 0.184*** | 1.896*** |
| | (0.487) | (3.176) | (0.205) | (0.059) | (0.584) |
| *Ind_tangi* | 0.242 | -0.895 | 0.176 | 0.075 | 0.821 |
| | (0.390) | (3.163) | (0.265) | (0.046) | (0.629) |
| *Ln_age* | -0.218*** | 1.506*** | -0.154*** | -0.027*** | -0.432*** |
| | (0.026) | (0.220) | (0.012) | (0.005) | (0.053) |
| *Early_dum* | 0.897*** | -2.109*** | 0.318*** | 0.104*** | 1.362*** |
| | (0.123) | (0.422) | (0.020) | (0.012) | (0.176) |
| *Ln_amt1st* | -0.195*** | 5.762*** | -0.208*** | 0.031*** | 0.230*** |
| | (0.033) | (0.300) | (0.006) | (0.004) | (0.073) |
| *Acq_dum* | 0.540*** | -2.352*** | 0.120*** | 0.057*** | 0.743*** |
| | (0.133) | (0.498) | (0.018) | (0.010) | (0.065) |
| *IPO_dum* | 0.360 | -4.405*** | 0.229*** | 0.047*** | 1.028*** |
| | (0.222) | (0.740) | (0.022) | (0.008) | (0.141) |
| *Constant* | 2.119 | -6.260 | 4.432*** | | 0.883 |
| | (1.830) | (9.780) | (0.431) | | (1.175) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| Observations | 13,185 | 10,312 | 31,219 | 9,110 | 13,185 |
| Adj./Pseudo $R^2$ | 0.266 | 0.850 | 0.044 | 0.290 | 0.307 |

**Table 3**

Endogeneity tests with the instrumental variable approach.

This table reports the 2SLS instrumental variable regression results on the effects of stock price informativeness of public firms in the same industry of a venture on VC staging and syndication. The sample consists of 13,185 ventures completing 53,084 rounds of VC financing between 1980 and 2012. The instrument 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 venture 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 headquarter or closest to the analysts' offices. The instrumental variable is calculated using information within the calendar year prior to the first round of VC financing for models in Column (1) - (4) and (8) – (9), and within the calendar year of the previous round for models in Column (5) and (6). Marginal effects and Pseudo $R^2$ are reported for Probit regression (8), otherwise OLS coefficients and adjusted $R^2$ are reported. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | (1)<br>*N_round/N_VC*<br>*1st Stage* | (2)<br>*N_round*<br>*2nd Stage* | (3)<br>*Skewness*<br>*1st Stage* | (4)<br>*Skewnesss*<br>*2nd Stage* | (5)<br>*ΔR_amount*<br>*1st Stage* | (6)<br>*ΔR_amount*<br>*2nd Stage* | (7)<br>*Prob. Syn*<br>*1st Stage* | (8)<br>*Prob. Syn*<br>*2nd Stage* | (9)<br>*N_VC*<br>*2nd Stage* |
|---|---|---|---|---|---|---|---|---|---|
| *Ln_canc_days* | -0.101*** | | -0.093*** | | -0.090*** | | -0.108*** | | |
| | (0.012) | | (0.015) | | (0.006) | | (0.011) | | |
| *Info* | | -1.070** | | 9.719** | | 0.688*** | | -0.134* | -1.006** |
| | | (0.439) | | (4.336) | | (0.227) | | (0.071) | (0.458) |
| *Ind_Q* | -0.011*** | -0.017** | -0.012*** | 0.085 | 0.007*** | -0.004 | -0.010*** | -0.001 | -0.017* |
| | (0.002) | (0.006) | (0.002) | (0.089) | (0.001) | (0.003) | (0.001) | (0.001) | (0.008) |
| *Ind_RD* | 1.313*** | 1.322** | 1.328*** | -16.506** | 1.408*** | -0.828** | 1.221*** | 0.341*** | 2.317** |
| | (0.108) | (0.597) | (0.126) | (6.884) | (0.063) | (0.402) | (0.103) | (0.111) | (0.930) |
| *Ind_tangi* | -0.600*** | -0.430 | -0.591*** | 4.728 | 0.445*** | 0.009 | -0.640*** | -0.030 | -0.340 |
| | (0.116) | (0.372) | (0.135) | (4.065) | (0.084) | (0.314) | (0.095) | (0.091) | (0.502) |
| *Ln_age* | 0.007 | -0.199*** | 0.007 | 1.434*** | -0.013*** | -0.149*** | 0.005 | -0.028*** | -0.380*** |
| | (0.006) | (0.026) | (0.007) | (0.256) | (0.004) | (0.013) | (0.006) | (0.005) | (0.051) |
| *Early_dum* | -0.029** | 0.702*** | -0.020 | -1.669*** | -0.034*** | 0.333*** | -0.048*** | 0.101*** | 1.008*** |
| | (0.014) | (0.099) | (0.016) | (0.448) | (0.006) | (0.023) | (0.015) | (0.014) | (0.116) |
| *Ln_amt1st* | -0.004 | -0.243*** | -0.000 | 5.757*** | 0.003 | -0.202*** | -0.002 | 0.027*** | 0.090*** |
| | (0.005) | (0.019) | (0.005) | (0.345) | (0.002) | (0.006) | (0.005) | (0.003) | (0.031) |
| *Acq_dum* | -0.032** | 0.616*** | -0.032* | -1.561*** | -0.024*** | 0.133*** | -0.016 | 0.068*** | 0.766*** |
| | (0.015) | (0.132) | (0.017) | (0.411) | (0.008) | (0.021) | (0.015) | (0.012) | (0.060) |
| *IPO_dum* | -0.072*** | 0.419 | -0.069*** | -3.779*** | -0.010 | 0.245*** | -0.062*** | 0.055*** | 1.000*** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (0.019) | (0.271) | (0.022) | (0.727) | (0.010) | (0.025) | (0.020) | (0.007) | (0.180) |
| *Constant* | -0.432** | 1.662 | -0.574 | -12.289 | -0.201 | 3.047*** | 1.532*** | | 1.386 |
| | (0.216) | (1.771) | (0.385) | (8.965) | (0.786) | (0.609) | (0.527) | | (1.320) |
| Lead VC FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Rounds FE | N | N | Y | Y | N | N | N | N | N |
| | | | | | | | | | |
| Observations | 11,389 | 11,389 | 8,878 | 8,878 | 27,491 | 27,491 | 7,659 | 7,659 | 11,389 |
| Adj./Pseudo $R^2$ | 0.577 | 0.248 | 0.585 | 0.854 | 0.645 | 0.045 | 0.563 | 0.283 | 0.278 |

**Table 4**

Endogeneity tests with the Regulation SHO experiment.

