Three Essays on Corporate Disclosure and Information Externalities

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Abstract

Three Essays on Corporate Disclosure and Information Externalities

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This dissertation includes three essays on corporate disclosure and information externalities. In the first essay, I examine the disclosure behavior of rival firms identified by an Initial Public Offering (IPO) candidate during the IPO quiet period when the IPO candidate is restricted in its communication. I find that the tone of disclosures made by identified rivals becomes more positive during the quiet period, and reverses after the quiet period ends. The strategic disclosure behavior is mainly driven by identified rivals' concerns over product market competition. I also find that this behavior hurts the IPO candidate and benefits the identified rivals. In the second essay, I investigate the relations between IPO firms' peer choice and peer information environment. I find that IPO firms tend to select peer companies with a better information environment, and this effect is more pronounced for IPO firms with greater information uncertainties. I also find support that peer information environment is positively associated with upward offering price revision, post-offering analyst coverage, and negatively associated with the number of amendment filings. Overall, this essay shows that IPO firms can make use of the externalities of peer information to facilitate their initial public offerings. In the third essay, I switch my focus from intra-industry relations to supply chain relations. More specifically, I study the effects of layoff announcements by customers on the valuation and operating performance of their supply chain partners. I find that suppliers experience a negative stock price reaction around their major customers' layoff announcements. The negative price effect is exacerbated when industry rivals of layoff-announcing customers also suffer from negative intra-industry contagion effects. Moreover, these supply chain spillover effects are asymmetric, with only "bad news" layoff announcements causing significant value implications for suppliers, but not "good news" announcements. Supplier firms also reduce their investment in and sales dependence on layoff-announcing customers in subsequent years.

Keywords: Disclosure; Product market competition; IPO quiet period; Identified rivals; Information externalities; Peer information environment; Corporate layoffs, Supply chain relations; Stock market return

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Chapter 1: Introduction

Economic connections are widespread in the current economies. Information about one business entity is going to have implications for other related parties. To understand an individual firm's decision making, it is not enough to only look within the firm. Prior literature on intra-industry information transfer and information transfer along the supply chain relations has documented that information externalities occur when one firm's disclosure affects the decision making of another economically related firm or the valuation of that firm's securities. For instance, early studies in this stream of literature find that firm's management earnings forecasts, earnings announcements, bankruptcy announcements, and accounting restatements are associated with stock market reactions of other economically related parties, such as industry peers, supply chain partners or strategic partners (e.g., Boone and Ivanov, 2012; Pandit et al., 2011; Gleason et al., 2008; Lang and Stulz, 1992; Foster, 1981). The theory underlying the above-documented relation is that one firm's disclosure contains information about other related firms (Roychowdhury et al., 2019). Not only do managers learn from other related firms' disclosure and adjust their investment decisions (Durnev and Mangen, 2019), investors also keep track of these related firms' disclosed information and react accordingly (Baranchuk and Rebello, 2018; Thomas and Zhang, 2008).

Most recent studies, however, take a different approach. Instead of taking firm's disclosure events, such as management earnings forecasts or earnings announcements as exogenous, these studies show that managers have incentives to disclose information strategically to take advantage of the externalities of their firms' disclosure to gain benefits (Aobdia and Cheng, 2018; Kim et al., 2018). In the first two essays of this dissertation, I attempt to extend this stream of literature by investigating the intra-industry information externalities in the context of initial public offerings. More specifically, in the first essay, I examine whether rival firms identified (identified rivals) by an initial public offering (IPO) candidate take advantage of intra-industry information externalities of their disclosure to strategically preempt the competitive effects of the IPO during the IPO quiet period. In the second essay, I investigate if IPO firms capitalize on peer information environment by identifying peers with better information quality in their registration statements.

While prior studies on information externalities and corporate disclosure have examined a few interesting settings, such as labor negotiations or merger negotiations, where firms alter their disclosure if doing so negatively affects other peer firms and help the disclosing firms gain strategic benefits (Aobdia and Cheng, 2018; Kim, Verdi, and Yost, 2018; Ahern and S Ahern and Sosyura, 2014), very few studies have looked at the IPO setting, where information asymmetry between managers and potential investors is extremely high, and industry peer's disclosure provides additional information and context to lower information uncertainty and help understand the IPO firm and value its securities (Shroff et al., 2017). Initial public offering is not only an important event in a firm's life cycle, it also has competitive effects on industry peers. It is well documented in prior literature that industry peers are negatively affected by a new issuance, and a successful public offering could reshape the competitive environment of the whole industry (e.g., Hsu et al., 2010; Chemmanur and He, 2011). This strong contrast between a lack of knowledge about the information externalities of peer information in the IPO setting and extensive research on the competitive effects of IPOs on industry peers leads to an intriguing question: Do industry peers take advantage of the information externalities of their disclosure and disclose information strategically to preempt the competitive effects of IPOs? To shed light on this question, I examine the changes in identified rivals' disclosure behavior around the IPO quiet period.

