Startup Press Releases *†

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July 31, 2024

Abstract

This study examines voluntary disclosure incentives in a highly opaque environment – startups. Using a novel dataset of press releases, we document that high-quality startups tend to stay "silent," as disclosure frequency is actually negatively associated with both the likelihood of securing future funding and gaining higher valuation. Low-quality startups and those with capital-constrained inside investors both issue press releases to compete for outside investor attention, with textual analysis further suggesting that the former is more inclined to resort to "spin." Our results contradict theories predicting information unravelling, instead highlighting the dominant role of inside investors in restricting startup disclosure.

KEYWORDS: Startups, Venture capital, Voluntary disclosure, Information design
JEL CLASSIFICATION: D82, G24, G32, M13

*We thank Lin William Cong, Diego García, Franz J. Hinzen, Yiming Ma, Gordon Philips, Buhui Qiu, Felipe Severino, David Solomon, Byoung-Hyoun Hwang, Gaoqing Zhang, Ron Masulis, and attendees of the seminars and brown bags at Macquarie University, University of Sydney, UNSW, UTS, and Tuck School of Business, for their valuable feedback. Special acknowledgment is due to Phillip Stocken for his guidance and insights on voluntary disclosure theory. Any errors in this work are solely our responsibility.

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1 Introduction

Startups are the engine of economic progress. In their peak in 2021, the amount of funding received by startups surpassed $600 billion, while their contribution to the global economy reached the equivalent of the GDP of an entire G7 economy (World Economic Forum, 2020). Given their growing size and prominence, startups are attracting increased investor attention. However, the extent to which potential investors can access information to evaluate investment opportunities in private markets is limited. Unlike publicly traded companies, startups do not need to disclose financial and operational information regularly to the public. Rather, details about their progress and future business plans are only available if a startup *chooses* to voluntarily disclose such information.

In this paper, we explore the extent to which startups use voluntary disclosure to attract investor attention. The focus of our analysis is decisions by startups to issue a press release. In particular, we study whether such disclosure possesses a strategic dimension, whereby certain startups may have an incentive to use the media to shape a positive narrative regarding their progress and potential success for fundraising purposes.

Firms' incentives to voluntarily disclose private verifiable information have long been a research focus in finance, accounting, and economics.[1] The theory of voluntary information disclosure, based on an "unraveling" equilibrium described in Grossman and Hart (1980), Grossman (1981), and Milgrom (1981), suggests that since rational market participants view nondisclosure negatively, then all firms have the incentive to disclose all relevant information. According to these models, the lack of mandatory disclosure rules for startups is inconsequential because they all have the incentive to fully reveal their private information to the public.

Contrary to the above theoretical insight, a cursory investigation of our data suggests that the majority of the startups in our sample are "silent". They never make a press

[1]See Dye (2001); Verrecchia (2001); Dranove and Jin (2010); Goldstein and Yang (2017) for more comprehensive reviews.

release despite the importance of media coverage a form of public communication. This observation suggests that there are important frictions that disrupt the unraveling of information, motivating the rest of our study. To better understand the motives behind a startup's voluntary information disclosure behavior, we examine several important research questions: First, on the extensive margin, we ask why some startups issue press releases while others remain silent. In particular, we consider whether a startup's lack of communication is driven by a lack of success or a deliberate choice to withhold information. Second, on the intensive margin, we consider the nature of the information being conveyed by a disclosing startup. We examine whether the information is related to the startup's achievements or milestones (as in the unraveling hypotheses) or whether the content reflects a public relations exercise, seeking attract the attention of a wider base of potential investors.

To empirically address these questions, we examine press releases as the primary channel through which startups voluntarily share information with the public. Press releases are a long established public relation tool and are regularly used by public companies to communicate with investors and stakeholders. Startups may have incentives to adopt the same practice in order to present themselves as professionally mature firms. Press releases also provide a credible form of *public communication* due to the fact that they are subject to potential external verification: the information released can be further investigated by the media or used against the firm in legal proceedings.

Our study constructs a novel dataset of press releases of U.S. startups distributed by PR Newswire and Business Wire, the two leading public relation platforms. We match the issuing startups of these press releases to a sample of startups in the Pitchbook database that obtained a VC funding round between 2004 to 2022. Among the 34,302 U.S. startups included in our analysis, around 19.8% have published at least one press release through PR Newswire or Business Wire. These startups have collectively generated 43,636 articles, averaging at 6.4 press releases per company and an annual frequency 5.9 press releases per year. The number of press releases issued by startups rises with its development stage. In Series A (early stage), a startup typically issues around 2 press releases, while in Series G (late stage), this number increases to about 4 press releases per company. In terms of contents, press releases typically cover news related to new product launches, financial results, key hires, strategic partnerships, and fundraising rounds.

Our baseline analysis examines the association between startup press releases and their likelihood of securing a follow-on financing round. Compared to silent startups, we find that startups issuing press releases are 7% less likely to secure subsequent funding. Additionally, we investigate the round returns of financing rounds that follow press releases and compare them to round returns where there are no press releases. We find that rounds preceded by a press release experience an approximately 20% lower return compared to those without such disclosures. That is, the growth in the valuation of a firm is significantly lower if it issues a press release in between rounds. The above two results remain statistically significant and robust after controlling for several round-level characteristics and various fixed effects such as industry, year, stage, and company.

This baseline evidence is generally inconsistent with an "unraveling" equilibrium (see Grossman (1981); Milgrom (1981)), whereby firms with favorable information will optimally disclose it. Instead, strong performing startups stay "silent": they choose *not* to voluntarily disclose information through press releases. This points to a possible selection effect whereby startups that issue press releases may be associated with lower quality, raising a question as to why some startups would contemplate taking such a course of action.

To characterize the equilibrium underpinning our findings, we rely on the theoretical framework on relationship investing provided by Azarmsa and Cong (2020). For simplicity, consider a staged financing scenario where the first-round (inside) investors in a startup have the ability to assess the startup's quality based on its subsequent progress, before making a decision of whether to provide another round of funding. Suppose the startup turns out to be a highly promising firm, the inside investors will concentrate their remaining capital (reserved dry powder) to funding the second round. [2] Because the inside investors hold an information advantage, they would prefer to restrict the startup from making voluntary disclosure to avoid increased competition with new (outside) investors. This strategy implies that, if the investors have limited reserved dry powder, other marginal startups in their portfolios will find it difficult to attract second-round funding. These marginal startups may need to issue press releases to draw interests from outside investors, that is, to demonstrate that they still present a compelling investment opportunity. This situation creates an opportunity for low-quality startups to also make press releases and try to pool with these marginal quality peers.

Thus, when a startup commences issuing press releases, the action could indicate that either i) existing investors, having observed the startup's quality, decide to discontinue financing due to its deteriorating prospects (the *firm quality channel*) or ii) because of capital constraints, these investors find it difficult to provide follow-on funding (the *capital constraints channel*) after committing their reserved dry power to funding another winner startup in their portfolio. This results in two groups of startups issuing press releases: those of acceptable quality but whose investors are capital constrained (or have other priorities), or lower-quality startups that try to mimic the former group. In equilibrium, the average valuation observed for startups with press releases will reflect the mixed quality types based on the above scenarios, leading to lower average returns (and funding continuation) for press-releasing startups, when compared to startups without press releases, i.e., those winner startups in each VC investors' portfolios.

The equilibrium described above relies on two key assumptions: i) that high-quality startups will issue press releases to attract new investors when their existing investors are capital constrained (*the capital constraints channel*) and ii) press releases will be used when a startup experiences a deterioration in its prospects (*the firm quality channel*). We

[2] Details about the venture capital fund reserves can be found at https://kruzeconsulting.com/blog/what-are-vc-fund-reserves/.

next provide evidence for the validity of these assumptions. To demonstrate *firm quality channel*, we examine cases where a startup's patent application is rejected within a year of its financing round. Applying a difference-in-difference methodology, we show that treated startups (those whose prospects have deteriorated due to a patent application rejection), have a 45% higher probability of issuing press releases compared to a control group of startups selected from the same industry, at the same stage, and in the same year. As for the *capital constraints channel*, we examine cases where the committed capital of a startup's lead investor is absorbed by other large investment opportunities in the VCs fund's portfolio. We find that when the capital of the lead investors becomes constrained due to the capital demands of another firm in the portfolio, there is a 16% higher likelihood of treated startups issuing press releases within one year compared to the overall probability.

We next assess whether startup quality can be detected from the content of its press releases. We are particularly interested in whether startup's of low quality instigate press releases with content that might appear to obfuscate a lack of significant progress through the use of "spin", as described by Solomon (2012). We employ a textual analysis to scrutinize the content of a startup's press releases across three dimensions: sentiment (Loughran and Mcdonald (2011); García, Hu, and Rohrer (2023)), subjectivity (Liberti and Petersen (2019)), and readability (Loughran and McDonald (2014)). The analysis indicates that rounds following press releases characterized by higher sentimentality, greater subjectivity, and reduced readability – traits that are likely to be associated with mediocre startups lacking progress on substantial milestones – tend to yield comparatively lower returns. For example, an increase of one percent in the proportion of sentiment words in startup press releases is linked to a decrease of 2.78% in the return of the subsequent round. Conversely, press releases containing more objective and concrete performance information are associated with a higher return in their follow-on round. For instance, a one percent increase in the proportion of numerical information is correlated with a 1.46% increase in the round return. As for the readability, an increase of one percent in the proportion of complex words correlates with a 1.46% reduction in the returns of the subsequent funding round, indicating that lower readability is associated with impacts valuation outcomes.

Our research advances the literature's understanding of optimal disclosure theory, offering empirical findings that diverge from theories that predict that full disclosure is optimal (Grossman (1981); Milgrom (1981)). We identify that well-supported startups tend to withhold information, whereas those facing quality concerns or diminished investor support are more likely to engage in disclosure. This study adds to the discourse on information withholding in scenarios where that are significant disclosure costs (Jovanovic (1982); Verrecchia (1983)), lack of information (Dye (1985); Jung and Kwon (1988)), market competition (Darrough and Stoughton (1990); Wagenhofer (1990)), receiver preference uncertainty (Teoh and Hwang (1991); Suijs (2007); Bond and Zeng (2022)), receiver's uncertainty about the sender's intentions (Einhorn (2007)), and dynamics in multi-period settings (Einhorn and Ziv (2008)). We examine a unique setting, that of private companies that lack any sort of mandatory public disclosure requirements, suggesting that such disclosures occur primarily under financial duress. This leads to an equilibrium where startups with a strong backing seldom disclose, while those that do either have constrained investor capacity or are lesser-performing entities attempting to pool with higher-potential counterparts, culminating in a negative selection in the market.

Our study extends empirical support to the burgeoning field of persuasion in finance, particularly by examining the role of communication in investment pitches, as highlighted in persuasion theory (Mullainathan and Shleifer (2005); Azarmsa and Cong (2020); Rappoport (2020); Szydlowski (2021)). To the best of our knowledge, this research is the first to empirically explore the startup setting to test information disclosure as a persuasion tool to secure future financing.[3] It also contributes empirically to the evolving discourse on attention and valuation (Gossner, Steiner, and Stewart (2021)). Echoing the findings from Lou (2014), where public firm managers use advertising to attract investor attention

[3]Empirical findings based on other settings of persuasion can be found in the survey DellaVigna and Gentzkow (2010).

and influence stock returns, our findings suggest that entrepreneurs in startups employ press releases strategically to capture external investor interest, thereby enhancing their prospects for subsequent funding rounds.

Our research contributes to the empirical literature on press releases and their impact on company valuations. Previous studies, such as Ahern and Sosyura (2014), have shown that companies use press releases to strategically manage media coverage. In public companies, press releases serve as an information intermediary (Bushee, Core, Guay, and Hamm (2010)) and influence market reactions (Neuhierl, Scherbina, and Schlusche (2013)), analyst revisions (Bradshaw, Lock, Wang, and Zhou (2021)), and merger success (Ahern and Sosyura (2014)). Our paper is the first to empirically examine the strategic use of press releases by startups, a key segment of private capital markets known for their opaque information environment. Our findings underscore the importance of such releases in such a context, especially for drawing investor attention.

Last but not least, our research expands the understanding of interactions among startups, existing inside VC investors, and external VC investors. Building upon previous empirical studies that explore the dynamics of contracting and monitoring between VCs and startups (Kaplan and Strömberg (2003, 2004)) and the pivotal role of VCs in startup operations and decision-making (Fitza, Matusik, and Mosakowski (2009); Hellmann and Puri (2002); Lerner and Nanda (2020)), our study provides a novel investigation of how the level of support from existing investors influences startups' information disclosure strategies. Our findings reveal that startups backed by strong VCs typically remain silent, while those issuing press releases often do so either due to diminished support from their current VCs or the need to attract new VC investment due to existing investor capital constraints.