This table reports the regression results on the effects of US Regulation SHO pilot program on VC staging and syndication. The sample includes observations from 2001-2003 and 2005-2012. The treatment group includes ventures with at least one of the largest 3 public firms in the same industry is randomly selected as a pilot firm for the SHO program in 2004. *During* is a dummy that equals one if the first/current round occurred between November 2, 2005 and 7 August, 2007, and zero otherwise. *Post* is a dummy that equals one if the first/current round occurred after 7 Aug, 2007 and zero otherwise. *R_amount* is defined as the natural logarithm difference between the current round amount and the financing amount of round one. For Column (3) the sample includes ventures with at least 1 round of financing both within and outside the period from November 2, 2005 to 7 August, 2007, otherwise the sample includes industries with at least 15 ventures receiving the first round of financing both during and in either the pre- or post- event period. Marginal effects and Pseudo $R^2$ are reported for the Probit regression in Column (4), otherwise OLS coefficients and adjusted $R^2$ are reported. Other variables are defined as in Table 2. 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.

| | (1)<br>*N_round* | (2)<br>*Skewness* | (3)<br>*R_amount* | (4)<br>*Prob. Syn* | (5)<br>*N_VC* |
|---|---|---|---|---|---|
| *Treat*During* | -0.710** | 7.104 | 0.096* | -0.046** | -0.820** |
| | (0.265) | (7.164) | (0.054) | (0.022) | (0.324) |
| *Treat*Post* | -0.410 | 4.882 | 0.165 | -0.001 | -0.143 |
| | (0.526) | (6.186) | (0.122) | (0.035) | (0.659) |
| *During* | -0.068 | 0.522 | 0.082 | 0.052*** | 0.340 |
| | (0.204) | (1.464) | (0.069) | (0.007) | (0.244) |
| *Post* | -0.287 | -1.863 | -0.050 | 0.135*** | 0.539* |
| | (0.267) | (3.282) | (0.102) | (0.007) | (0.272) |
| *Ind_Q* | -0.081* | 0.393 | 0.000 | 0.003 | 0.021 |
| | (0.036) | (0.379) | (0.001) | (0.005) | (0.031) |
| *Ind_RD* | 1.344 | -15.258 | 0.092 | -0.150 | -3.492 |
| | (1.788) | (27.291) | (0.370) | (0.216) | (2.549) |
| *Ind_tangi* | -0.141 | -8.999 | 1.856** | -0.504 | -6.236 |
| | (2.622) | (37.704) | (0.811) | (0.374) | (5.901) |
| *Log_age* | -0.399* | 3.559** | -0.282*** | -0.080*** | -0.464*** |
| | (0.200) | (1.215) | (0.061) | (0.011) | (0.135) |
| *Early_dum* | 0.529** | 0.113 | -0.193*** | 0.096*** | 0.513** |
| | (0.170) | (2.160) | (0.034) | (0.023) | (0.192) |
| *Log_amt1st* | -0.114 | 5.984*** | -0.899*** | 0.035*** | 0.025 |
| | (0.081) | (0.826) | (0.024) | (0.005) | (0.047) |
| *Acq_dum* | 0.887*** | -0.770 | -0.029 | 0.145*** | 0.592** |
| | (0.238) | (3.213) | (0.173) | (0.045) | (0.207) |
| *IPO_dum* | 2.416*** | -1.643 | 0.451* | 0.066** | 2.063*** |
| | (0.343) | (4.154) | (0.215) | (0.027) | (0.409) |
| *Constant* | 2.493 | -44.900* | 5.346*** | | 2.292 |
| | (1.576) | (24.231) | (0.993) | | (1.501) |
| Lead VC FE | Y | Y | Y | N | Y |
| Year FE | Y | Y | Y | Y | Y |

| | | | | | |
|---|---|---|---|---|---|
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | N | Y |
| Rounds FE | N | Y | N | N | N |
| | | | | | |
| Observations | 1,737 | 1,043 | 4,487 | 1,737 | 1,737 |
| Adj./Pseudo $R^2$ | 0.327 | 0.852 | 0.526 | 0.134 | 0.378 |

**Table 5**

VC experience and the effects of public market price informativeness on VC staging and syndication.

This table reports the 2SLS regression results on the effects of VC experience on the relationship between stock price informativeness of public firms and VC staging and syndication. VC industry experience is measured by a dummy variable that equals one if the venture's lead VC ranks in the top quintile by the number of successful exits (IPOs) in the same three-digit SIC industry of a venture from 1962 to the date of the first round of financing and zero otherwise for models in Column (1) - (4) and (7) - (10), and from 1962 to the date of the previous round of financing for models in Column (5) and (6). VC general experience is measured by a dummy variable that equals one if the venture's lead VC ranks in the top quintile by the number of successful exits (IPOs) and zero otherwise. Marginal effects and Pseudo $R^2$ are reported for the second-stage Probit regressions (7) and (8), otherwise the second-stage regression coefficients and adjusted $R^2$ are reported. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