Drawing upon literature on the economic determinants of strategic disclosures and their information externalities, I predict that identified rivals could benefit from a product-market standpoint if they can strategically disclose more positive information during the quiet period. Prior research has documented the importance of peer information for investor decision-making in the initial year of capital issuance when firm disclosure is relatively lacking and less reliable (Shroff et al., 2017). Peer disclosure provides a benchmark and context for investors to better interpret firm disclosure (Roychowdhury et al., 2019; Baranchuk and Rebello, 2018). The positive information released by identified rivals about themselves during the quiet period strategically reveals to the market the extent of industry competition and injects more uncertainties into the IPO process.

However, there are some counter-arguments that identified rivals might not adjust their disclosures during the quiet period. First, as identified rivals release more positive information concerning their product development and future investment plans, they run the risk of leaking proprietary information to other industry peers. It is not clear whether the strategic benefits associated with disclosing information in the quiet period outweigh its costs. Second, strategic disclosure behavior cannot last forever. As suggested in Kothari, Shu, and Wysocki (2009), firms that withhold bad news to a certain point will experience a much greater magnitude of negative stock price reaction than the positive stock price reaction they initially generate from their good news disclosures. Identified rivals may strategically release more positive information during the IPO quiet period, however, at some point in the future, the tone of the information will reverse back to normal since they have to disclose the less positive news that has been withheld during the quiet period. It is less obvious how identified rivals make this trade-off.

Using hand-collected data on identified rivals and their firm-initiated press releases, I find that the tone of disclosures made by identified rivals becomes more positive during the quiet period, and reverses after the quiet period ends. I also find that identified rivals initiate highly positive press release articles about their product market condition during the quiet period and that the tone reversal is mainly driven by identified rivals experiencing their competitor's IPO withdrawal. Together, these results suggest that this strategic disclosure behavior is mainly driven by identified rivals' concerns over product market competition. Further evidence indicates that this behavior hurts the IPO candidate and benefits the identified rivals.

Regarding the incentives of IPO firms in reducing information asymmetry and facilitating a more effective valuation, prior literature mainly focuses on IPO firms' attempt to lower information uncertainty through the disclosed content in their prospectus. For instance, IPO firms tend to discuss their competitive environment a bit more when there is greater uncertainty about the firm value (Crain et al., 2017). And IPO firms providing specific use-of-proceeds disclosure experience less underpricing, as higher-level specificity lowers the information uncertainty and assists investors in obtaining a more accurate price estimate (Leone et al., 2017). However, very few studies investigate whether IPO firms take advantage of the information externalities of peer information to bridge the gap of information asymmetry. Investors often use comparable firm multiples together with financial information analysis to value IPOs, and their choice of comparable peers is often based on peer firms identified in the registration statement as direct competitors of the IPO firm (Paleari et al., 2014; Roosenboom, 2012; Kim and Ritter, 1999). In the second essay of my dissertation, I examine the relationship between peer firm information environment and peer choice by IPO firms.

On the one hand, when firm-specific information is relatively scarce around the initial public offering, the information environment of peer firms could affect the overall amount of information investors gather in their attempt to value the IPO firms (Shroff et al., 2017). Therefore, IPO firms are very likely to identify industry peers with a better information environment in their registration statements to reduce the information asymmetry between managers and investors.

On the other hand, as investors derive more information from identified peers, they also compare the economic viability of the new issuer against that of its industry peers. To the extent that a lower information asymmetry reduces the risk of investment and enables investors to better gauge the present value of IPO firms' future cash flows, identifying peer firms with higher information quality and potentially better corporate governance and economic performance likely puts the IPO firms themselves in an unfavorable position.

Focusing on a large sample of IPOs that take place between 2001 and 2017, I test the hypothesis of whether IPO firms tend to identify peers with a better information environment. The empirical findings show that IPO firms tend to identify peers with a higher quality information environment. Specifically, a one standard deviation increase in the composite proxy for the quality of the peer information environment increases the likelihood of being identified as direct industry peers by 40%. Further cross-sectional tests show that IPO firms are more likely to select peers with a higher quality information environment when facing greater information uncertainty. Meanwhile, I find that the relation between peer information environment and peer selection is much weaker for IPO firms operating in the biotech industry, suggesting that peer information environment plays a less important role in IPO firms' peer choice when high proprietary costs limit the extent of relevant peer disclosure. In terms of the real implications of the peer information environment, I find that peer information is positively associated with upward offering price revision, post-offering analyst coverage, and reduces the number of amendment filings.