The remainder of the paper is organized as follows. Section 2 presents the hypothesis development process. Section 3 provides an overview of our data sources and the construction process. Section 4 describes the empirical specifications and presents our baseline regressions, as well as other empirical findings. Finally, Section 6 concludes the paper.

2 Hypothesis Development

In a situation where a company is unable to effectively communicate its information to investors due to asymmetric information, a problem known as the "lemons problem" arises. This problem leads to the exit of all firms from the market, except for those of the lowest quality, ultimately resulting in the collapse of the market (Akerlof (1970); Myers and Majluf (1984)). Consequently, firms must disclose at least some of their information in order for capital markets to exist. The academic literature on the optimal disclosure strategy has now become well-established, extensive, and intricate. It encompasses various areas in finance and economics, builds upon different fundamental economic forces, examines a wide range of corporate decisions, and emphasizes that conclusions are often nuanced and heavily dependent on the type of disclosure and the characteristics of the environment in which the companies operate.[4]

Studying the effects of disclosure in startups is particularly intriguing and can offer valuable insights amidst the various settings. To begin with, it is crucial to differentiate the impact of voluntary disclosure from that of mandatory reports when empirically examining the information content of a firm's disclosures. This differentiation is challenging to achieve with public firms due to their legal obligation to disclose information. In contrast, startups, being private firms, are not legally obligated to make disclosures to the public. Therefore, all the disclosures made by startups are voluntary in nature. Furthermore, theoretical papers in persuasion theory often use communication during investment pitches as an example where entrepreneurs disclose private information to investors in order to secure funding. However, there is a scarcity of empirical studies exploring this specific setting. Lastly, the objective function for startups is clearly defined, which is to survive for the next round of financing and, if possible, increase their valuation. Moreover, the primary investors for startups typically consist of venture capital (VC) investors who actively seek information which may reflect the quality of the startups and tend to make investment

[4]See Goldstein and Yang (2017), Stocken (2013) and many other surveys for comprehensive reviews.

allocation to potential startups.

Based on the distinctive characteristics mentioned above, we initiate our hypothesis by building a baseline model of stage finance and information disclosure. This model shares similarities with the one presented in Azarmsa and Cong (2020), but it focuses on different aspects. In this model, we consider a capital-constrained entrepreneur who has a startup project that requires two rounds of financing. The first round of investment, known as the initial round, allows the entrepreneur to engage in early stage activities such as team formation, product development, and acquiring initial users. This initial round also involves investors who can be referred to as "insider investors" or "existing investors". These investors closely observe the interim experiments conducted by the startup and make a decision on whether to continue supporting it in the next round. In the subsequent round of financing, if the startup demonstrates its potential quality, the existing investors would be willing to invest further. If these existing investors also have the financial capacity to continue investing, the next round would be financed without the need for outside investors. It is worth noting that VC investors play a significant role in the operations and decision-making processes of startups (Fitza, Matusik, and Mosakowski (2009); Hellmann and Puri (2002)). Therefore, we assume that the power of current shareholders can fundamentally influence the disclosure decision of startups, as discussed in Hummel, Morgan, and Stocken (2016). If the startup has the potential for growth and the current internal investors are willing and able to continue investing in the next round, there may be no requirement for the startup to disclose information voluntarily to the public. In fact, the existing investors may prefer that the startup avoids attracting public attention, as this could lead to increased competition from external investors when seeking investment in the next round. Hence, when the startups commence issuing press releases to attract public attention, the message conveyed is intricate. It could indicate that the existing investors have observed the startup's quality and are no longer interested in providing financial support. Alternatively, it could signify that the existing investors have reached their capacity limits and this limitation may not directly related to the startup's quality. In order to provide a clearer explanation, we will divide the scenarios and have a more focused discussion.

Startup type \ Insider investor	Enough	Limited
Good	No need to disclose	Disclose for outside investor
Bad	Disclose to pool with (G, L)	Disclose to pool with (G, L)

Based on the information presented in the table above, it is evident that successful startups tend to receive continued investment from their existing investors in the next funding round. In such cases, there is no need for these startups to seek public exposure through press releases. However, there may be instances where existing investors have limited capacity to support the next round, prompting startups to voluntarily disclose information through press releases in order to attract external investors. This situation creates an opportunity for underperforming startups to associate themselves with successful startups, despite having limited support from insider investors. Since external investors lack perfect information about the capacity of existing investors and the types of startups, they may perceive these less promising startups to be on par with strong startups that lack sufficient investor support. Consequently, external investors are likely to assign a median valuation to startups that issue press releases, based on their expectations of these varying scenarios. Given the mixed signal from the startups' press releases have on external investors, we propose the following empirical hypotheses:

Hypothesis 1: Startups that issue press releases are more likely to have a lower probability of securing the next round of financing compared to startups that do not issue press releases.

Hypothesis 2: Among startups that do secure the next round of financing, the return of rounds that follow press releases is expected to be lower compared to rounds that do not follow press releases.

In order to provide additional support for the pooling situation discussed earlier, we would like to test the following hypotheses that aim to explain why startups make press releases:

Hypothesis 3: Startups with limited capacity existing investors may engage in voluntary disclosure, such as press releases, in order to increase their visibility to the public and attract more investment for the next round of financing.

Hypothesis 4: Startups that are underperforming may also make press releases in an attempt to pool with startups that have good performance but limited capacity existing investors.

In order to further investigate how investors interpret information conveyed through press releases and whether the variability in press release practices can help investors determine the quality of startups to some extent, we will utilize textual analysis. This analysis will allow us to assess the efforts made by bad startups to mimic good ones in their press releases. Our hypothesis is as follows:

Hypothesis 5: External investors are more likely to consider startups as bad if the press releases contain a higher number of "spin" factors. Therefore, among all the rounds that follow the press releases, those that are accompanied by press releases containing more sentiment words, more subjectivity, and lower readability will result in lower returns.

3 Data

3.1 Startup Financing Data

Our data consists of two major parts. The first part is PitchBook, which provides unique and detailed financing round characteristics of privately funded companies, including the timing, deal type, amount raised, and investors participating in a given round. Our sample starts with a broad set of VC-funded startup firms during the period from 2000 to 2021. Specifically, firms are selected based on "*CompanyFinancingStatus*", which are either 'Formerly VC-backed', 'Venture Capital-Backed', or 'Pending Transaction (VC)'.

The transaction level data consist of columns such as *DealType*, *DealNo*, *VCRound*. Based on the information provided, we construct the timeline of the startup life cycle. For these deals to be included in the timeline, they can be separated into two parts: the type of deal for VC rounds [5] and the deal type for the exit of VC.[6] We filter the deal level data based on all these selected deal types, which ends up with all the deals related with VC investment and exit. We then exclude those startups which were founded recently, therefore, no enough time period to develop, specifically, we filter out the firms which received the first round of financing after the year 2020. As mentioned in Pham, Turner, and Zein (2021), compared to other VC data, such as VentureXpert and Venture Source, Pitchbook has relatively higher coverage of valuation data. Although not all firms in Pitchbook have valuation data, coverage is reasonably complete among those that do, with about 80% financing rounds covered for firms with available valuation information.

3.2 Startup Press Release Data

Our data set contains press releases issued by the startups in our sample, obtained through web links provided by Pitchbook and supplemented with additional data collection of articles published in Factiva. Press releases are issued through the newswire service, which further disseminates the firm news via their Web interfaces and news distribution networks. Newswire companies do not levy any charges on the members of their news distribution networks; instead, they charge the firms that issue the press releases. Distribution networks comprise local and global media outlets, including newspapers, magazines, radio and television stations, trade magazines, and financial news service providers.

Our data set is consolidated from two largest wire services firms, PR Newswire and Business Wire. We limit our analysis to news releases that are directly issued by corpo-

[5]'Seed Round', 'Early Stage VC', 'Later Stage VC', 'Angel(individual)', 'Restart - Later VC', 'Restart - Early VC'

[6]'Merger/Acquisition', 'Bankruptcy: Admin/Reorg', 'Buyout/LBO', 'Bankruptcy: Liquidation', 'IPO', 'Investor Buyout by Management', 'Merger of Equals', 'Dividend Recapitalization', 'Share Repurchase', 'Leveraged Recapitalization', 'Reverse Merger', 'Out of Business'.

rations themselves, which can be identified by the news 'source' printed at the bottom of the report, as opposed to those issued by news agencies. The process is easier with PR Newswire, as they provided the source of the press release, confirming that the source of the release is the company itself rather than being covered by other media. For Business Wire, the press releases posted on it have a less standard format than those on PR Newswire. We conducted three verification tests to validate the source of the releases. First, we examine the title of the releases to ensure that the startup company is mentioned. If not, we looked at the web links in the article to see if the name of the startup company was linked to the homepage of the website. Lastly, we check whether the name of the startups was frequently mentioned in the main content of the article.

3.3 Data Construction

We linked the press release data with the financing data by matching the names of the startups with the source of the press release. We applied two measures to capture the difference between the company's official names from Pitchbook and the source of press releases either provided in PR Newswire articles or validated in the Business Wire articles. The first one is the Levenshtein distance, a text similarity measure that compares two words and returns a numeric value representing the distance between them. The distance reflects the total number of single-character edits required to transform one word into another. The second one is SequenceMatcher, a class in the difflib module which can be used to find the longest contiguous matching sub-sequence (LCS). The restrictions we set for the difference are either the Levenshtein distance is at most two characters or the sequence matcher is no less than 70%. After linking two major datasets together, we have a sample contains the deals happened for the startup firms and the press releases made by them during their life cycle. The ultimate sample comprises 43,636 articles of press releases that were issued by 6,778 startups based in the United States. These startups belong to 34,302 firms in total. The data spans from 2004 to 2022.

4 Empirical Design and Results

4.1 Press Releases Trends

We begin our empirical investigation by showing the general trends in press releases between the different stages of startup firms. Since startups encounter various challenges and have different tasks, their behavior varies according to their financial stages. To achieve this, we have classified the press releases issued by a particular startup company into separate financial stages, including Seed, Series-A, Series-B, and so forth, up to Series-G and above. Then we summarized, by each financial stages, the total number of press releases, the total number of startup companies, and the average number of press releases per startup in Figure 1.

[Figure 1 is about here]

Figure 1a shows a reduction in the total number of startups from Series A,[7] implying a lower survival rate for startups in subsequent financing stages. Nevertheless, when examining the proportion of startups that issue press releases as in Figure 1b, and the number of press releases per startup as illustrated in Figure 1c, it becomes clear that both the probability for startups to make the press releases, and the number of press releases issued by each company, are rising alongside the growth of startup firms. This trend is logical; as startups progress to later stages, they may have more information to share or face more situations that necessitate public disclosure.

4.2 Common Press Release Topics

To enhance understanding of what startups are disclosing to the public, we employ state-of-the-art topic modeling techniques using large language models (LLMs). For this pur-

[7] The number of startups that identified as "Seed" is less than that of "Series-A", it could be due to two reasons: first, "Seed" rounds are less official compared with "Series A" rounds, hence have less chance to be reported by firm or investors, thus less chance to be recorded in Pitchbook dataset; second, unlike "Series-A", "Seed" rounds are not a necessary for startups, there are many startups which start with "Series-A" instead of "Seed".

pose, we utilize an open-source LLM called Llama 3, developed by Meta (formerly Facebook), which has achieved performance comparable to commercial options such as ChatGPT 4. Our approach to classifying press releases is inspired by a thematic model of startup success factors from Thomas Hellman's entrepreneurial finance textbook, encompassing Sales Strategy, Technology, Competition, Development/Production, Investment, Team/Network/Collaboration Organization, and financially related press releases. We manually classified 100 articles based on the intent of each article into these factors. Subsequently, each article and its corresponding factor were input into the LLM, which was tasked with explaining in one sentence why the article reflects its assigned factor. After gathering these responses, we instructed the LLM to summarize the answers for each factor, formulating a central theme for these factors that aids in further classifications. Based on this method, we derived the following classifications: 1. Announcing Partnerships and Collaborations, Joint Ventures or Alliances, 2. New Agreements, Licensing; Describing the Firm's New Production Plant and/or Making New Investments or Mergers and Acquisitions; 3. Announcing a New Team, New Board, and New Division; 4. Announcing the Disbanding of Teams or Selling Divisions/Businesses, Bankruptcy, or Divestiture; 5. Announcing Awards, Success, and Leadership of Products, Firm Growth, Increased Market Share; 6. The Firm Secures New Funding, Receives New Investment; 7. Describing Customer Needs or Having a New Customer; 8. Describing Market Trends, Market Survey Results, Sales Strategy; 9. Announcing Changes in CEO/Board of Directors/Key Executives. 10. Announcing Financial Results, Earnings Release, Revenue Numbers; 11. Announcing the Firm has a Brand-New Product, New Function.