*Panel A: Results on VC industry experience*

| | *N_round* | | *Skewness* | | *ΔR_amount* | | *Prob. Syn* | | *N_VC* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *$Exp\_exit_{ind}$*Info* | 0.255** | | -1.889** | | 0.010 | | 0.043* | | 0.422*** | |
| | (0.120) | | (0.962) | | (0.065) | | (0.022) | | (0.160) | |
| *$Exp\_IPO_{ind}$*Info* | | 0.273** | | -0.934 | | -0.014 | | 0.022 | | 0.384** |
| | | (0.125) | | (1.027) | | (0.062) | | (0.022) | | (0.176) |
| *Info* | -1.105** | -1.110** | 10.001** | 9.997** | 0.687*** | 0.688*** | -0.137** | -0.138** | -1.055* | -1.054* |
| | (0.468) | (0.469) | (4.105) | (4.122) | (0.249) | (0.249) | (0.069) | (0.070) | (0.614) | (0.615) |
| *Ind_Q* | -0.018** | -0.018** | 0.094 | 0.092 | -0.004 | -0.004 | -0.001 | -0.001 | -0.019** | -0.018* |
| | (0.008) | (0.008) | (0.065) | (0.066) | (0.003) | (0.003) | (0.001) | (0.001) | (0.009) | (0.009) |
| *Ind_RD* | 1.291* | 1.351* | -16.407*** | -17.323*** | -0.833* | -0.822* | 0.330*** | 0.345*** | 2.227** | 2.301** |
| | (0.749) | (0.758) | (6.345) | (6.469) | (0.453) | (0.451) | (0.105) | (0.106) | (0.958) | (0.971) |
| *Ind_tangi* | -0.496 | -0.471 | 5.362 | 5.228 | 0.008 | 0.009 | -0.028 | -0.035 | -0.404 | -0.370 |
| | (0.519) | (0.519) | (4.608) | (4.605) | (0.357) | (0.357) | (0.080) | (0.082) | (0.686) | (0.686) |
| *Ln_age* | -0.201*** | -0.201*** | 1.455*** | 1.454*** | -0.149*** | -0.149*** | -0.028*** | -0.028*** | -0.384*** | -0.383*** |
| | (0.028) | (0.028) | (0.256) | (0.256) | (0.017) | (0.017) | (0.004) | (0.004) | (0.034) | (0.034) |
| *Early_dum* | 0.706*** | 0.705*** | -1.685*** | -1.674*** | 0.333*** | 0.333*** | 0.101*** | 0.101*** | 1.013*** | 1.012*** |
| | (0.071) | (0.071) | (0.554) | (0.554) | (0.026) | (0.026) | (0.011) | (0.011) | (0.091) | (0.091) |
| *Ln_amt1st* | -0.244*** | -0.244*** | 5.766*** | 5.768*** | -0.202*** | -0.202*** | 0.026*** | 0.026*** | 0.089*** | 0.088*** |
| | (0.024) | (0.024) | (0.190) | (0.190) | (0.010) | (0.010) | (0.003) | (0.003) | (0.030) | (0.030) |
| *Acq_dum* | 0.617*** | 0.617*** | -1.573*** | -1.583*** | 0.133*** | 0.133*** | 0.068*** | 0.068*** | 0.766*** | 0.766*** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (0.070) | (0.070) | (0.559) | (0.558) | (0.033) | (0.033) | (0.011) | (0.011) | (0.094) | (0.094) |
| *IPO_dum* | 0.416*** | 0.415*** | -3.748*** | -3.751*** | 0.245*** | 0.245*** | 0.054*** | 0.055*** | 0.995*** | 0.995*** |
| | (0.098) | (0.098) | (0.770) | (0.772) | (0.041) | (0.041) | (0.011) | (0.011) | (0.134) | (0.134) |
| $Exp\_exit_{ind}$ | -0.731*** | | 5.656** | | -0.042 | | -0.101 | | -1.104*** | |
| | (0.279) | | (2.268) | | (0.148) | | (0.065) | | (0.366) | |
| $Exp\_IPO_{ind}$ | | -0.820*** | | 4.045* | | 0.020 | | -0.076 | | -1.028** |
| | | (0.296) | | (2.457) | | (0.140) | | (0.063) | | (0.409) |
| *Constant* | 1.927 | 1.829 | -14.697 | -13.588 | 3.058** | 3.046** | | | 1.761 | 1.575 |
| | (1.533) | (1.533) | (10.097) | (10.136) | (1.260) | (1.261) | | | (1.082) | (1.086) |
| Lead VC FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Rounds FE | N | N | Y | Y | N | N | N | N | N | N |
| | | | | | | | | | | |
| Observations | 11,389 | 11,389 | 8,878 | 8,878 | 27,491 | 27,491 | 7,659 | 7,659 | 11,389 | 11,389 |
| Adj./Pseudo $R^2$ | 0.248 | 0.248 | 0.854 | 0.854 | 0.045 | 0.045 | 0.283 | 0.283 | 0.278 | 0.278 |

| Panel B: Results on VC general experience | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *N_round* | | *Skewness* | | *ΔR_amount* | | *Syndication* | | *N_VC* | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *$Exp\_exit_{gen}$*Info* | -0.198* | | 0.510 | | -0.056 | | 0.023 | | -0.002 | |
| | (0.110) | | (0.912) | | (0.052) | | (0.018) | | (0.143) | |
| *$Exp\_IPO_{gen}$*Info* | | -0.273** | | 0.768 | | -0.047 | | 0.019 | | -0.165 |
| | | (0.110) | | (0.926) | | (0.052) | | (0.018) | | (0.144) |
| *Info* | -1.031** | -1.003** | 9.666** | 9.508** | 0.698*** | 0.699*** | -0.139** | -0.139** | -1.009* | -0.966 |
| | (0.466) | (0.466) | (4.080) | (4.078) | (0.250) | (0.250) | (0.069) | (0.069) | (0.613) | (0.613) |
| *Ind_Q* | -0.017** | -0.017** | 0.085 | 0.084 | -0.004 | -0.004 | -0.001 | -0.001 | -0.017* | -0.017* |
| | (0.008) | (0.008) | (0.065) | (0.065) | (0.003) | (0.003) | (0.001) | (0.001) | (0.009) | (0.009) |
| *Ind_RD* | 1.333* | 1.321* | -16.689*** | -16.480*** | -0.820* | -0.831* | 0.341*** | 0.342*** | 2.323** | 2.313** |
| | (0.738) | (0.738) | (6.223) | (6.220) | (0.452) | (0.452) | (0.103) | (0.104) | (0.944) | (0.944) |
| *Ind_tangi* | -0.421 | -0.422 | 4.885 | 4.752 | 0.016 | 0.017 | -0.031 | -0.032 | -0.350 | -0.338 |
| | (0.512) | (0.511) | (4.511) | (4.512) | (0.357) | (0.357) | (0.080) | (0.080) | (0.678) | (0.678) |
| *Ln_age* | -0.199*** | -0.197*** | 1.417*** | 1.430*** | -0.149*** | -0.148*** | -0.028*** | -0.028*** | -0.380*** | -0.380*** |
| | (0.028) | (0.028) | (0.256) | (0.256) | (0.017) | (0.017) | (0.004) | (0.004) | (0.034) | (0.034) |
| *Early_dum* | 0.699*** | 0.700*** | -1.655*** | -1.674*** | 0.332*** | 0.332*** | 0.101*** | 0.101*** | 1.007*** | 1.007*** |
| | (0.071) | (0.071) | (0.555) | (0.554) | (0.026) | (0.026) | (0.011) | (0.011) | (0.091) | (0.091) |
| *Ln_amt1st* | -0.243*** | -0.244*** | 5.762*** | 5.761*** | -0.202*** | -0.202*** | 0.027*** | 0.027*** | 0.090*** | 0.089*** |
| | (0.024) | (0.024) | (0.190) | (0.190) | (0.010) | (0.010) | (0.003) | (0.003) | (0.030) | (0.030) |
| *Acq_dum* | 0.616*** | 0.616*** | -1.548*** | -1.558*** | 0.133*** | 0.133*** | 0.068*** | 0.068*** | 0.765*** | 0.766*** |
| | (0.070) | (0.070) | (0.560) | (0.560) | (0.033) | (0.033) | (0.011) | (0.011) | (0.094) | (0.094) |
| *IPO_dum* | 0.418*** | 0.420*** | -3.746*** | -3.777*** | 0.245*** | 0.245*** | 0.055*** | 0.055*** | 0.998*** | 1.000*** |
| | (0.098) | (0.098) | (0.771) | (0.771) | (0.041) | (0.041) | (0.011) | (0.011) | (0.134) | (0.134) |
| *$Exp\_exit_{gen}$* | 0.364 | | -3.311 | | 0.127 | | -0.055 | | 0.116 | |
| | (0.274) | | (2.271) | | (0.125) | | (0.051) | | (0.355) | |
| *$Exp\_IPO_{gen}$* | | 0.623** | | -2.743 | | 0.188 | | -0.048 | | 0.510 |
| | | (0.294) | | (2.471) | | (0.134) | | (0.055) | | (0.384) |
| *Constant* | 1.568 | 1.477 | -11.250 | -11.665 | 3.076** | 3.048** | | | 1.331 | 1.228 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1.546) | (1.540) | (10.342) | (10.287) | (1.263) | (1.263) | | | (1.115) | (1.117) |
| Lead VC FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Rounds FE | N | N | Y | Y | N | N | N | N | N | N |
| | | | | | | | | | | |
| Observations | 11,389 | 11,389 | 8,878 | 8,878 | 27,491 | 27,491 | 7,659 | 7,659 | 11,389 | 11,389 |
| Adj./Pseudo $R^2$ | 0.248 | 0.248 | 0.854 | 0.854 | 0.045 | 0.045 | 0.283 | 0.283 | 0.278 | 0.278 |