Information externalities not only exist under intra-industry context, they are also quite prevalent in supply chain relations. To some extent, as supply chain relations often involve important and explicit contractual arrangements, the bond between suppliers and customers and the potential implications of one party's disclosure on its supply chain partners' future earnings and cash flows are much stronger and significant. Therefore, in my third essay, I focus on information externalities of corporate disclosure in supply chain relations. Employee downsizing has fundamentally reshaped the global economy. Previous research has provided abundant evidence about the antecedents and implications of corporate layoff decisions. However, few studies examine this decision in a broader context, namely the implications of corporate layoff on other economically linked entities. I attempt to address this gap and provide fresh evidence on whether suppliers suffer from information externalities when their major customers make layoff announcements.

Using hand-collected data on firm layoff announcements and supply chain relations from the 2004-2017 period, I find that suppliers experience an overall negative information externality at the time of their major customers' layoff announcements. The extent of information externality is determined by the content of the layoff announcement, the strength of the economic bond between suppliers and layoff-announcing customers, and the intra-industry effects of layoff announcements. Further evidence shows that suppliers tend to reduce their sales dependence on layoff-announcing customers in the post-announcement years, and they also cut their investments accordingly.

The rest of the dissertation is organized as follows: the next three chapters present my three essays, and the fifth chapter concludes my dissertation.

Chapter 2: Competitive Threat and Strategic Disclosure During the IPO Quiet Period

2.1 Introduction

This study investigates the disclosure behavior of rival firms identified (identified rivals) in the Initial Public Offering (IPO) registration statement by an IPO candidate around the quiet period. I examine whether identified rivals strategically release more positive information to preempt the competitive effects of a major IPO within the industry during the IPO firm's quiet period, a time during which the IPO firm and its affiliated analysts are prohibited from offering opinions or forward-looking statements about the firms' prospects and future plans.[1] Becoming a public company brings various financial and non-financial benefits to a company, such as large capital funding, increased public awareness, more attractiveness to best talents, and enhanced contracting efficiency. Fueled by these advantages, an IPO firm can grab more market share from its rivals. An extensive prior literature analyzes the competitive effects of IPO events. This literature investigates how industry rivals are negatively affected by the new issuance, and how IPO candidates reshape the competitive environment of the whole industry (e.g., Hsu et al. 2010; Chemmanur and He 2011). There is, however, little evidence on whether and how industry rivals strategically respond to the IPO filing. I extend this literature by focusing on the "active measures" taken by identified rivals in the form of strategic disclosure activities to preempt the competitive effects of large IPOs.

Considered as a gag order imposed by the SEC on IPO candidate's communication activities, the quiet period rules take effect once the firm files its registration statement, and the

[1] The Section 5 of Securities Act of 1933 regulates the public offering process. An important function of Section 5 is to restrain the marketing or salesmanship of registered public offerings, often referred to as "gun-jumping" provisions. Firms violating this "gun-jumping" provision could face delay or derail of public offering, or even worse, legal lawsuit.

order remains effective up until 40 days after the IPO offering date.[2] During the quiet period, management and affiliated analysts are not allowed to speak freely about the IPO firm just in case the information contained in their speech will hype the stock price and prevent the market from establishing a fair value for the stock.[3] Protecting investors from the greater uncertainty arising from the information asymmetry related to an initial public offering though, this quiet period rules create an "information seesaw," an time period during which public incumbents are free to communicate to the market the kind of information that suits their interests, whereas the IPO firms have to remain silent even facing negative publicity.[4] The competitive effects from the largest IPOs are well documented, but one question is left unanswered: will identified rivals provide voluntary disclosures during the quiet period in a manner that weakens the competitive position of the IPO candidate?

I predict that identified rivals could benefit from a product-market standpoint if they can strategically disclose more positive information during the quiet period. Prior research finds that investors put more weight on peer disclosure in their decision making especially for firms in the initial year of capital issuance when firm disclosure is relatively lacking and less reliable (Shroff et al. 2017). Peer disclosure provides benchmark and richer context for investors to better interpret

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[2] The SEC has a very vague definition of when an IPO quiet period officially begins. However, as described in Cedergen (2014), PR Newswire noted in its January 2005 comment letter that a majority (66 out of 125 surveyed participants) of investor relations professionals thought the quiet period started when the firm filed its first registration statement.