For each press release, we utilize the LLM to categorize it according to the aforementioned classifications based on the press release's purpose. The distribution of each type of press release is depicted in Figure 2. The predominant categories include announcements of new products or product functions, awards, successes of products, or firm growth/increased market share, and announcements of partnerships or collaborations, each constituting approximately 20-25% of the total. The remaining press releases are split among reports of new funding, changes in team composition, financial results, investments, and other topics.

4.3 Distribution by Industry

Examining how press releases are distributed in different industries could provide additional evidence to support the representativeness of our sample. Given that the majority of startups are concentrated in Healthcare and information technology, it would be reasonable to expect these industries to also generate the highest number of press releases due to the concentration of firms within them. Thus, we generate Figure 3 that displays the distribution of press releases based on the industries in which the startups issued them.

[Figure 3 is about here]

We utilized industry classification codes, referred to as 'Primary Industry Sector', sourced from PitchBook to categorize the issuers of the press releases into seven categories. Among these, 44.1% of the press releases were issued by startups in the information technology sector, while the second largest proportion, accounting for 29.8% of the total articles, originated from startups in the healthcare industry. This distribution aligns with our expectations based on the number of startups distributed across various industries, thereby validating the credibility of our sample.

4.4 Press Releases on Fundraising Events & Others

The main objective for startups is to obtain the next round of funding, so we consider the fundraising of startups as our main focus. As startups often issue press releases after successfully securing funding, our aim is to exclude these press releases from our analysis to prevent potential concerns regarding reverse causality. To achieve these, we first tokenize all the titles of press release articles using the Python package Natural Language Toolkit (NLTK). Then we exclude the tokenized words that are listed in the stopwords library and punctuation in the string library. Press releases are divided into two groups: those related to financial events and press release that are not. For press releases on financing rounds, the most frequent words include ”raise,” ”million,” and ”funding,” among others. On the other hand, for press releases that are not related to fundraising, the most frequent words are ”partner,” ”solution,” ”platform,” ”technology,” and others. As there is little overlap between the keywords of fundraising press releases and those not related to fundraising, we can exclude fundraising press releases by identifying the key frequent words.

We compare the two types of press release, fundraising-related and non-fundraising-related. Among all the articles in our sample, about 9% are press release on the fundraising events, indicating that fundraising is indeed an important event for startup firms which needs to be reported. Also, by the distribution of firm-level proportions, it is worth noting that startup firms have different preference in reporting financial related events, press release on fundraising events on average takes less than 10% of the all the press releases made by each firm, while there also exist firms that only report press release on fundraising events. Thus, we would like to further investigate on startups' different press release strategies and how this would affect its chance to have the next round of financing, or its valuation while raising next round of funds.

4.5 Empirical Approach

In order to investigate the empirical evidence for the hypothesis we proposed, we initially built regression models to examine the relationship between the press release behavior of startups and their fundraising events and valuation. It is important to note that the process of valuing startups is fundamentally different from valuing public companies. Unlike public companies, which have their shares openly traded on stock exchanges, startups are privately held and do not have their shares traded in an open market. As a result, the valuation of startups is not determined by ongoing market transactions. Instead, the value of a startup is typically determined during discrete fundraising events. These events involve negotiations between the startup and potential investors, who consider various factors such as the company's growth potential, market size, product uniqueness, team strength, and financial performance. Therefore, the valuation of a startup at any given fundraising event is a snapshot that represents its perceived value at that specific moment in time.

Considering the inherent nature of startups' valuation, the analysis will be conducted at the level of each financing round. The outcome of interest will center around two aspects: firstly, whether a startup company will secure the subsequent round of financing after the previous round; and secondly, the return on investment based on the valuation of the new round compared to the previous round. On the other hand, the explanatory variable will be based on the activities mentioned in the startups' press releases during the period between the end of the previous round and the start of the next round of financing.

4.5.1 Outcome of Interest: Fundraising Event & Round Return

Our primary focus is on the probability that startups will secure their next round of funding, a crucial milestone for most of these companies. To analyze this, we have developed a round-level dummy variable called *Next Round*. This variable is set to one if a startup secures another round of financing within 1,264 days after the completion of its previous round. The chosen period of 1,264 days corresponds to the 90th percentile of the time gaps between financing rounds in our sample, reflecting the upper limit of the duration most startups require to secure subsequent funding. Conversely, the *Next Round* variable is assigned a value of zero if a startup fails to secure another round of funding within this cut-off period, or if it undergoes bankruptcy. Additionally, we exclude deals involving successful exit strategies, such as an Initial Public Offering (IPO) or an acquisition, that occur after a particular round of financing. Our analysis is exclusively focused on the financing rounds undertaken by VC investors.

After first exploring the likelihood of startups securing a subsequent financing round, our next analytical objective is to assess whether rounds preceded by press release activities exhibit a different level of return compared to those achieved without any prior press releases. Our primary metric, *Round Return on Equity Valuation*, quantifies the valuation increase of a financing round. It is calculated for each round as the pre-money valuation of the current round divided by the post-money valuation of the previous round. To account for variations in the duration of rounds (specifically, the time gap between the current and previous rounds), we annualize this return measure. This annualization is only applied to rounds exceeding one year in duration, as applying it to shorter rounds (which are comparatively rare in our sample) can sometimes yield excessively high and impractical return figures. In a robustness check, we also utilize an alternative valuation metric, *Round Return on Price Per Share*, which reflects the valuation increase of a financing round based on the percentage change in the price paid for the company's securities from one round to the next. We meticulously adjust these security price returns for stock splits using the relevant split factors provided by PitchBook. To minimize the impact of extreme outliers, which are common in startup and venture capital data, we apply winsorization at the 1% level to both round return metrics, as well as to all other continuous variables introduced later in our analysis.

4.5.2 Explanatory Variable: Measurements of Press Releases Activities

The primary explanatory variables in our study are based on the press releases issued by the startups. The first variable, *Round with PR*, indicates whether a startup issued at least one non-fundraising press release between the previous and the current financing round. This variable is designed to reflect the pattern of press release issuance from one financing round to the next. Alongside this, we compute the logarithm of the number of press releases issued after the previous round but before the current, which we have named *Log No of PR*. Furthermore, to understand the impact of a firm's initial press release, we created the deal-level indicator variable *Round with First PR*. This variable is set to one if the startup issued its first press release prior to the current financing round. In addition, to capture the varied patterns of startups in terms of press release issuance, we categorize firms based on the distribution of their press releases throughout their life cycle. A startup is classified as a *regular releaser* if it consistently issues at least one press release in more than half of its total rounds.

Our central hypothesis contends that startups, being private entities primarily accountable to a limited group of VC investors, are not typically required to disclose information to the public. For a promising startup with existing deep-capacity VC investors willing and able to finance the next round, the optimal strategy might be to remain silent, focusing quietly on development. This discretion also serves to deter other investors from competing with current investors for a stake in the startup. Consequently, when startups begin issuing press releases, it could indicate one of two scenarios. First, it might suggest that existing investors or founders are reluctant to continue funding the startup due to its mediocre performance. Alternatively, it could mean that the startup is performing well, but the current investors lack the capacity to support the next financing round. Both scenarios might compel startups to seek attention from external investors, who often struggle to distinguish between high-potential startups and those with less supportive existing investors. This situation allows less promising startups to be perceived similarly to strong startups with inadequate investor support. As a result, external investors are likely to assign a median valuation to startups issuing press releases, based on their expectations of these varying scenarios. Therefore, we anticipate that startups that begin to seek public attention generally have a reduced likelihood of securing their next round of financing. Moreover, for all realized rounds, we expect the returns on rounds following press releases to be lower compared to those without preceding press releases. We aim to demonstrate this equilibrium in the subsequent round-level regression analysis.

4.6 Summary Statistics

Table 1 presents the main characteristics of our final sample with a sample period from 2004 to 2022.

[Table 1 is about here]

Table 1 indicates that within our sample of 81,623 rounds, 57.9% of the rounds have a follow-on round within 3.4 years, which is our cutoff period. This is determined by the mean value of the *Next Round* indicator variable. It is important to note that not all fundraising rounds in our sample have valuation information available to calculate the return. Approximately 32,000 rounds have valuation information for both the previous round and itself, allowing us to calculate the return. On average, the annualized return on the valuation of these rounds is approximately 77.7%.[8] This suggests that, in general, startups experience an increase in valuation when they secure another funding round. Additionally, it is worth mentioning that about 14.7% of the rounds with press releases are from firms that consistently make press releases. This small portion alleviates our concern that press releases are a regular behavior rather than a strategic move for most startups.

4.7 Baseline Results

4.7.1 Press Releases & Chance of Next Round

We began our analysis by examining the relationship between the press releases issued by startups after a financing round and their likelihood of securing a subsequent round. Our initial approach involves applying regression tests using the following specification:

$$Next\ round = \beta \cdot PR\ measures + \delta_i + \omega_s + \theta_t + \epsilon_{i,s,r} \tag{1}$$

[8] We also calculate the return based on price per share and the two measures are consistent.

In this model, the outcome of interest, *Next Round*, indicates whether a startup secures the next round of financing following the focal round within the cut-off period (1,264 days,[9] about 3.4 years). We have also excluded deals that occurred after 2020 from our sample. This ensures that all observations have a complete cutoff period for progressing to the next round before the most recent update of our dataset. The explanatory variable, *PR Measures*, quantifies the startup's press release activities during the specified period after the completion of the current round. There are two ways to measure the press releases activities. The first measure is called *With PR between Rounds* and it is a binary variable that takes the value of one if startups issue press releases between the current round and the next round, and zero otherwise. The second measure is called *Log No of PR between Rounds* and it calculates the natural logarithm of the number of press releases issued during this period. The model incorporates fixed effects to facilitate the comparison of the treated rounds with control rounds possessing similar characteristics. Industry fixed effects, denoted as δ_i, categorize firms into 41 unique industries as defined by PitchBook. The fixed effects of stages, ω_s, reflect the distinct attributes of companies at different stages of development. As suggested in Gompers, Gornall, Kaplan, and Strebulaev (2020), these stages significantly influence how VC investors select, price, and monitor their investments. ω_s is constructed based on the series label of a round, ranging from seed through series A to H, and all subsequent series aggregated into one category.[10] The fixed effects of the year, θ_t, account for broader market conditions influencing the financing environment in a given year. The regression results are provided in the table below.

[Table 2 is about here]

Table 2 reveals a negative correlation between a startup's post-financing round press release

[9] 90th percentile of the time gaps between financing rounds in our sample

[10] In instances where PitchBook data lacks clear series information, we infer the series label from the preceding or subsequent round's data. For example, if the preceding round is series A, the current round is assumed to be series B. In the absence of such data, we estimate the series label based on the sequence of the round. For example, the first round is presumed to be a seed round, followed by series A for the second round, etc.

activities and its probability of securing subsequent funding. The data consistently shows that startups engaging in press release activities after a financing round are less likely to receive further funding compared to their counterparts who do not. Specifically, our primary model, which includes fixed effects for industry, stage, and year, demonstrates in column (1) a noticeable trend: startups that issue press releases have a lower chance of progressing to the next financing round. This reduction in probability is substantial — approximately 7 percent less than the unconditional probability of securing funding, which stands at 57.89 percent across all deals. Column (2) further examines this trend through continuous measures. Here, it's indicated that a one percent increase in the volume of press releases a startup issues after a financing round correlates with a 0.12 percent decrease in the unconditional probability of obtaining the next round of financing. This finding is consistent even when applying a more rigorous analytical approach, as demonstrated in columns (3) and (4), which involve an interaction of the three fixed effects for a more precise comparison between treated and control rounds across similar industry, development stage, and financing year conditions. Moreover, column (5) explores comparisons within the same startup firms across different years. After adjusting for unobservable firm-specific and year-specific characteristics, the data suggests that startups issuing press releases after a financing round face an average 41.34 percent decrease in their likelihood of securing the next round of funding, compared to those that do not issue press releases. Column (6) reinforces this, indicating that within the same firm and year context, a one percent increase in the number of press releases correlates with a 0.32 percent reduction in the unconditional probability of advancing to the next financing round. This result holds true even under a more stringent analytical framework, as shown in columns (7) and (8). Here, the model integrates an interaction of the three fixed effects — industry, development stage, and financing year, as well as the firm level fixed effects.

Based on the results presented, there is a compelling connection between the frequency of press releases issued by startups post-financing and their success in securing future funding. Contrary to popular belief, our findings suggest that increased visibility through press releases may not always be advantageous for startups in pursuit of further funding. As hypothesized, this phenomenon could imply that press releases are often interpreted by potential investors as indicators of a startup's need for external funding or as signs of underlying challenges, rather than as markers of strength or success. To reinforce our hypothesis, we will next examine the relationship between the returns of realized financing rounds and the press release behaviors of these startups. This analysis aims to further explore whether investor expectations regarding firm valuation differ based on the presence or absence of press releases surrounding financing rounds.