**Table 6**

Geographical distances and the effects of public market price informativeness on VC staging and syndication.

This table reports the 2SLS regression results on the effects of geographical distances between the offices of a venture and its lead VC on the relationship between stock price informativeness of public firms and VC staging and syndication. The geographical distance is measured by a dummy variable that equals one if a venture and its lead VC share the same zip code and zero otherwise, and a dummy variable that equals one if the geographical distance between a venture and its lead VC ranks in the top decile among all venture-VC pair distances and zero otherwise. Marginal effects and Pseudo $R^2$ are reported for the second-stage Probit regressions (7) and (8), otherwise OLS coefficients and adjusted $R^2$ are reported. Other variables are defined as in Table 2. See Appendix A for definitions of variables. For simplicity only the second-stage results are reported. Standard errors reported in parentheses are adjusted for heteroscedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | *N_round* | | *Skewness* | | *ΔR_amount* | | *Prob. Syn* | | *N_VC* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Samezip*Info* | -0.176 | | -7.131*** | | 0.284 | | -0.022 | | 0.073 | |
| | (0.282) | | (2.318) | | (0.174) | | (0.047) | | (0.355) | |
| *Distant*Info* | | -0.322*** | | 0.982 | | -0.039 | | -0.004 | | -0.249* |
| | | (0.105) | | (0.901) | | (0.059) | | (0.017) | | (0.138) |
| *Info* | -0.946* | -0.936** | 8.761* | 9.347** | 0.689** | 0.696*** | -0.171** | -0.114* | -0.909 | -0.875 |
| | (0.547) | (0.467) | (4.830) | (4.080) | (0.278) | (0.250) | (0.078) | (0.068) | (0.720) | (0.612) |
| *Ind_Q* | -0.015 | -0.017** | 0.056 | 0.083 | -0.003 | -0.004 | -0.001 | -0.001 | -0.014 | -0.016* |
| | (0.010) | (0.008) | (0.083) | (0.065) | (0.004) | (0.003) | (0.001) | (0.001) | (0.012) | (0.009) |
| *Ind_RD* | 1.253 | 1.242* | -15.751** | -16.365*** | -0.952* | -0.830* | 0.407*** | 0.310*** | 2.134** | 2.218** |
| | (0.843) | (0.737) | (7.057) | (6.216) | (0.496) | (0.452) | (0.117) | (0.102) | (1.077) | (0.944) |
| *Ind_tangi* | -0.676 | -0.390 | 1.614 | 4.641 | 0.158 | 0.010 | 0.023 | -0.033 | -0.212 | -0.300 |
| | (0.583) | (0.512) | (5.085) | (4.516) | (0.399) | (0.357) | (0.086) | (0.079) | (0.770) | (0.677) |
| *Ln_age* | -0.214*** | -0.200*** | 1.455*** | 1.439*** | -0.157*** | -0.149*** | -0.032*** | -0.029*** | -0.410*** | -0.382*** |
| | (0.033) | (0.028) | (0.289) | (0.256) | (0.018) | (0.017) | (0.005) | (0.004) | (0.040) | (0.034) |
| *Early_dum* | 0.724*** | 0.699*** | -1.392** | -1.672*** | 0.337*** | 0.333*** | 0.090*** | 0.096*** | 1.005*** | 1.002*** |
| | (0.078) | (0.070) | (0.611) | (0.554) | (0.028) | (0.026) | (0.012) | (0.011) | (0.102) | (0.091) |
| *Ln_amt1st* | -0.242*** | -0.243*** | 5.644*** | 5.762*** | -0.196*** | -0.202*** | 0.027*** | 0.026*** | 0.097*** | 0.090*** |
| | (0.026) | (0.023) | (0.206) | (0.190) | (0.011) | (0.010) | (0.003) | (0.003) | (0.033) | (0.030) |
| *Acq_dum* | 0.706*** | 0.608*** | -1.487** | -1.551*** | 0.127*** | 0.132*** | 0.066*** | 0.063*** | 0.767*** | 0.755*** |
| | (0.078) | (0.070) | (0.617) | (0.560) | (0.036) | (0.033) | (0.012) | (0.011) | (0.105) | (0.094) |
| *IPO_dum* | 0.526*** | 0.418*** | -3.825*** | -3.779*** | 0.236*** | 0.244*** | 0.048*** | 0.053*** | 1.042*** | 0.997*** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (0.110) | (0.098) | (0.852) | (0.771) | (0.044) | (0.041) | (0.012) | (0.010) | (0.151) | (0.134) |
| *Samezip* | -0.395 | | 17.401*** | | -0.659 | | -0.055 | | -1.125 | |
| | (0.635) | | (5.387) | | (0.414) | | (0.141) | | (0.751) | |
| *Distant* | | 0.362 | | -1.533 | | 0.076 | | -0.148** | | 0.093 |
| | | (0.251) | | (2.157) | | (0.139) | | (0.060) | | (0.331) |
| *Constant* | 2.875 | 1.528 | -21.365* | -11.762 | 3.045** | 3.029** | | | 1.464 | 1.349 |
| | (1.760) | (1.570) | (11.583) | (10.325) | (1.288) | (1.262) | | | (1.583) | (1.123) |
| Lead VC FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Rounds FE | N | N | Y | Y | N | N | N | N | N | N |
| | | | | | | | | | | |
| Observations | 9,705 | 11,389 | 7,552 | 8,878 | 24,117 | 27,491 | 6,279 | 7,659 | 9,705 | 11,389 |
| Adj./Pseudo $R^2$ | 0.246 | 0.250 | 0.859 | 0.854 | 0.042 | 0.045 | 0.299 | 0.297 | 0.274 | 0.280 |

**Table 7**

Venture riskiness and the effects of public market price informativeness on VC staging and syndication.