4.7.2 Press Releases & Return on Round-level Valuation

Having established that startups' press release behaviors are associated with a decreased likelihood of securing their next financing round, this suggests that external investors might perceive voluntary information disclosure by startups as a negative signal. To further substantiate this observation, we will now formally test whether financing rounds that follow press releases yield lower returns compared to those that do not. The details of our regression model, which will be used to examine this hypothesis, are outlined below:

$$\textit{Round Return} = \beta \cdot \textit{PR measures} + \gamma \cdot X + \delta_i + \omega_s + \theta_t + \epsilon_{i,s,r} \tag{2}$$

In our model, the key variable of interest, *Round Return*, measures the valuation increase of a financing round. This is calculated as the pre-money valuation of the current round divided by the post-money valuation of the previous round. To adjust for variations in round durations, particularly the time gap between the current and previous rounds, we annualize this return measure. The explanatory variable, *PR Measures*, quantifies the extent of a startup's press release activities in the period following the completion of the current round. We employ two metrics to assess these activities. The first, *Round with*

PR, is a binary variable assigned a value of one if the startup issued any press releases between the last and the current round, and zero otherwise. The second, *Log No of PR*, calculates the natural logarithm of the number of press releases issued during this period. Our model also includes fixed effects to ensure accurate comparisons between treated rounds and control rounds with similar characteristics. Industry fixed effects, represented as δ_i, categorize firms into 41 distinct industries following PitchBook's classification. Stage fixed effects, ω_s, capture the unique characteristics of companies at different stages of their development journey. Additionally, our model accounts for several control variables that could influence round pricing patterns. Firm size, a significant factor, is considered, as larger firms are generally more established and may exhibit lower information opacity, potentially leading to more moderate valuation growth compared to smaller startups. To adjust for differences in firm size, we use the natural logarithm of the post-money valuation from the previous round (Log Pre-round Firm Size). Furthermore, the founders' capacity to negotiate over the pricing of a new round, influenced by their existing ownership stakes and the potential dilution of these stakes by the round, is also factored into our analysis.

Table 3 shows the estimates from regressing Round Return on Round with PR using the model outlined in Equation 2. We present the results of four different specifications in columns 1 to 4: columns 1 is firm, year fixed effects, column 2 and 3 employing either additive or interactive industry, year, and stage fixed effects. In column 4, we further include portfolio firm fixed effects with interactive industry, year, and stage fixed effects.

[Table 3 is about here]

Our estimates suggest that there is a negative and statistically significant relationship between *Round with PR* and *Round Return* across all specifications. When firm fixed effects are not considered (columns 1 and 3), rounds with press releases have relative valuation changes that are 17.95% - 19.39% lower per year compared to control rounds. Given that the average return among all realized rounds in our sample is 77.69%, this implies a decrease of about 23% - 25% in the average return of deals. When firm fixed effects are included (columns 5 and 7), the magnitude of the *Round with PR* coefficient decreases to around 12%, which is approximately 15% of the average deal return, and remains highly statistically significant. For the continuous variable *Log No of PR*, the coefficients in columns (2) and (4) indicate that a 1 percent change in the number of press releases made by startups during round gaps is negatively correlated with a decrease of about 0.14 percent in the following round return, after accounting for year, industry, and stage fixed effects or their interaction. Including firm fixed effects (columns 6 and 8) does not affect the significance of this relationship. It is important to note that the observed round return discount associated with rounds following press releases cannot be attributed to other potentially confounding factors, such as round characteristics represented in the control variable, or unobservable time-invariant characteristics controlled for by different levels of fixed effects. Similar results are also found in Table A2, when using the round return based on the price per share as the outcome of interest as a robustness test.

The findings from both Table 3 and Table A2 support the notion that rounds following press releases tend to have lower returns on valuation compared to rounds without any press releases preceding them. This aligns with the previous test, which revealed a negative relationship between press releases and the probability of securing the next round of financing. These results further validate our expectation that startups' voluntary disclosure is perceived as a negative signal by outside investors, indicating that the startups may face difficulties in securing future financing. Consequently, startups disclose information to gain public exposure. Therefore, in comparison to silent startups, startups that issue press releases have a lower likelihood of obtaining the next round of financing. And with the situation that they do secure it, the returns from these rounds are significantly lower. Having established the baseline regression model, our subsequent analytical endeavor involves delving into the underlying mechanisms driving these results. In line with our theoretical framework, we make a fundamental assumption that the behavior of press releases, which are a significant form of voluntary information disclosure for startups, reflects the strong desire of startups to gain public attention and attract external investors. This assumption arises from the fact that existing investors may lack the willingness or ability to continue financing the startup. To examine these two potential mechanisms, we employ two types of shocks - one related to the capacity of investors and the other related to their willingness - to conduct diff-in-diff tests.

4.8 What Drives the Startups Press Releases?

To explore the reasons why startups issue press releases, we propose a hypothesis that suggests a strategic approach for promising startups with venture capital (VC) investors who are capable and willing to invest. This approach involves keeping a low profile and focusing on internal development to prevent other investors from competing for a stake in the startup. By doing so, the interests of the existing investor base can be protected. However, if startups begin issuing press releases to attract outside investors, it is likely driven by one of two factors. Firstly, the startup may be seen as deserving of further financing, but the existing investors may lack the resources to continue supporting the startup at the same level in the next round of funding. Secondly, if the startup's information has been disclosed and observed by existing investors, these insider investors may no longer intend to provide the same level of support in the next funding round. However, as discussed in the hypothesis development section, outside investors cannot fully determine whether the issuance of press releases is due to the startup's quality or the reduced capacity of existing investors. This situation creates an opportunity for lower-quality startups to be perceived on par with higher-quality startups, even if the latter have less capable existing investors. This dynamic can potentially obscure the true potential of the startups involved.

To evaluate the credibility of this hypothesis, we aim to provide empirical evidence that demonstrates how both the nature of startups and the capabilities of current investors can influence the necessity of public exposure for attracting new investors in the subsequent funding round. Consequently, we employ two shocks: The first shock is the significant fundraising that occurs for other startups backed by the same lead investor. Since most venture capital investors prioritize startups with the highest potential to become the next unicorn, once a substantial fundraising round is completed, the investor devotes all their efforts and attention to that particular startup. As a result, other startups held by the same investor are expected to experience a significant decrease in financial support and monitoring. The second shock is the rejection of a patent application, which directly impacts startup companies and may influence their classification as either a potential firm or a mediocre one.

4.8.1 Existing Investors Capacity

Venture capitalists, limited by both their capacity to process information (Miller (1956)) and available capital, face the challenge of allocating support levels for their portfolio startups. This constraint compels them to focus more attention and resources on those startups within their portfolio that show greater promise, thereby optimizing their investment and support strategies. In this context, the reduction in support for certain startups within a portfolio, such as financial assistance and monitoring, serves as a prime example of a natural experiment for causal inference. This change in support level is not necessarily reflective of the inherent quality of these startups. Rather, it's often a byproduct of the venture capitalists' strategic reallocation of resources towards startups demonstrating greater potential. The unaffected quality of the less-supported startups highlights the exogeneity of this shift in resource allocation, making it a suitable scenario for causal analysis on the effect of reduced capacity from existing investors and how this would affect the startups disclosure decisions.

In order to conduct our analysis, we make use of detailed investor relationship data from PitchBook, along with transaction-level deal information. This dataset provides information on the investors involved in funding rounds, their specific roles, and categorizes them as either new or follow-on investors. However, one limitation is that we do not have detailed data on the exact investment amounts contributed by individual investors. For example, if five investors collectively invest $10 million, we do not know the specific contribution of each investor. Consequently, our focus is primarily on lead investors in each fundraising round. Lead investors are important not only for their significant capital contribution, but also for their role in guiding the strategic direction and overall success of startups. Specifically, if a VC investor is the lead investor in the fundraising round of a startup X, we consider them as the lead investor for startup X until they exit or the startup goes bankrupt. As shown in Figure 4, there is a situation where the same lead investor is simultaneously holding two startups, X and Y. When startup Y successfully secures a large round of financing that exceeds the 90th percentile of all fundraising deals in the sample, the lead investor will allocate more resources to startup Y, which is believed to have the potential to become the next unicorn. As a result, the capacity to support startup X will decrease. This decrease in support is not related to the quality of startup X; it is still considered a good startup worthy of continued investment. Therefore, startup X is identified as a treated firm. On the other hand, the control firms, such as startup Z, are startups in the same industry and at the same development stage as startup X, but they are not experiencing a decrease in support from their lead investors due to the sudden rise of other startups held by their investors.

[Figure 4 is about here]

Based on the identification strategy above, we construct a firm-year level panel consists of both the treatment company and the control company in each of the (-3, +3) years around the peer-startups' major deal completion date. We then estimated differences-in-differences regressions, where the dependent variables are a dummy variable, *PR Dummy*, which equals one if the startup company made press releases in that year and zero otherwise, and a numerical variable, *PR Numbers*, which quantifies the total number of press releases a startup made in that particular year. The independent variable of interest is the *treatment* $\times$ *post*, where *treatment* is a dummy equal to one of the startup firm belongs to the treatment sample and *post* is a dummy equal to one if the year follows the peer-startups' major deal completion date. The regression include either firm fixed effect or industry, year, stage fixed effects, as well as the *treatment* and *post* dummy (not tabulated). The results are shown in Table 4.

[Table 4 is about here]

The regression results presented in Panel A of Table 4 demonstrate a significant increase in the likelihood of treated firms issuing press releases compared to control firms. In column (1), it is observed that within 1 year of the reduction in supporting capacity of lead investors, the probability of treated companies issuing press releases increases by 0.009, representing a 16% increase relative to the unconditional probability of 0.05518. This increase in probability persists over a 2-year window (19% increase) and a 3-year window (18% increase) as well. These results account for unobservable time-invariant characteristics of the firms and remain consistent even when considering such characteristics from the industry, stage, and year, as shown in columns (4) to (6). Panel (B) indicates a notable trend: post-event, treated firms show a significant rise in the frequency of press releases compared to control firms. Specifically, in the year following the event, there's an average increase of 0.0265 in the number of press releases per firm, approximately a 16% jump from the baseline average (0.1593). This increase further escalates to about 23% in the two and three-year windows post-event. Interestingly, even when adjusting for industry, stage, and year effects instead of firm-specific effects, the significance of these findings remains robust, underscoring the treatment effect's resilience.

The insights from Table 4 point towards a compelling conclusion. They suggest that startups may issue press releases in response to reduced support from their current investors, using this as a strategy to increase public visibility and attract new external investors for future financing rounds. It's important to note that this reduced support is likely not a reflection of the startups' inherent quality. Even high-potential startups might find themselves in this situation if their existing investors choose to allocate more resources to other ventures. Thus, while these promising startups increase public exposure through press releases, this creates an opportunity for less successful startups to mimic this behavior and blend in, potentially misleading external investors. This scenario highlights a challenge for investors: the difficulty in discerning the true potential of startups based solely on their public exposure. And we are going to show that, the reflection of quality, as another driven force, for the startups to make press releases in the next section.

4.8.2 Rejection of Patent Application

In our previous analysis, we demonstrated that high-potential startups with limited support from existing investors might increase their public exposure, notably through frequent press releases, to attract new investors. This situation, however, can create an opportunity for lower-quality startups to blend in with these promising ones. Since the cost of voluntary disclosure is low and external investors may not be able to fully differentiate between startups losing investor support due to quality issues versus those facing a reduction in investor capacity, this can be a strategic move. To support this hypothesis, we aim to show that startups affected by events that reflect on their quality and potential are more likely to issue press releases, or increase their frequency, as their current investors decrease support following these quality reflections. For almost all the startups, innovation is fundamentally crucial and it is one of the major determinants of VC valuations (see Lerner and Nanda (2020), Nanda and Rhodes-Kropf (2013)). And patenting plays a pivotal role in safeguarding a startup's unique innovations, shielding them from imitation or theft by competitors. This legal protection is essential for preserving a startup's distinct market position and often becomes a key asset in various business negotiations and collaborations. Therefore, the outcome of a startup's patent application can be a significant indicator of its quality and growth potential. We use the event of a patent application rejection as a specific shock to examine how it influences startup behavior. This approach allows us to analyze the impact of existing investors reducing support due to perceived changes in the startup's quality on their press release strategies.

According to Sampat and Williams (2019), we analyze the information regarding the census of patent applications published by the United States Patent and Trademark Office (USPTO). Our focus is on identifying unsuccessful patents, which are determined by the event code "CTFR" indicating the final rejection of the application. Next, we align the patent rejections with the startups by comparing their names, and we verify the accuracy of this alignment by ensuring that the patent rejections occurred after the year the startups were founded. A startup that faces a patent application rejection is classified as a 'treated firm.' Conversely, 'control firms' are those in the same industry and development stage but without a patent rejection. Our identification strategy involves constructing a firm-year level panel for both treatment and control companies across a six-year span (-3 to +3 years) around the patent rejection event.

We estimate differences-in-differences regressions, where the dependent variables are a dummy variable, *PR Dummy*, which equals one if the startup company made press releases in that year and zero otherwise, and a numerical variable, *PR Numbers*, which quantifies the total number of press releases a startup made in that particular year. The independent variable of interest is the *treatment* × *post*, where *treatment* is a dummy equal to one of the startup firm belongs to the treatment sample and *post* is a dummy equal to one if the year follows the treated firms rejection of patent application. The regression include either firm fixed effect or industry, year, stage fixed effects, as well as the *treatment* and *post* dummy (not tabulated). The results are shown in Table 5.

[Table 5 is about here]

The regression analysis in Panel A of Table 5 shows that startups experiencing patent application rejections (treated firms) are significantly more likely to issue press releases compared to their counterparts (control firms). Within the first year after rejection, the likelihood of issuing press releases rises by 0.0261, a 45% increase. This trend extends into the second year. However, significance diminishes in the three-year window, possibly due to the inability of many startups to weather the impact of patent rejection. Furthermore, the rejection of a patent application is among the various negative events that can occur for startups, exposing them to potential setbacks. The increase in making press releases might be a strategy for struggling startups to mimic the startups which is good enough but just with limited capacity from current investors. Startups that are facing financial challenges due to their poor performance frequently opt to voluntarily disclose information. The purpose behind this is to attract external investors. However, it becomes challenging for these potential investors to differentiate between press releases issued by underperforming startups and those made by successful startups that have limited resources and existing investors.

4.9 Can Press Releases Attract More Investors?

As previously indicated, startups often issue press releases in response to a need for external investment, particularly when facing reduced support from existing investors. This decrease in support may stem from either the startup's under-performance or the limited capacity of existing investors. Consequently, press releases can serve as a nuanced indicator of a startup's quality. An important question arises: How do external investors respond to these press releases? Are they motivated to participate in the subsequent financing round, or is the effect not always as expected? To address this, we conduct a linear regression analysis to explore the relationship between pre-round press releases and the composition of investors in the subsequent financing round. The regression model is outlined below:

$$Log\ Number\ of\ (new)\ investors = \beta \cdot PR\ measures + \gamma \cdot X + \delta_i + \theta_t + \epsilon_{i,t} \tag{3}$$

In our updated linear regression model, the primary variable of interest, *Log Number of (new) investors*, represents the logarithm of the total number of investors and specifically, the logarithm of the number of new investors in the financing round. The key explanatory variable, *PR Measures*, evaluates the extent of a startup's press release activities following the completion of the latest round. To assess these activities, we use two metrics: *Round with PR* as a binary variable, and *Log No of PR*, which computes the natural logarithm of the count of press releases in the given period. Additionally, we introduce *PR Frequency*, calculated by dividing the total number of press releases between rounds by the months elapsed in this period, to examine if the intensity of press releases correlates with investor attraction. Our model incorporates both company and year fixed effects to facilitate accurate comparisons between rounds and to understand the influence of press release activities on attracting investors within the same company. The regression results are detailed in the Table 6.

[Table 6 is about here]

The regression analysis in the table confirms our hypothesis. Panel A shows a significant positive correlation between rounds with press releases and the number of investors participating in those rounds. Specifically, a round with a press release sees a 7.13% increase in investor numbers compared to rounds without. This trend holds true even when controlling for firm and year effects. Moreover, Panel B focuses on new investors, revealing that rounds following press releases attract on average 3.24% more new investors. This relationship is consistent across various press release measures, with a 2.86% increase in new investors for every 1% rise in press release numbers, and a 14.76% increase in new investor participation with every 1% increase in press release frequency.

The findings indicate that startups can leverage press releases to boost public awareness and attract a greater number of investors, including newcomers, for their upcoming funding rounds. These insights are particularly relevant for startups moving towards another round of financing. It's crucial to understand that these results are specific to startups that not only issue press releases but also successfully secure additional financing, typically attracting an increased pool of investors. This trend doesn't automatically suggest that existing investors are stepping back. It might be a case where current investors, despite their willingness to support, are constrained in their capacity, prompting the startup to seek new investors through public disclosures. However, the entry of new investors, who lack prior stakes in the startup, might lead to negotiations for lower valuations to maximize their benefits. Additionally, there's a possibility that underperforming startups might also issue press releases to blend in, creating a challenge in distinguishing between these different types of startups. Our subsequent analysis will delve into whether external investors can identify, even to a certain extent, these distinct categories of startups.

4.10 Textual Analysis: Heterogeneity of Press Releases

Our empirical analysis reveals that the motivation behind startups issuing press releases is multifaceted. It could indicate a reduction in support from existing investors, which may not necessarily reflect on the startup's inherent quality. Alternatively, it might signal efforts by underperforming startups to appeal to external investors who lack complete information. Subsequent investigations corroborate that rounds following press releases typically involve a higher average number of investors, including an increase in new investors. This raises critical questions about investor interpretation of information conveyed through press releases and whether the variability in press release practices assists investors in discerning, at least partially, the quality of startups.

Solomon (2012) identifies the practice among companies of employing investor relations (IR) firms to shape public perception positively. This tactic, prevalent in various studies, involves strategic language use in media coverage, which not only conveys specific company information (Tetlock, Saar-Tsechansky, and Macskassy (2008)) but also influences broader market sentiment (Tetlock (2007)), subsequently impacting company returns. It's hypothesized that underperforming startups might employ similar tactics to attract external investment, possibly by embellishing press releases with more positive spins, subjective opinions, and complex jargon, masking their lack of substantial milestones. This study aims to discern such strategies by applying textual analysis, focusing on sentiment, subjectivity, and readability. The goal is to examine how these aspects in post-press release rounds influence the returns, distinguishing between genuine achievements and spun narratives in startup communications. We use the model below to perform our linear tests:

$$Round\ Return = \beta \cdot Textual\ Measures + \gamma \cdot X + \delta_i + \omega_s + \theta_t + \epsilon_{i,s,r} \tag{4}$$

In the proposed linear regression model, the focal variable is the valuation-based round return. Explanatory variables utilized encompass textual analysis metrics spanning three dimensions: sentiment, subjectivity, and readability. The model also integrates control variables, alongside fixed effects for industry, year, and development stage, to account for factors potentially influencing valuation returns. Detailed discussions of these results are segmented into subsequent subsections for in-depth examination.

4.10.1 Sentiment & Return on Round-level Valuation

Our analytical approach begins with an examination of the sentiment expressed in press releases. This involves preprocessing the text: tokenizing, removing stopwords, and lemmatizing the words. We then apply sentiment analysis using two finance-specific sentiment dictionaries. The first is Loughran and Mcdonald (2011) bag-of-words approach (LM), and the second is a machine learning-based dictionary from García, Hu, and Rohrer (2023) (ML). By categorizing positive and negative words in the press release texts and calculating their proportion relative to the total word count, we construct sentiment measures. These measures are then employed as explanatory variables in our regression model to assess their impact. The outcomes of this analysis are detailed in Table 7.

[Table 7 is about here]

The table below demonstrates that there is a negative correlation between the return of follow-on rounds and sentiment words, regardless of whether they are positive or negative. This correlation remains consistent even after controlling for round specific variables, industry, stage, year fixed effects, or their interaction. Specifically, a one percent increase in positive sentiment words from the LM dictionary is associated with approximately a 3.05% decrease in the return of the subsequent round, while a one percent increase in negative words is associated with about a 3.26% decrease in the return. When using the ML dictionary, a one percent increase in the proportion of positive sentiment is correlated with a 2.94% decrease in round return, and a one percent increase in negative sentiment is correlated with a 6.38% decrease in round return.[11]

The observed negative correlation in our study indicates that the sentiment tone of a startup's press release—whether positive or negative—may not be as impactful as one might assume. Considering that startups are unlikely to frame their own press releases negatively, and that approximately 82% of our sample press releases have more positive than negative words, investors seem to be indifferent to overly positive tones in these releases. Instead, press releases laden with sentiment, irrespective of their positive or negative nature, often indicate an attempt to "spin" information and are associated with lower returns compared to more objective announcements detailing startup milestones. Further analysis will focus on the subjectivity embedded in these press releases.

4.10.2 Subjectivity & Return on Round-level Valuation

To delve deeper into how the subjectivity or objectivity of press releases influences the returns of subsequent funding rounds, we developed four metrics. The first metric assesses the proportion of numerical tokens relative to the total token count in the article, underlining the notion that numerical data tend to be more objective and less open to varied interpretation (Liberti and Petersen (2019)). The second and third metrics evaluate the total proportion of sentiment-laden words, both positive and negative, to the overall token count, with a higher ratio indicating a lean towards subjective opinions over factual presentation. The final metric employs TextBlob's subjectivity analysis, quantifying the

[11] The larger difference in magnitude between the positive and negative sentiment measures suggests that the machine learning dictionary better captures the negative tone conveyed in press releases.

balance between personal opinion and factual content in the text. A higher subjectivity score suggests a predominance of personal views over objective information. These four metrics, representing different facets of subjectivity, are then incorporated into our regression model, with the outcomes detailed in the subsequent table.

[Table 8 is about here]

The analysis presented in the table highlights a relationship between the objectivity of press releases and subsequent round returns. Specifically, column (1) shows that a one percent increase in numerical content corresponds to a 1.46% increase in round valuation return. In contrast, columns (2) and (3) illustrate that an increase in sentiment words (as per the LM and ML dictionaries) is associated with decreased round valuation returns. Moreover, column (4) indicates that increased subjectivity negatively impacts these returns. These effects are consistent even after controlling for the intersection of industry, year, and stage fixed effects, as demonstrated in columns (5) to (8). The results imply that while startups with substantial achievements tend to communicate objectively, those lacking such milestones may resort to more subjective reporting, influencing investor to discount valuations in future funding rounds.

4.10.3 Readability & Return on Round-level Valuation

We evaluate the readability dimension in our analysis of the press release articles. Previous studies Loughran and McDonald (2014, 2020) have shown that the readability of financial disclosures impacts the market value of companies. Our hypothesis is that startups with limited achievements tend to produce more complex press releases with lower readability. This may be due to their use of complicated words in an attempt to conceal their under performance. To measure readability, we construct three measures. The first measure is the standard measure of article length, which is represented by the logarithm of the total number of words in the article. The second measure is the proportion of complicated words, identified using the "complex-word-identification" package. Lastly, we use the Gunning fog index, which estimates the number of years of formal education required to understand the text on the first reading. A higher index indicates a more difficult text to comprehend. We include these three measures in a regression analysis, and the estimated results are presented in Table 9.

[Table 9 is about here]

The results presented in the table above provide evidence for a negative association between the level of difficulty in understanding a startup's press release and the subsequent return of realized funding rounds. In column (1), it is observed that a one percent increase in the number of words in a press release is, on average, associated with a 0.0952% decrease in the valuation of the funding round. Similarly, a one percent increase in the proportion of complex words in a press release is, on average, related to a 0.0146% decrease in the round return, as shown in column (2). The findings in column (3) indicate that press releases with higher Gunning fog index scores are more difficult to read, leading to lower returns in follow-on funding rounds. These effects hold true even after controlling for industry, year, and stage fixed effects, as demonstrated in columns (5) to (8). These results further support our hypothesis that startups with weaker achievements tend to rely more on exaggeration in their press releases, resulting in decreased readability. Consequently, external investors respond to these less readable press releases by offering lower valuations in subsequent financing rounds.

5 Conclusion

In this paper, we seek to better understand how startups communicate with the public, why they would voluntarily share their private information with the public, and the impact this has on investor perceptions and company valuations. By exploring the press releases issued by US startups and their fundraising information, we show that the issuance of press releases is negatively associated with both the likelihood for startups to raise a follow-on round and the rounds completed after press release activities have on average a lower return of round valuation compared to those rounds not. We proposed and tested a pooling equilibrium to explain the negative correlation. In this equilibrium, both low-quality startups and better quality startups make press releases to attract the attention of potential external investors. The low-quality startups do this because their existing investors are unwilling to support their next round, while the better quality startups do it because their existing investors do not have enough capacity to support their next round. Since external investors cannot distinguish between these two types of startups, they assign a median valuation to startups making press releases compared to those that remain silent. Among the startups making press releases, the lower-quality ones try to hide their lack of significant achievements by putting more effort into "spinning," which is reflected in their greater subjectivity and lower readability. This ultimately leads to worse valuation outcomes for these startups.