This table reports the 2SLS regression results on the effects of venture riskiness on the relation between stock price informativeness of public firms and VC staging and syndication. *Intensive* is a R&D-intensive industry dummy that equals one if the R&D spending in a venture's industry ranks in the top tercile in all industries and zero otherwise. *Early_dum*, is a dummy variable that equals one if a venture is in its seed/startup or early stage when receiving the first/previous round of VC financing and zero otherwise. Marginal effects and Pseudo $R^2$ are reported for the second-stage Probit regression (4), otherwise the second-stage regression coefficients and adjusted $R^2$ are reported. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Standard errors reported in parentheses are adjusted for heteroscedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| *Panel A: VC staging and syndication in R&D intensive industries* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | *N_round* | *Skewness* | *ΔR_amount* | *Prob. Syn* | *N_VC* |
| *Intensive*Info* | 0.195* | -2.140** | 0.054 | 0.028* | 0.711*** |
| | (0.119) | (0.934) | (0.055) | (0.016) | (0.149) |
| *Info* | -1.132** | 10.331** | 0.641*** | -0.125* | -1.078* |
| | (0.500) | (4.463) | (0.238) | (0.067) | (0.656) |
| *Ind_Q* | -0.016** | 0.074 | -0.005 | -0.001 | -0.015 |
| | (0.008) | (0.065) | (0.003) | (0.001) | (0.009) |
| *Ind_tangi* | -0.746 | 7.084 | 0.150 | -0.036 | -0.825 |
| | (0.586) | (5.219) | (0.337) | (0.082) | (0.783) |
| *Log_age* | -0.199*** | 1.425*** | -0.148*** | -0.028*** | -0.382*** |
| | (0.028) | (0.257) | (0.017) | (0.004) | (0.034) |
| *Early_dum* | 0.704*** | -1.657*** | 0.332*** | 0.103*** | 1.015*** |
| | (0.071) | (0.555) | (0.026) | (0.011) | (0.092) |
| *Log_amt1st* | -0.242*** | 5.757*** | -0.202*** | 0.027*** | 0.092*** |
| | (0.024) | (0.190) | (0.010) | (0.003) | (0.030) |
| *Acq_dum* | 0.616*** | -1.550*** | 0.133*** | 0.067*** | 0.762*** |
| | (0.070) | (0.560) | (0.033) | (0.011) | (0.094) |
| *IPO_dum* | 0.423*** | -3.778*** | 0.243*** | 0.056*** | 1.006*** |
| | (0.097) | (0.769) | (0.041) | (0.010) | (0.134) |
| *Intensive* | -0.379 | 3.098 | -0.168 | -0.017 | -1.511*** |
| | (0.290) | (2.346) | (0.130) | (0.040) | (0.364) |
| *Constant* | 1.717 | -12.900 | 3.161** | | 1.586 |
| | (1.534) | (10.288) | (1.250) | | (1.077) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| | | | | | |
| Observations | 11,389 | 8,878 | 27,491 | 7,659 | 11,389 |
| Adj./Pseudo $R^2$ | 0.248 | 0.854 | 0.045 | 0.284 | 0.279 |

| *Panel B: VC staging and syndication for ventures at their early-stages* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | *N_round* | *Skewness* | *ΔR_amount* | *Prob. Syn* | *N_VC* |
| *Early_dum*Info* | 0.333*** | -2.819*** | 0.042 | -0.023 | 0.394*** |
| | (0.095) | (0.823) | (0.042) | (0.015) | (0.122) |
| *Info* | -1.198** | 10.721*** | 0.673*** | -0.130* | -1.157* |
| | (0.467) | (4.092) | (0.250) | (0.069) | (0.611) |
| *Ind_Q* | -0.017** | 0.086 | -0.004 | -0.001 | -0.017* |
| | (0.008) | (0.065) | (0.003) | (0.001) | (0.009) |
| *Ind_RD* | 1.218* | -15.486** | -0.825* | 0.349*** | 2.194** |
| | (0.738) | (6.227) | (0.452) | (0.104) | (0.946) |
| *Ind_tangi* | -0.440 | 4.798 | 0.012 | -0.029 | -0.352 |
| | (0.512) | (4.517) | (0.357) | (0.080) | (0.677) |
| *Log_age* | -0.204*** | 1.488*** | -0.149*** | -0.028*** | -0.387*** |
| | (0.028) | (0.257) | (0.017) | (0.004) | (0.034) |
| *Early_dum* | -0.072 | 4.876** | 0.237** | 0.159*** | 0.092 |
| | (0.225) | (1.956) | (0.097) | (0.040) | (0.289) |
| *Log_amt1st* | -0.246*** | 5.784*** | -0.202*** | 0.027*** | 0.086*** |
| | (0.024) | (0.190) | (0.010) | (0.003) | (0.030) |
| *Acq_dum* | 0.620*** | -1.605*** | 0.133*** | 0.067*** | 0.771*** |
| | (0.070) | (0.560) | (0.033) | (0.011) | (0.094) |
| *IPO_dum* | 0.416*** | -3.738*** | 0.245*** | 0.055*** | 0.996*** |
| | (0.098) | (0.770) | (0.041) | (0.011) | (0.134) |
| *Constant* | 1.848 | -13.766 | 3.052** | | 1.606 |
| | (1.560) | (9.738) | (1.258) | | (1.118) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| | | | | | |
| Observations | 11,389 | 8,878 | 27,491 | 7,659 | 11,389 |
| Adj./Pseudo $R^2$ | 0.249 | 0.854 | 0.045 | 0.283 | 0.281 |

**Table 8**
Evidence on VC investment performance.
This table reports the Probit regression results on the effects of VC staging and syndication on their investment performance. The dependent variable is the successful exit dummy that equals one if investing VCs exit the firm either by IPO or acquisition and zero otherwise. Other variables are defined as in Table 2. See Appendix A for definitions of variables. Columns (1) and (4) report regression results in the full sample; Columns (2) and (5) report regression results using ventures in industries with average price nonsynchronicity ranking in the top decile (the highest decile) among all industries; Columns (3) and (6) report results on ventures in industries with average price nonsynchronicity ranking in the bottom decile. Standard errors reported in parentheses. Marginal effects, pseudo $R^2$, and the Wald chi-square statistics for testing the difference between coefficient estimates in Columns (2) and (3) are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