To the best of our knowledge, this paper is the first empirical study to investigate the voluntary disclosure of information by startups. It makes contributions in two main areas. Firstly, it offers empirical insights into which theoretical model may be most applicable in understanding the voluntary disclosure behavior of startups. It highlights a potential reason why full disclosure is not achieved in startup firms, as existing investors of promising startups may prefer to maintain an information advantage. Secondly, it contributes to the existing empirical literature by examining the impact of voluntary disclosure on startups, separate from mandatory reporting. The findings suggest that voluntary disclosure can serve as a signal for negative selection, which is associated with a lower average valuation. In addition to these points, our research contributes to the broader discussions on voluntary disclosure, persuasion in finance, and the strategic use of press releases. Overall, this research enhances our understanding of startups' strategic communication, particularly in relation to voluntary disclosure and persuasion in finance, and sheds light on the dynamic interplay between startups, their insider investors, and potential external financiers.

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6 Tables and Figures

Figure 1: Press Releases by Funding Stages

Figure below shows the general trend in startups' press releases at different financial stages including Seed, Series-A, Series-B, ..., Series-G and above. Figure 1a shows the total number of startups at different financial stages. Figure 1b shows the percentage of startups making press releases in our sample with different financial stages. Figure 1c shows the average number of press releases made per startup at each financial series.

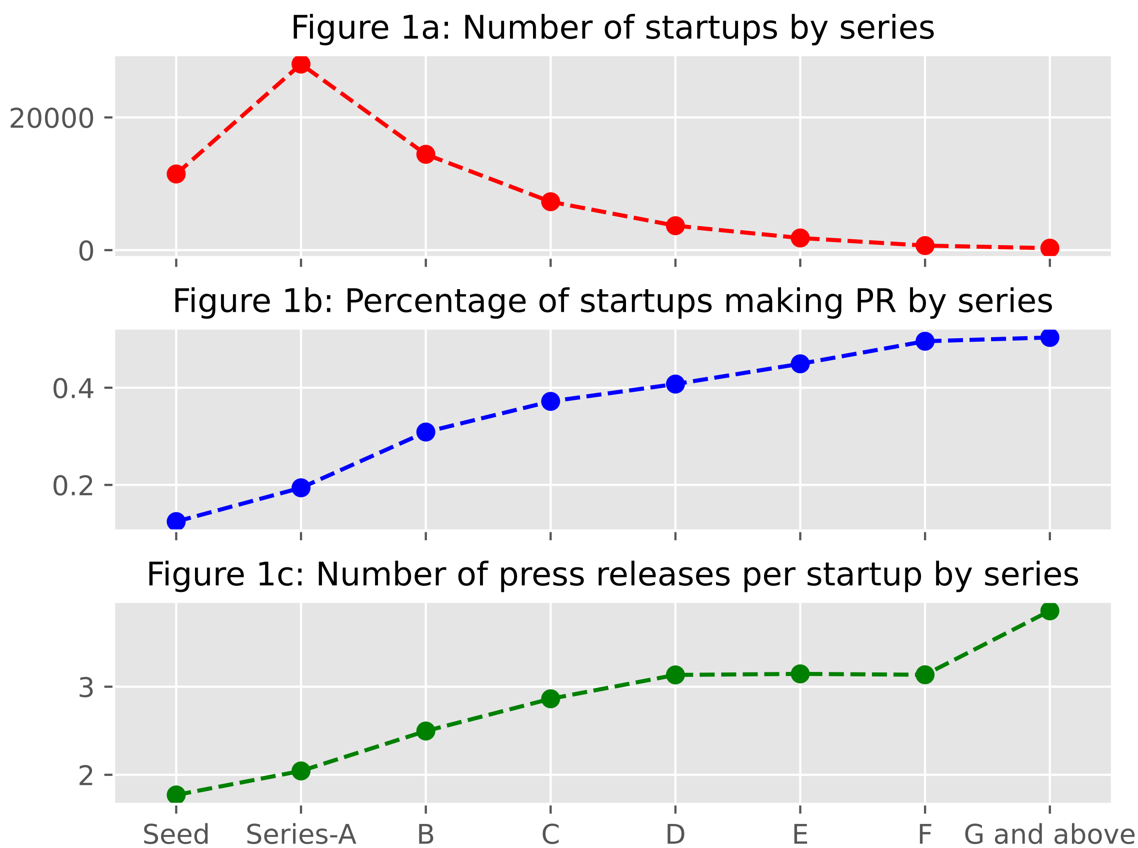
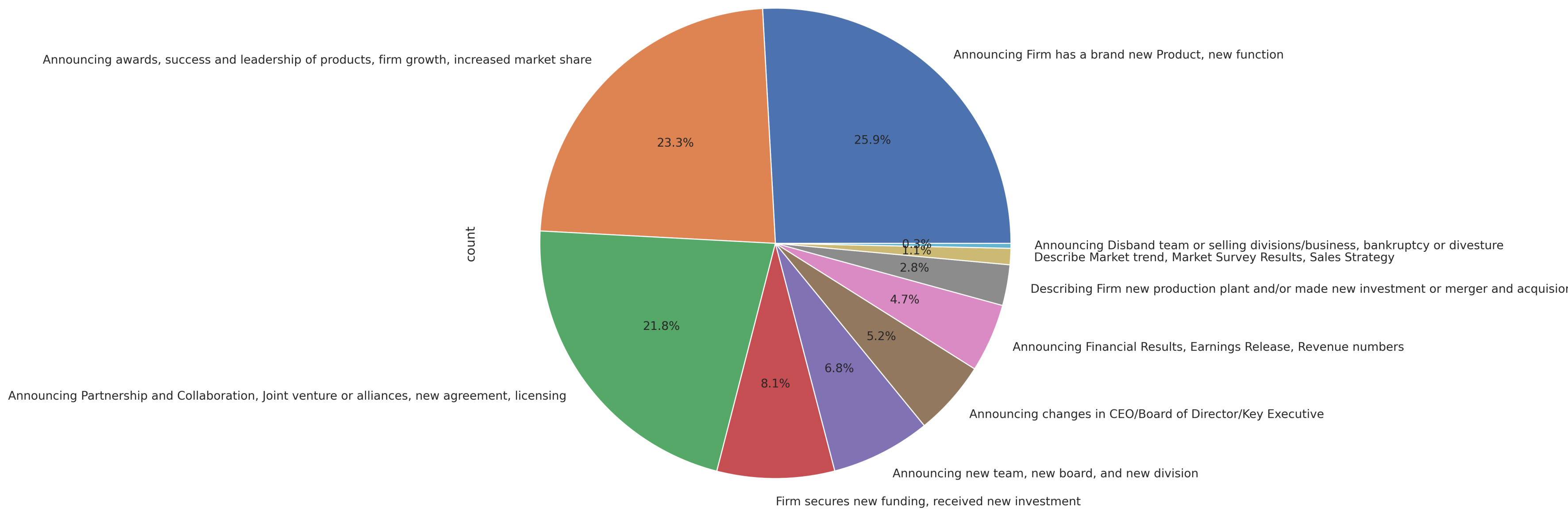
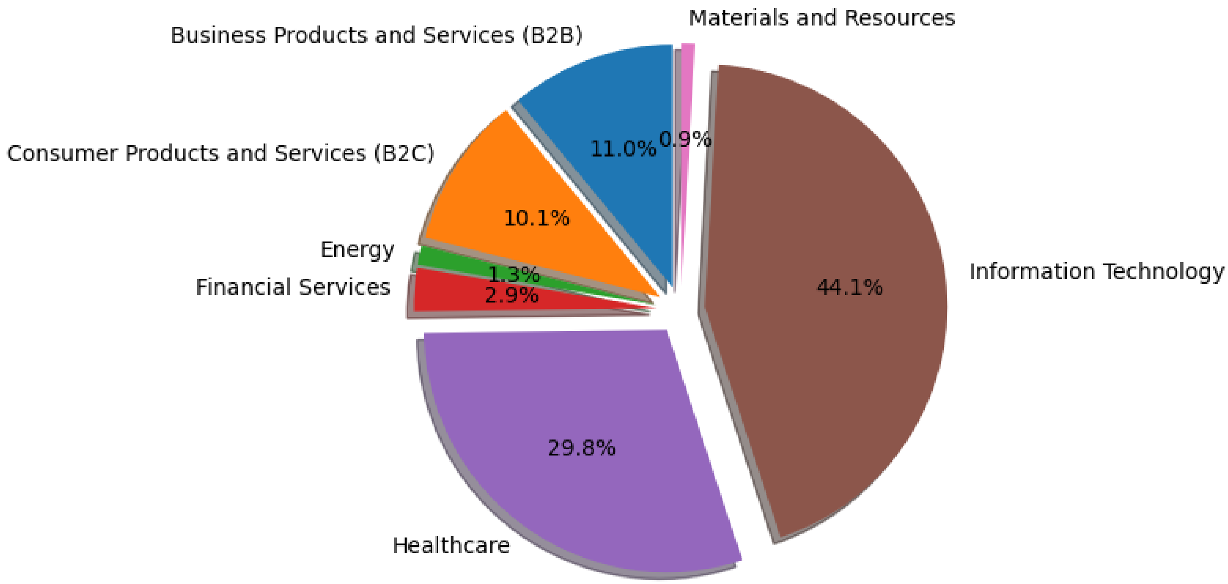


Figure 2: Press Releases by Topic



This figure present the percentage of each topic in the press releases. The topics are classified based on a large language model with detailed procedure in section 4.2. The percentage is calculated as the number of press releases with the topic divided by the total number of press releases.

Figure 3: Press Releases Distribution by Industry



The graph in the illustration displays the spread of press releases across various industries. Press releases are classified based on the industry sector in which the companies issuing them are located. The industry sector information is based on the "Primary Industry Sector" sourced from Pitchbook.

Table 1: Summary Statistics

This table presents the statistical summary of the variables we used in this paper. It provides an overview of the key variables, including the round-level dummy variable ”Next Round” and ”Round Return,” as well as explanatory variables related to press release actions, the number of press releases, and the textual analysis of press releases (such as sentiment, subjectivity, and readability). Additionally, it includes round-level control variables such as pre-round insider ownership and pre-round firm size. The statistics provided consist of the mean, median, and standard deviation for each variable, along with the number of observations. For a more detailed explanation of how these variables were constructed, please refer to A1. The sample period covers the years 2004 to 2022.

Variables	N	Mean	Median	std. dev
Next Round	81,623	0.579	1.000	0.494
With PR between Rounds	81,623	0.153	0.000	0.360
Log No of PR between Rounds	81,623	0.231	0.000	0.616
Round Return Equity Valuation	32,728	0.777	0.357	1.345
Round Return Price Per Share	31,429	0.592	0.250	1.124
% Raised in Round	37,708	0.231	0.211	0.137
Pre-round Insider Ownership	36,872	0.460	0.456	0.179
Log No of Investors in Round	55,985	1.171	1.099	0.846
Log No of New Investors in Round	48,289	0.897	0.693	0.797
Log Pre-round Firm Size	41,556	3.135	2.996	1.464
Round with PR	71,835	0.162	0.000	0.369
Round with First PR	71,835	0.443	0.000	0.497
Log No of PR	71,835	0.210	0.000	0.533
PR Frequency	71,835	0.032	0.000	0.099
Regular Releaser Indicator	71,835	0.147	0.000	0.355
LM Positive	11,562	0.047	0.044	0.022
LM Negative	11,562	0.017	0.012	0.017
ML Positive	11,562	0.038	0.035	0.021
ML Negative	11,562	0.020	0.018	0.014
% of Numbers	11,562	0.023	0.017	0.024
Subjectivity	11,562	0.449	0.450	0.061
Log No of Words	11,562	5.660	5.656	0.373
% of Complex Words	11,562	0.253	0.255	0.042
Gunning Fog Index	11,562	20.618	20.467	2.739

Table 2: Press Releases and the Likelihood of Raising the Next Financing Round

Each observation is a follow-on financing round. The dependent variable *Next Round* is a dummy variable which equals to one if there is another round within the cutoff period (0.9 quantile of all the deals, 1,264 days, about 3.4 years) after this round and 0 if there is no next round or there is a record of bankruptcy. The explanatory variables are based on the press release situation after the round, including the indicator variable whether there is a press release and the log number of the press release, during the in-between period. For round n, *With PR between Rounds* is the dummy codes to 1 if the startup issues press releases after round n and before the completion of round $n+1$, or before the exceeding of cutoff period. *Log No of PR between Rounds* is the natural logarithm of number of press releases the startup issued between round n and the completion of round $n+1$, or before the exceeding of cutoff period. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