*Panel A: Price informativeness and the effects of VC staging on exits*

| | | *N_round* | | | *Skewness* | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Sample=* | *Full* | *H. Info.* | *L. Info* | *Full* | *H. Info.* | *L. Info* |
| *Staging var.* | 0.013*** | 0.021*** | -0.005 | -0.001*** | -0.002*** | -0.000 |
| | (0.001) | (0.007) | (0.004) | (0.000) | (0.001) | (0.000) |
| *Ind_Q* | -0.005*** | -0.000 | -0.005* | -0.006*** | 0.001 | -0.006* |
| | (0.001) | (0.005) | (0.003) | (0.001) | (0.006) | (0.003) |
| *Ind_RD* | 0.004 | 0.042 | 0.059 | -0.018 | 0.181 | 0.010 |
| | (0.061) | (0.244) | (0.324) | (0.072) | (0.291) | (0.388) |
| *Ind_tangi* | -0.263*** | -0.178 | -0.433** | -0.338*** | -0.192 | -0.585*** |
| | (0.053) | (0.231) | (0.172) | (0.061) | (0.264) | (0.197) |
| *Ln_age* | 0.029*** | 0.050*** | 0.027** | 0.030*** | 0.056*** | 0.033** |
| | (0.004) | (0.016) | (0.012) | (0.005) | (0.018) | (0.013) |
| *Early_dum* | -0.033*** | 0.003 | -0.025 | -0.038*** | -0.004 | -0.033 |
| | (0.009) | (0.040) | (0.027) | (0.010) | (0.047) | (0.031) |
| *Ln_amt1st* | 0.023*** | 0.031*** | 0.020*** | 0.025*** | 0.033** | 0.019** |
| | (0.003) | (0.011) | (0.007) | (0.003) | (0.013) | (0.009) |
| *VC Exp. Control* | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y |
| *Wald test for diff. in staging var.* | | 10.138*** | | | 4.500** | |
| Observations | 13,159 | 922 | 1,188 | 10,288 | 718 | 948 |
| Pseudo $R^2$ | 0.0555 | 0.127 | 0.107 | 0.0632 | 0.145 | 0.127 |

| Panel B: Price informativeness and the effects of VC syndication on exits | | | | | | |
|---|---|---|---|---|---|---|
| | | *Syn* | | | *N_VC* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Sample=* | *Full* | *H. Info.* | *L. Info* | *Full* | *H. Info.* | *L. Info* |
| *Syn. var.* | 0.010*** | 0.028*** | 0.001 | 0.059*** | 0.084* | -0.003 |
| | (0.001) | (0.006) | (0.002) | (0.011) | (0.043) | (0.030) |
| *Ind_Q* | -0.005*** | -0.001 | -0.005* | -0.005*** | -0.001 | -0.005* |
| | (0.001) | (0.005) | (0.003) | (0.001) | (0.005) | (0.003) |
| *Ind_RD* | 0.003 | -0.030 | 0.029 | 0.013 | 0.052 | 0.028 |
| | (0.061) | (0.245) | (0.322) | (0.061) | (0.245) | (0.322) |
| *Ind_tangi* | -0.294*** | -0.201 | -0.466*** | -0.237*** | -0.183 | -0.455*** |
| | (0.053) | (0.231) | (0.173) | (0.053) | (0.231) | (0.172) |
| *Ln_age* | 0.030*** | 0.055*** | 0.029** | 0.026*** | 0.048*** | 0.029** |
| | (0.004) | (0.016) | (0.012) | (0.004) | (0.016) | (0.011) |
| *Early_dum* | -0.036*** | -0.020 | -0.035 | -0.026*** | 0.018 | -0.031 |
| | (0.009) | (0.040) | (0.027) | (0.009) | (0.039) | (0.027) |
| *Ln_amt1st* | 0.019*** | 0.023** | 0.020*** | 0.019*** | 0.025** | 0.020*** |
| | (0.003) | (0.011) | (0.007) | (0.003) | (0.011) | (0.007) |
| *VC Exp. Control* | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y | Y |
| *Wald test for diff. in syn. var.* | | 13.000*** | | | 1.643 | |
| Observations | 13,159 | 922 | 1,188 | 13,159 | 922 | 1,188 |
| Pseudo $R^2$ | 0.0560 | 0.140 | 0.105 | 0.0508 | 0.122 | 0.105 |

**Appendix A**

Variable definitions.

In *N_round*, *Skewness*, *Syn* and *N_VC* regressions, we calculate variables using data within/at the end of the calendar year prior to the first round of VC financing. In *ΔR_amount* regressions, we use variables calculated using data within/at the end of the calendar year of the previous round of VC financing.

| *Variable Name* | *Definition* |
|---|---|
| *N_Round* | The total number of VC financing rounds a venture receives. |
| *Skewness* | The skewness of VC investments in a venture, calculated as the amount a venture receives from round one divided by total amount of VC financing across all financing rounds. |
| *ΔR_amount* | The increase in round amount, calculated as the natural logarithm difference between the current round and the previous round. |
| *R_amount* | The natural logarithm of difference between the current round amount and the first round amount. |
| *Syn* | A syndication dummy that equals one if a venture is financed by a VC syndicate and zero otherwise. |
| *N_VC* | The number of VC investors in a syndicate co-investing in a venture. |
| *Info* | The average of the stock price nonsynchronicity measure across all public firms in the same industry of a venture. For individual stocks, the price nonsynchronicity is calculated as Ln($R^2$/(1-$R^2$)), where $R^2$ is obtained by regressing daily stock returns on market and industry returns. |
| $PIN_{DY}$ | The average probability of information-based trading for public firms in the same industry of a venture, as defined in Duarte and Young (2009). |
| *Ind_Q* | The industry average of Tobin's Q, calculated as the market value of equity minus long-term liability, divided by total assets minus long-term liability. |
| *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. |
| *Ind_illiq* | The industry average of the Amihud (2002) illiquidity ratio, multiplied by 1,000. |
| *Ln_age* | The natural logarithm value of venture age, defined as the number of years since the venture's inception. |
| *Early_dum* | A dummy variable that equals one if a venture is in its seed/startup or early stage, and zero if the entrepreneurial firm is in its expansion, late, or buyout/acquisition stage. |
| *Ln_amt1st* | The natural logarithm value of the first round investment amount in thousand dollars. |
| *Acq_dum* | A dummy variable that equals one if a venture is acquired or merged with another firm and zero otherwise. |
| *IPO_dum* | A dummy variable that equals one if a venture goes public and zero otherwise. |
| *Ln_canc_days* | Instrument variable. The natural logarithm value of average days in a year when there are severe flight cancellations either in the airports closest to the public firm's headquarter or closest to the offices of the analysts covering the firm, which prevents financial analysts from physically visiting the firms they cover. |
| *Yr06_dum* | A dummy variable for year 2006. |
| *Yr09_dum* | A dummy variable for year 2009. |
| *Treat* | The treatment group dummy variable that equals one if at least one of the largest 3 public firms in the same industry of a venture is randomly selected as a pilot firm for the SHO program in 2004 and zero otherwise. |
| $Exp\_exit_{gen}$ | A VC general experience dummy variable that equals one if the lead VC firm ranks in the top quintile by the number of exits from 1962 and zero otherwise. |
| $Exp\_exit_{ind}$ | A VC industry experience dummy variable that equals one if the lead VC firm ranks in the top quintile by the number of exits in the same three-digit SIC industry of a venture from 1962 and zero otherwise. |
| $Exp\_IPO_{gen}$ | A VC general experience dummy variable that equals one if the lead VC firm ranks in the top quintile by the number of IPOs from 1962 and zero otherwise. |

| | |
|---|---|
| $Exp\_IPO_{ind}$ | A VC industry experience dummy variable that equals one if the lead VC firm ranks in the top quintile by the number of IPOs in the same three-digit SIC industry of a venture from 1962 and zero otherwise. |
| *Samezip* | A dummy variable that equals one if a venture and its lead VC firm share the same zip code and zero otherwise. |
| *Distant* | A dummy variable that equals one if the geographical distance between a venture and its lead VC is in the top decile (the longest decile) among all venture-VC pair distances and zero otherwise. |
| *Intensive* | A dummy variable that equals one if the R&D spending in a venture's industry ranks in the top tercile in all industries and zero otherwise. |
| *Exit* | A dummy variable that equals one if investing VCs exit the venture by IPO or acquisition and zero otherwise. |

**Appendix B**

Data and procedures for computing the instrumental variable.

We follow the following steps to construct our instrument variable *Ln_canc_days*, 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, US Department of Transportation.[8] The dataset contains information on flight delays, cancellations and diversions due to weather, air traffic, security, and airline reasons for 14 US 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 due to reasons mentioned above, 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

$$Distance = 3963 * \arccos(\sin(latitude1)\sin(latitude2) + \cos(latitude1)\cos(latitude2)\cos(longitude1 - longitude2))$$

with hand-collected analyst office zip codes data, firm headquarter zip codes information from Compustat, geological coordinates information for zip codes from CivicSpace US ZIP Code Database,[9] and airport coordinates from OpenFlights.org.[10] The analysts following the public firms are obtained from the IBES dataset.

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. Lastly, the number of flight-cancellation days are averaged across analysts following the firm to compute firm-level annual cancellation days, then averaged across firms and taken natural logarithm of to compute the industry-level annual flight-cancellation-days, *Ln_canc_days*.

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

[9] Webste: http://www.boutell.com/zipcodes/.

[10] Website: http://openflights.org/data.html.

**Appendix C**
Robustness tests.

We perform a number of additional analyses to check the robustness of our 2SLS results in this appendix. All these robustness check tests are undertaken in the 2SLS framework using the instrument discussed in Section 5.1.

*C.1. Alternative measurement horizons for price nonsynchronicity*

In the baseline regressions, 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 construction of this measure, we construct the price informativeness measure using an alternative measurement horizon, i.e., 250 trading days prior to the first or previous round of VC financing. Table A1 Panel A reports the results using this alternative price informativeness measure. The results are qualitatively the same as in the 2SLS regression tests with higher significance levels. The magnitudes of the coefficient estimates of *Info* are similar. In unreported analyses, we re-run the baseline 2SLS tests with 3-year and 5-year measurement horizons prior to the first round of VC financing and obtain consistent results.

*C.2 Alternative proxies for price informativeness*

The probability of information-based trading, $PIN$, developed by Easley, Kiefer, and O'Hara (1996, 1997a, 1997b) is a widely used price informativeness proxy in the literature (e.g., Chen, Goldstein, and Jiang, 2007; Vega, 2006; Easley, Hvidkjaer, and O'Hara, 2002). 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 Young (2009) further decompose the original *PIN* measure into an asymmetric information component and an illiquidity component. They develop a modified $PIN_{DY}$ measure for the asymmetric information component:

$$PIN_{DY} = \frac{a(d\mu_B + (1-d)\mu_S}{a(d\mu_B + (1-d)\mu_S) + (\Delta_B + \Delta_S)(a\theta' + (1-a)\theta) + \epsilon_S + \epsilon_B} \quad \text{(A1)}$$

where $d$ is the probability that informed traders receive a positive signal if an event with private information happens, $\mu_B$ and $\mu_S$ denote the arrival rate of informed buyers and sellers, respectively. $\theta$ and $\theta'$ denote the probabilities that a symmetric order shock occurs with/without private information arrival. $\Delta_B$ and $\Delta_S$ are additional arrival rates of buyers and sellers with symmetric order flow shocks.

Panel B of Table A1 reports the regression results estimating equation (3) with $PIN_{DY}$ as an alternative price informativeness measure. The coefficient estimates of $PIN_{DY}$ exhibit consistent signs with those reported in Table 3 and are statistically significant in all columns, suggesting that more informative public stock prices are associated with less VC staging and syndication. In unreported analyses, we use the original *PIN* measure as defined in Easley, Hvidkjaer, and O'Hara (2002) and obtain similar results.

*C.3 Controlling for liquidity effects*

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, Ostergaard, and Schindele, 2015), innovation (Fang, Tian, and Tice, 2014), and takeovers (Roosenboom, Schlingemann, and Vasconcelos, 2014). In addition, as argued by Duarte and Young (2009) and Lai, Ng, and Zhang (2014), the widely-tested *PIN* measure defined by Easley, Hvidkjaer, and O'Hara (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 A1 reports the regression results estimating equation (3) with Amihud (2002) illiquidity ration included. The evidence shows that our baseline results are robust after controlling for the liquidity effect. We still observe a significant price informativeness effect in all regressions. The Amihud (2002) illiquidity proxy, *Ind_illiq*, does not show consistent and significant effects in VC staging and syndication regressions.

**Table A1**
Robustness checks.

This table reports robustness checks for the 2SLS regression results on the effects of stock price informativeness of public firms in the same industry of a venture on VC staging and syndication. The sample consists of 13,185 ventures completing 53,084 rounds of VC financing between 1980 and 2012. Panel A reports 2SLS regression results with the stock price nonsynchronicity measure calculated with returns during the 250 days prior to the first round of VC financing for models in Column (1), (2), (4) and (5), and during the 250 days prior to the previous round for the model in Column (3). Panel B reports 2SLS results with the modified $PIN_{DY}$ defined in Duarte and Young (2009) as the price informativeness measure. Panel C reports 2SLS regression results with the Amihud (2002) illiquidity measure controlled. Other variables are defined as in Table 2. Marginal effects and Pseudo $R^2$ are reported for the second-stage Probit regression (4), otherwise the second-stage regression coefficients and adjusted $R^2$ are reported. 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: Alternative measurement horizon*