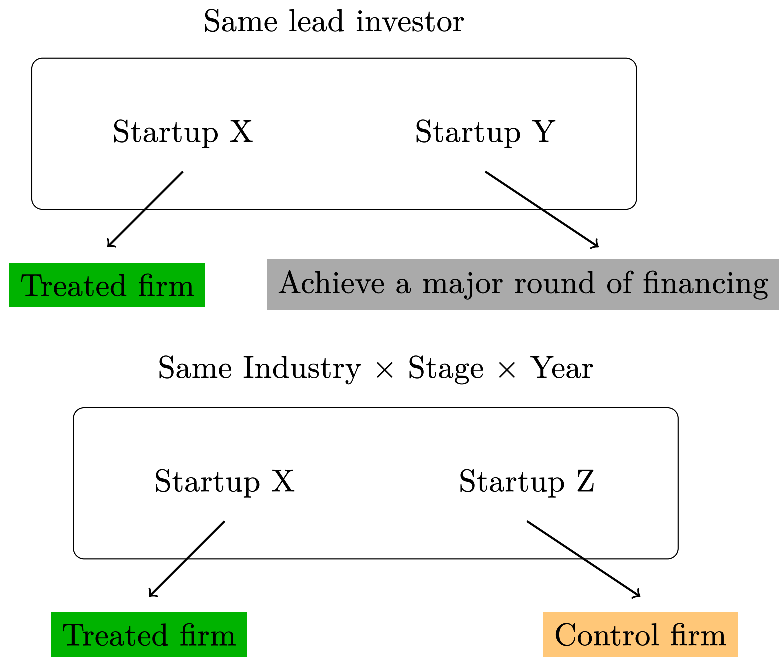
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
With PR between Rounds	-0.0402***		-0.0370***		-0.2393***		-0.2198***	
	(-8.28)		(-7.42)		(-36.35)		(-32.29)	
Log No of PR between Rounds		-0.0732***		-0.0705***		-0.1919***		-0.1849***
		(-27.30)		(-25.29)		(-49.53)		(-45.92)
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	81,622	81,622	81,042	81,042	61,546	61,546	60,809	60,809
Adj. R^2	0.02	0.02	0.02	0.03	0.11	0.13	0.14	0.16

Table 3: Press Releases and Next-round Valuation Change

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round on the equity valuation. **Round with PR** is an indicator variable equal to one if the company make at least one press release (not about the deal event itself) after the last round and before this round. **Log No of PR** is the natural logarithm of number of press releases the startup issued after the last round and before this round. This table provides the relationship between the press release during rounds made by startup firms and its effects on the outcome of the next funding round. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round with PR	-0.1795***		-0.1939***		-0.1221***		-0.1263***	
	(-9.21)		(-9.17)		(-3.62)		(-3.29)	
Log No of PR		-0.1433***		-0.1576***		-0.0795***		-0.0892***
		(-12.73)		(-13.02)		(-3.93)		(-3.90)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	23,015	23,015	22,215	22,215	15,887	15,887	14,786	14,786
Adj. R^2	0.12	0.12	0.11	0.11	0.20	0.20	0.21	0.21

Figure 4: Sample Construction for the Shock of Lead Investors' Capacity



In this example, there is a situation where the same lead investor is simultaneously holding two startups, X and Y. When startup Y successfully secures a large round of financing, exceeding the 90th percentile of all fundraising deals in the sample, the lead investor will allocate more resources to startup Y, which is believed to have the potential to become the next unicorn. As a result, the capacity to support startup X will decrease. This decrease in support is not related to the quality of startup X; it is still considered a good startup worthy of continued investment. Therefore, startup X is identified as a treated firm. On the other hand, the control firms, such as startup Z, are startups in the same industry and at the same development stage as startup X, but they are not experiencing a decrease in support from their lead investors due to the sudden rise of other startups held by their investors.

Table 4: Press Releases after Lead Investor Made Significant Investment to Other Startups

This diff-in-diff regression analysis is conducted at the firm-year level. The event of interest is whether the lead investor in a startup makes a significant investment in another portfolio firm. The outcome variable of interest is either the indicator variable for a press release (PR Dummy) or the number of press releases (PR Number) for the focal startup in a given year. Three different length of the windows are applied here: ±1, ±2 and ±3. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at levels 1%, 5% and 10%, respectively.

Panel A: PR Dummy	±1 yr	±2 yrs	±3 yrs	±1 yr	±2 yrs	±3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
treatment×post	0.0090***	0.0111***	0.0100***	0.0048***	0.0059***	0.0036***
	(9.47)	(9.98)	(8.09)	(5.11)	(5.32)	(2.92)
Firm FE	✓	✓	✓	✗	✗	✗
Year FE	✗	✗	✗	✓	✓	✓
Industry FE	✗	✗	✗	✓	✓	✓
Stage FE	✗	✗	✗	✓	✓	✓
Obs.	896,926	1,757,614	2,514,396	900,851	1,757,614	2,514,396
Adj. R^2	0.34	0.36	0.36	0.03	0.03	0.03

Panel B: PR Number	±1 yr	±2 yrs	±3 yrs	±1 yr	±2 yrs	±3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
treatment×post	0.0265***	0.0380***	0.0377***	0.0162***	0.0249***	0.0217***
	(10.31)	(12.27)	(10.88)	(6.45)	(8.12)	(6.28)
Firm FE	✓	✓	✓	✗	✗	✗
Year FE	✗	✗	✗	✓	✓	✓
Industry FE	✗	✗	✗	✓	✓	✓
Stage FE	✗	✗	✗	✓	✓	✓
Obs.	896,926	1,757,614	2,514,396	900,851	1,757,614	2,514,396
Adj. R^2	0.33	0.34	0.34	0.03	0.03	0.03

Table 5: Press Releases after Rejection for Patent Application

This diff-in-diff regression analysis is conducted at the firm-year level. The event of interest is whether a startup experiences rejection for their patent application. The outcome variable of interest is either the indicator variable for a press release (PR Dummy) or the number of press releases (PR Number) for the focal startup in a given year. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at levels 1%, 5% and 10%, respectively.

Panel A: PR Dummy	±1 yr	±2 yrs	±3 yrs	±1 yr	±2 yrs	±3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
treatment×post	0.0261*	0.0276*	0.0235	0.0293*	0.0310*	0.0253
	(1.67)	(1.76)	(1.40)	(1.81)	(1.85)	(1.39)
Firm FE	✓	✓	✓	✗	✗	✗
Year FE	✗	✗	✗	✓	✓	✓
Industry FE	✗	✗	✗	✓	✓	✓
Stage FE	✗	✗	✗	✓	✓	✓
Obs.	578,887	1,135,521	1,617,971	582,537	1,135,521	1,617,971
Adj. R^2	0.34	0.36	0.36	0.02	0.03	0.03

Panel B: PR Numbers	±1 yr	±2 yrs	±3 yrs	±1 yr	±2 yrs	±3 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
treatment×post	0.0483	0.0467	0.0448	0.0498	0.0501	0.0441
	(1.14)	(1.00)	(0.90)	(1.19)	(1.08)	(0.90)
Firm FE	✓	✓	✓	✗	✗	✗
Year FE	✗	✗	✗	✓	✓	✓
Industry FE	✗	✗	✗	✓	✓	✓
Stage FE	✗	✗	✗	✓	✓	✓
Obs.	578,887	1,135,521	1,617,971	582,537	1,135,521	1,617,971
Adj. R^2	0.32	0.33	0.34	0.02	0.02	0.02

Table 6: Press Releases and Number of Investors & New Investors

Each observation is a follow-on financing round. The dependent variable **Log Num of (New) Investors** is calculated as the logarithm of the number of (new) VC investors participated in this deal. **Round with PR** is an indicator variable equal to one if the company make at least one press release (not about the deal event itself) after the last round and before this round. **PR Freqency** is calculated as the number of total press release from last deal date to current deal date, divided by the total months of this period. This table provides the relationship between the press release and number of investors participated in the next round. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Log Number of Investors			
	(1)	(2)	(3)
Round with PR	0.0713***		
	(4.43)		
Log No of PR		0.0518***	
		(4.94)	
PR Frequency			0.3040***
			(5.68)
Controls	✓	✓	✓
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Obs.	22,468	22,468	22,468
Adj. R^2	0.35	0.35	0.35

Panel B: Log Number of New Investors			
	(1)	(2)	(3)
Round with PR	0.0324*		
	(1.76)		
Log No of PR		0.0268**	
		(2.22)	
PR Frequency			0.1476**
			(2.38)
Controls	✓	✓	✓
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Obs.	19,188	19,188	19,188
Adj. R^2	0.26	0.26	0.26

Table 7: Regressions between Press Releases Sentiment & Round Return

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round on the equity valuation. **LM Positive/Negative** is an variable calculated as the number of positive/negative words, as identified by the dictionary from Loughran and Mcdonald (2011), divided by the total number of words in the press releases. **ML Positive/Negative** measures the proportion of words as classified by the dictionary from García, Hu, and Rohrer (2023). This table provides the relationship between the sentiment press releases during rounds made by startup firms and its effects on the outcome of the next funding round. The sentiments measures are aggregated to a round level if there are more than one press releases before the rounds. Cluster-adjusted *t*-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LM Positive	-3.0526***				-4.3571***			
	(-3.44)				(-4.19)			
LM Negative		-3.2606***				-3.3520***		
		(-3.44)				(-2.92)		
ML Positive			-2.9410***				-3.4877***	
			(-3.25)				(-2.94)	
ML Negative				-6.3792***				-6.8676***
				(-4.77)				(-4.55)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✗	✗	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✗	✗	✗	✗
Year FE	✓	✓	✓	✓	✗	✗	✗	✗
Stage FE	✓	✓	✓	✓	✗	✗	✗	✗
Obs.	5,783	5,783	5,783	5,783	5,126	5,126	5,126	5,126
Adj. R^2	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11

Table 8: Regressions between Press Releases Subjectivity & Round Return

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round on the equity valuation. There are four explanatory variables. **% of Numbers** assesses the proportion of numerical tokens relative to the total token count in the article. **% of LM Sentiment words** and **% of ML Sentiment words** evaluate the total proportion of sentiment-laden words, both positive and negative, to the overall token count, with a higher ratio indicating a lean towards subjective opinions over factual presentation. **Subjectivity** employs TextBlob's subjectivity analysis, quantifying the balance between personal opinion and factual content in the text. This table provides the relationship between the subjectivity of press releases during rounds made by startup firms and its effects on the outcome of the next funding round. The subjectivity measures are aggregated to a round level if there are more than one press releases before the rounds. Cluster-adjusted *t*-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% of Numbers	1.4616*				2.0164**			
	(1.76)				(1.97)			
% of LM Sentiment words		-2.7800***				-3.5176***		
		(-4.58)				(-4.67)		
% of ML Sentiment words			-3.2262***				-3.6750***	
			(-4.67)				(-4.47)	
Subjectivity				-0.8793***				-1.0525***
				(-2.94)				(-2.80)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✗	✗	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✗	✗	✗	✗
Year FE	✓	✓	✓	✓	✗	✗	✗	✗
Stage FE	✓	✓	✓	✓	✗	✗	✗	✗
Obs.	5,783	5,783	5,783	5,783	5,126	5,126	5,126	5,126
Adj. R^2	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11

Table 9: Regressions between Press Releases Readability & Round Return

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round on the equity valuation. There are three explanatory variables. **Log No of Words** calculates the logarithm of the total number of words. **% of Complex Words** evaluates the total proportion complicated words to the overall token count, with a higher ratio indicating a more complicated article. **Gunning Fog Index** estimates the years of formal education a person needs to understand the text on the first reading. This table provides the relationship between the readability of press releases during rounds made by startup firms and its effects on the outcome of the next funding round. The readability measures are aggregated to a round level if there are more than one press releases before the rounds. Cluster-adjusted *t*-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Log No of Words	-0.0952*			-0.1003		
	(-1.75)			(-1.64)		
% of Complex Words		-1.4586***			-1.3349**	
		(-3.12)			(-2.43)	
Gunning Fog Index			-0.0200**			-0.0150*
			(-2.14)			(-1.84)
Controls	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✗	✓	✓	✓
Industry FE	✓	✓	✓	✗	✗	✗
Year FE	✓	✓	✓	✗	✗	✗
Stage FE	✓	✓	✓	✗	✗	✗
Obs.	5,783	5,783	5,783	5,126	5,126	5,126
Adj. R^2	0.12	0.12	0.12	0.11	0.11	0.11