| | (1) *N_round* | (2) *Skewness* | (3) *ΔR_amount* | (4) *Prob. Syn* | (5) *N_VC* |
|---|---|---|---|---|---|
| $Info_{250d}$ | -1.038** | 9.333** | 0.694*** | -0.136* | -0.975** |
| | (0.426) | (4.164) | (0.229) | (0.071) | (0.445) |
| *Ind_Q* | -0.014** | 0.052 | 0.001 | -0.001 | -0.014* |
| | (0.006) | (0.085) | (0.002) | (0.001) | (0.008) |
| *Ind_RD* | 0.562 | -9.372** | -0.683* | 0.246*** | 1.603** |
| | (0.453) | (4.411) | (0.363) | (0.077) | (0.722) |
| *Ind_tangi* | -0.552 | 6.107 | 0.363 | -0.050 | -0.455 |
| | (0.392) | (4.422) | (0.298) | (0.099) | (0.509) |
| *Ln_age* | -0.202*** | 1.434*** | -0.159*** | -0.029*** | -0.383*** |
| | (0.026) | (0.256) | (0.013) | (0.005) | (0.051) |
| *Early_dum* | 0.691*** | -1.494*** | 0.317*** | 0.100*** | 0.997*** |
| | (0.098) | (0.449) | (0.022) | (0.014) | (0.115) |
| *Ln_amt1st* | -0.240*** | 5.739*** | -0.203*** | 0.027*** | 0.093*** |
| | (0.020) | (0.347) | (0.006) | (0.003) | (0.031) |
| *Acq_dum* | 0.623*** | -1.603*** | 0.128*** | 0.068*** | 0.772*** |
| | (0.131) | (0.414) | (0.021) | (0.012) | (0.061) |
| *IPO_dum* | 0.449 | -3.963*** | 0.233*** | 0.058*** | 1.028*** |
| | (0.268) | (0.744) | (0.025) | (0.007) | (0.175) |
| *Constant* | 2.437 | -18.430** | 2.530*** | | 2.114* |
| | (1.711) | (8.170) | (0.739) | | (1.119) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| Observations | 11,389 | 8,878 | 27,491 | 7,659 | 11,389 |
| Adj./Pseudo $R^2$ | 0.552 | 0.854 | 0.045 | 0.283 | 0.278 |

| *Panel B: Alternative informativeness measure* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | *N_round* | *Skewness* | *ΔR_amount* | *Prob. Syn* | *N_VC* |
| $PIN_{DY}$ | -63.599** | 589.293** | 15.172*** | -7.786* | -56.613** |
| | (24.564) | (261.821) | (5.109) | (4.287) | (26.591) |
| *Ind_Q* | -0.017** | 0.070 | 0.004 | -0.001 | -0.016* |
| | (0.006) | (0.089) | (0.003) | (0.001) | (0.009) |
| *Ind_RD* | -0.295 | -0.928 | -0.221 | 0.121 | 0.852 |
| | (0.508) | (3.607) | (0.251) | (0.078) | (0.636) |
| *Ind_tangi* | -1.018* | 13.287* | -0.002 | -0.110 | -0.869 |
| | (0.499) | (7.080) | (0.318) | (0.133) | (0.602) |
| *Ln_age* | -0.193*** | 1.267*** | -0.169*** | -0.028*** | -0.376*** |
| | (0.027) | (0.266) | (0.013) | (0.005) | (0.053) |
| *Early_dum* | 0.681*** | -1.304** | 0.316*** | 0.099*** | 0.987*** |
| | (0.096) | (0.484) | (0.022) | (0.014) | (0.114) |
| *Ln_amt1st* | -0.271*** | 6.036*** | -0.200*** | 0.022*** | 0.068* |
| | (0.019) | (0.330) | (0.006) | (0.003) | (0.036) |
| *Acq_dum* | 0.652*** | -2.003*** | 0.130*** | 0.074*** | 0.793*** |
| | (0.131) | (0.504) | (0.021) | (0.011) | (0.065) |
| *IPO_dum* | 0.488* | -4.221*** | 0.235*** | 0.063*** | 1.053*** |
| | (0.267) | (0.790) | (0.025) | (0.006) | (0.167) |
| *Constant* | 14.376*** | -140.189** | 2.476** | | 11.678** |
| | (4.969) | (56.272) | (1.255) | | (4.858) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| | | | | | |
| Observations | 11,260 | 8,765 | 27,241 | 7,530 | 11,260 |
| Adj./Pseudo $R^2$ | 0.246 | 0.853 | 0.046 | 0.280 | 0.276 |

| *Panel C: Control for liquidity effects* | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | *N_round* | *Skewness* | *ΔR_amount* | *Prob. Syn* | *N_VC* |
| *Info* | -1.109** | 9.602* | 0.608*** | -0.139* | -1.019** |
| | (0.465) | (4.843) | (0.217) | (0.076) | (0.488) |
| *Ind_illiq* | 3.293 | 10.251 | 2.300*** | 0.286 | 1.163 |
| | (2.850) | (43.268) | (0.788) | (0.570) | (4.214) |
| *Ind_Q* | -0.018** | 0.083 | -0.003 | -0.001 | -0.017* |
| | (0.007) | (0.085) | (0.003) | (0.001) | (0.008) |
| *Ind_RD* | 1.396** | -16.262** | -0.755* | 0.348*** | 2.343** |
| | (0.638) | (7.661) | (0.394) | (0.117) | (0.957) |
| *Ind_tangi* | -0.451 | 4.648 | -0.061 | -0.034 | -0.348 |
| | (0.378) | (4.239) | (0.318) | (0.093) | (0.510) |
| *Ln_age* | -0.199*** | 1.434*** | -0.152*** | -0.028*** | -0.381*** |
| | (0.027) | (0.256) | (0.013) | (0.005) | (0.051) |
| *Early_dum* | 0.703*** | -1.662*** | 0.331*** | 0.101*** | 1.008*** |
| | (0.098) | (0.458) | (0.023) | (0.014) | (0.116) |
| *Ln_amt1st* | -0.243*** | 5.757*** | -0.202*** | 0.027*** | 0.090*** |
| | (0.020) | (0.348) | (0.006) | (0.003) | (0.031) |
| *Acq_dum* | 0.615*** | -1.566*** | 0.131*** | 0.068*** | 0.765*** |
| | (0.132) | (0.409) | (0.021) | (0.012) | (0.061) |
| *IPO_dum* | 0.415 | -3.792*** | 0.243*** | 0.055*** | 0.998*** |
| | (0.272) | (0.700) | (0.025) | (0.007) | (0.179) |
| *Constant* | 1.675 | -12.180 | 3.284*** | | 1.391 |
| | (1.762) | (8.660) | (0.589) | | (1.312) |
| Lead VC FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y |
| State FE | Y | Y | Y | Y | Y |
| Rounds FE | N | Y | N | N | N |
| | | | | | |
| Observations | 11,389 | 8,878 | 27,491 | 7,659 | 11,389 |
| Adj./Pseudo $R^2$ | 0.248 | 0.854 | 0.045 | 0.283 | 0.278 |