Appendix A. Appendix

Table A1: Variable definitions

Financing round variables	
Next Round	For round n, dummy codes to 1 if the startup secures another round $n+1$ within the cutoff period (90th percentile of the time gaps between financing rounds in our sample) after current round n
Round Return Equity Valuation	For round n, its measure of round return on the valuation of equity is calculated as $\frac{\text{Pre-money valuation}_n}{\text{Post-money valuation}_{n-1}}$, annualized if more than one year between two rounds
Round Return Price Per Share	For round n, its measure of round return on the price per share is calculated as $\frac{\text{Price Per Share}_n}{\text{Price Per Share}_{n-1}}$, annualized if more than one year between two rounds
Press releases variables	
With PR between Rounds	For round n, dummy codes to 1 if the startup issues press releases after round n and before the completion of round $n+1$, or before the exceeding of cutoff period
Log No of PR between Rounds	The natural logarithm of number of press releases the startup issued between round n and the completion of round $n+1$, or before the exceeding of cutoff period
Round with PR	For round n, dummy codes to 1 if the startup issues press releases during the period between $n-1$ and n
Log No of PR	For round n, the natural logarithm of number of press releases the startup issued between round $n-1$ and n
PR Frequency	For round n, this measure is calculated as the total number of press releases the startup issued between round $n-1$ and n, divided by the total number of months between these two rounds
Round with first PR	For round n, dummy codes to 1 if the startup issues its very first press release during the period between $n-1$ and n
Round characteristics variables	
% Raised in Round	For round n, this measure is calculated as the percentage of new equity issued in the round
Pre-round Insider Ownership	For round n, this measure is calculated as one minus the total ownership of investors participating in this financing round
Log Pre-round Firm Size	For round n, this measure is calculated as the natural logarithm of the post-money valuation of round $n-1$
Log No of Investors in Round	For round n, this measure is calculated as the natural logarithm of the total number of investors in this round
Log No of New Investors in Round	For round n, this measure is calculated as the natural logarithm of the number of new investors in this round
Startup characteristics variables	
Regular Releaser Indicator	This is the dummy variable which equals to 1 for all the rounds made by startup company classified as regular releaser, which makes press releases among more than half of their rounds
Textual analysis variables	
LM Positive	For each article, this value is calculated as $\frac{\text{Number of positive tokens as classified in Loughran and Mcdonald (2011)}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
LM Negative	For each article, this value is calculated as $\frac{\text{Number of negative tokens as classified in Loughran and Mcdonald (2011)}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
ML Positive	For each article, this value is calculated as $\frac{\text{Number of positive tokens as classified in García, Hu, and Rohrer (2023)}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
ML Negative	For each article, this value is calculated as $\frac{\text{Number of negative tokens as classified in García, Hu, and Rohrer (2023)}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
% of Numbers	For each article, this value is calculated as $\frac{\text{Number of numerical tokens}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
Subjectivity	The level of subjectivity as measured by TextBlob for each article, aggregated to a round-level if there are more than one article among rounds
Log No of Words	For each article, this value is calculated as the natural logarithm of the total number of tokens, aggregated to a round-level if there are more than one article among rounds
% of Complex Words	For each article, this value is calculated as $\frac{\text{Number of complex tokens}}{\text{Total number of tokens}}$, aggregated to a round-level if there are more than one article among rounds
Gunning Fog Index	For each article, this value is calculated as $0.4 \times \frac{\text{words}}{\text{sentences}} + 100 \times \frac{\text{complex words}}{\text{words}}$, aggregated to a round-level if there are more than one article among rounds

Table A2: Regressions between Round Return on Price Per Share and Press Release Events

Each observation is a follow-on financing round. The dependent variable **Round Return PPS** is calculated as the annualized return from the previous round with the return on price per share while the main regression is the return on the equity valuation. **Round with PR** is an indicator variable equal to one if the company make at least one press release (not about the deal event itself) after the last round and before this round. This table provides the relationship between the press release during rounds made by startup firms and its effects on the outcome of the next funding round. Cluster-adjusted *t*-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round with PR	-0.1402***		-0.1567***		-0.1033***		-0.1038***	
	(-8.47)		(-8.77)		(-3.52)		(-3.13)	
Log No of PR		-0.1120***		-0.1282***		-0.0647***		-0.0687***
		(-11.48)		(-12.26)		(-3.74)		(-3.53)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	22,789	22,789	21,988	21,988	15,715	15,715	14,613	14,613
Adj. R^2	0.11	0.11	0.10	0.10	0.17	0.17	0.18	0.18

Appendix A.1. Press Releases Pattern & Round Valuation Returns

Appendix A.1.1. Round Valuation Changes on the First Press Releases

To further investigate on the effect for a startup makes its first press release, we next analyze whether the negative effect is more severe when a startup which was quiet started to make disclosure. This provides a more refined test of our negative signal hypothesis because it enables us to establish whether startups are valued relatively less valuable once they started to express their information to public. The results are presented in Table A3.

[Table A3 is about here]

Table A3 reports the regression analysis of the relationship between *Round with First PR*, *Round with PR* and *Round Return*. Columns (1) and (4) are with the firm and year fixed effects, and firm and year by stage by industry fixed effects. In both of these two columns, *Round with First PR* dominates, specifically, rounds with the first press release from firms have relative price changes that are 7.5% - 8.4% per annual less than control rounds, with the control for the *Round with PR*. This indicates that for a startup, controlling the year by stage by industry effect, together with firm effect, the round following its first press release will on average decrease about 7.5% valuation. Meanwhile, if not including the firm fixed effect (columns 2 and 3), then it is the *Round with PR* variable dominates, which indicates that the negative effect from the first press release only significant once we control for the unobservable time-invariant firm heterogeneity.

Appendix A.1.2. Round Valuation Changes on Press Releases Patterns

After capturing the effect from the very first press release, we next consider whether the behaviour pattern for startups' press release matters. Based on the distribution of press release made by startups during their life-cycle, we categorize startups by two groups: regular reporter and non-regular reporter. For a startup to be identified as a regular reporter, it needs to make at least one press release in more than half of its total rounds consistently, otherwise the startup is the non-regular reporter whose press releases are concentrated in some particular rounds. Our expectation is the market would learn from the behaviour pattern of startup firms, if a startup disclosures its information regularly, it may mitigate the negative impact from press release as the potential investors would treat it as a common pattern for these firms. However, if a startup keeps silent for the previous rounds until before a particular round, it can be a negative interpretation that the startup would like the attention or the awareness from public to attract as many as potential investors so that its likelihood to have the next round can increase. The results for the regressions of these two sub-samples are presented in Table A4.

[Table A4 is about here]

The regression results contained in the above table are consistent with our hypothesis. The negative effect of press release is only statistically significant in the sub-sample of startups which are not reporting regularly. We note that the number of regular firms are smaller than that of non-regular firms, which indicates that most startups are making press release strategically rather than reporting regularly. For non-regular reporter, compared with round without, the round with press release decreases firms by 11.2% with the control of firm and year fixed effects; if controlling both the firm and year by industry by stage fixed effects, the decrease magnitude becomes about 13%. These results suggest that for startups which keep silent, its valuation was overpriced due to the asymmetric information, however, once those startups begin their disclosure, the market takes it as a negative signal as it indicates that the inside investors are not able to keep financing the startup until new investors' participation.

Appendix A.1.3. Round Valuation Changes on Press Releases Frequency

To better capture the effect from different length during rounds, we construct the continuous variable, *Log PR Frequency*, computed as logarithm of the number of total press release from last deal date to current deal date, divided by the total months of this period, measuring the frequency for a startup makes press release during one particular period between rounds. Then we include frequency as the main explanatory variable and conduct the regressions in both the full sample and the sub sample with only non regular reporters. Table A5 contains the results from regressions.

[Table A5 is about here]

Our results in Table A5 show that the frequency of press release before rounds is significantly negatively correlated with the round return on valuation, which suggests that the more frequently for startups making press release before a particular round, the more decrease it may cause to the valuation of this round. Specifically, from columns (3) to (6), we show that one increase of press release per year would decrease 1.64% round return in general for all the firms and decrease 3.68% for non-regular reporting firms, with the control for year, stage and industry fixed effects either additively or interactively. Also, if we take firm fixed effect into consideration, then the results remain significant in the sub-sample, indicating that for startups which not make press release regularly, once they begin to disclose information more frequently before rounds, the related rounds would be negatively impacted.

Table A3: Regressions between Round Return and First Round with Press Releases

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round, Panel A is the return on price per share and Panel B is the return on the equity valuation. **Round with First PR** is an indicator variable equal to one if this is the first round a quiet startup begins making press release. **Round with PR** is an indicator variable equal to one if the company make at least one press release (not about the deal event itself) after the last round and before this round. This table provides the relationship between the begins for startups to make press release during rounds and its effects on the outcome of the next funding round. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Round with First PR	-0.2105***	-0.2104***	-0.1480***	-0.1398***
	(-7.04)	(-6.08)	(-4.10)	(-3.14)
Round with Non-first PR	-0.3331***	-0.3668***	-0.1449***	-0.1272**
	(-10.96)	(-10.42)	(-3.12)	(-2.23)
Controls	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✓	✗	✓
Firm FE	✗	✗	✓	✓
Year FE	✓	✗	✓	✗
Industry FE	✓	✗	✗	✗
Stage FE	✓	✗	✗	✗
Obs.	9,496	8,717	7,950	6,951
Adj. R^2	0.11	0.11	0.19	0.19

Table A4: Sub-sample of Startups: Regular V.S. Non-regular Press Releases

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round, Panel A is the return on price per share and Panel B is the return on the equity valuation. A startup company is classified as a regular releaser if it consistently makes at least one press release in more than half of its total rounds. **Round with PR** is an indicator variable equal to one if the company make at least one press release (not about the deal event itself) after the last round and before this round. This table provides that whether the consistency of the press releases made by startups will affect the relationship between the begins for startups to make press release during rounds and its effects on the outcome of the next funding round. Cluster-adjusted *t*-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Regular releaser

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round with First PR		-0.2719***		-0.2721***		-0.1735***		-0.1452*
		(-5.39)		(-4.57)		(-2.96)		(-1.89)
Round with Non-first PR		-0.5003***		-0.5574***		-0.1639**		-0.2062**
		(-9.41)		(-8.71)		(-2.41)		(-2.17)
Round with PR	-0.3522***		-0.3694***		-0.1715***		-0.1526**	
	(-7.57)		(-6.68)		(-3.06)		(-2.01)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	4,857	4,857	4,281	4,281	3,783	3,783	3,030	3,030
Adj. R^2	0.12	0.12	0.10	0.10	0.21	0.21	0.18	0.18

Panel B: Non-regular releaser

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round with First PR		-0.2402***		-0.2146***		-0.1348***		-0.0954
		(-6.16)		(-4.52)		(-2.88)		(-1.54)
Round with Non-first PR		-0.3030***		-0.2853***		-0.0857		0.0118
		(-6.06)		(-4.29)		(-1.33)		(0.13)
Round with PR	-0.2552***		-0.2305***		-0.1247***		-0.0757	
	(-7.19)		(-5.30)		(-2.89)		(-1.30)	
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	4,638	4,638	3,903	3,903	4,167	4,167	3,240	3,240
Adj. R^2	0.11	0.11	0.11	0.11	0.16	0.16	0.16	0.16

Table A5: Regressions between Round Return and Press Release Frequency

Each observation is a follow-on financing round. The dependent variable **Round Return** is calculated as the annualized return from the previous round, Panel A is the return on price per share and Panel B is the return on the equity valuation. A startup company is classified as a non-regular releaser if among half of the rounds it does not make any press release. **Log PR Freqency** is calculated as the number of total press release from last deal date to current deal date, divided by the total months of this period. This table provides the relationship between the frequency of startups' press release and its effects on the outcome of the next funding round, conditional on whether this startup regularly reports or not. Cluster-adjusted t-statistics are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Regular releaser

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log No of PR	-0.2424***		-0.2707***		-0.0956***		-0.1162***	
	(-11.53)		(-10.78)		(-3.34)		(-2.97)	
PR Frequency		-0.0519		-0.0850		0.0781		-0.1316
		(-0.48)		(-0.66)		(0.49)		(-0.65)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	4,857	4,857	4,281	4,281	3,783	3,783	3,030	3,030
Adj. R^2	0.11	0.09	0.09	0.07	0.21	0.20	0.18	0.18

Panel B: Non-regular releaser

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log No of PR	-0.1989***		-0.1919***		-0.0814***		-0.0334	
	(-8.55)		(-6.45)		(-2.73)		(-0.83)	
PR Frequency		-0.3981***		-0.3618*		-0.1410		0.1665
		(-2.70)		(-1.78)		(-0.77)		(0.69)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-Industry-Stage FEs	✗	✗	✓	✓	✗	✗	✓	✓
Firm FE	✗	✗	✗	✗	✓	✓	✓	✓
Year FE	✓	✓	✗	✗	✓	✓	✗	✗
Industry FE	✓	✓	✗	✗	✗	✗	✗	✗
Stage FE	✓	✓	✗	✗	✗	✗	✗	✗
Obs.	4,638	4,638	3,903	3,903	4,167	4,167	3,240	3,240
Adj. R^2	0.10	0.09	0.10	0.09	0.16	0.15	0.15	0.15