[3] For example, Scott Dietzen, the CEO of Pure Storage told the reporter from *Harvard Business Review* that "When you file an S-1 with the SEC disclosing your IPO plans, you enter a 'quiet period', with strict limits on what you may say publicly. If you're in a competitive space, as we are, you run the risk that competitors will spread 'fear, uncertainty, and doubt' at a time when you can't easily respond…" (Dietzen 2016) (See https://hbr.org/2016/06/pure-storages-ceo-on-choosing-the-right-time-for-an-ipo).

[4] As illustrated in an article published in *Wall Street Journal* on August 11, 2004, the article, titled " 'Quiet period' makes it tough for Google to counter critics", described how Google remained reticent about criticism on its auction IPO system and the skeptical comments on its business operations, citing the quiet period. As commented by a law professional in the article, "Google has been very, very conservative in this area…..it's the only appropriate thing they could have done" (Bialik 2004) (See https://www.wsj.com/articles/SB109214907584487555).

firm disclosure (Roychowdhury et al. 2019; Baranchuk and Rebello 2018). Thus, by releasing good news about themselves during the quiet period, identified rivals strategically reveal to the market how fierce competition the IPO firm is facing. Their disclosure could inject more uncertainties into the IPO process, diminish the survival profile of the issuer, and dampen investors' interests and expectations, all of which lead to achieving the goal of preempting the competitive effects of the IPO firm.

My predictions notwithstanding, there are several reasons why identified rivals may not adjust their disclosures to affect the IPO candidate. First, voluntary disclosure comes with proprietary costs. It is not clear ex ante whether any strategic benefits outweigh the costs of disclosing information to influence the success of an IPO. For instance, as identified rivals release more positive information concerning their product development and future investment plans, they run the risk of leaking proprietary information to other industry peers. Second, identified rivals may strategically release more positive information during the IPO quiet period, however, at some point in the future, the tone of the information will reverse back to normal since they have to disclose the less positive news that has been withheld during the quiet period. As suggested in Kothari et al. (2009), firms that withhold bad news to a certain point will experience a much greater magnitude of negative stock price reaction than the positive stock price reaction they initially generate from their good news disclosures. Therefore, it is not obvious whether identified rivals are willing to make this trade-off. Related, if the managers of the IPO firm respond to the identified rivals' strategic disclosures by releasing their own information during the quiet period, then the assumption that the IPO candidates will be negatively affected by the externalities of the identified rivals' strategic disclosures since these candidates cannot communicate freely does not hold. Although most IPO firms strictly follow the quiet period regulation for fear of "jumping the guns" and getting punished, evidence from prior research (Cedergren 2014) as well as from anecdotal cases suggests that some firms are willing to violate the regulation to get information, especially forward-looking information, across to the wider public.[5] To the extent that such strategic disclosures are not without costs, and it is not guaranteed that identified rivals can successfully exploit the externalities of their strategic disclosures without any response from the IPO candidates, whether identified rivals will strategically adjust their disclosure behavior during the quiet period is an empirical question.

I test the hypothesis through examining identified rivals' firm-initiated press release. There are several advantages to using press release as a measure of voluntary disclosure. First, compared to other forms of corporate disclosure, press release covers a broad range of topics and provides a channel for firms to release information in a more timely and comprehensive manner. More importantly, press releases are typically less regulated than official SEC filings, therefore, firms have considerable latitude over the content, timing and language to describe their business based on their own strategic preferences (Ahern and Sosyura 2014; Cedergren 2014; Kim et al. 2018; Dyck and Zingales 2003). Furthermore, the flexibility and comprehensiveness afforded by this disclosure channel allows me to measure the variation of disclosure tone as a result of the firm's strategic goals (Burks et al. 2018).

My initial tests compare the disclosure behavior of identified rivals to a control sample of non-identified industry peers matched by entropy balancing technique. Consistent with my hypothesis, I find that the press release initiated by identified rivals is more positive in tone during

[5] For example, in August 2004 right before Google made its IPO deal, the company founders Larry Page and Sergey Brin accepted the Playboy magazine interview and made several inaccurate statements about the company's performance during the interview. Although the company's IPO deal has not been totally derailed, it raised the possibility of delaying the IPO process (See https://www.marketwatch.com/story/will-playboy-article-delay-google-ipo).

the IPO quiet period relative to the press release issued in the pre-quiet period, and then the tone reverses back to the pre-quiet period level in the post-quiet period. Figure 1 plots the changes in tone around the IPO quiet period.[6] In economic terms, the coefficients in my result indicate that the average disclosure tone of firm-daily press release becomes more positive by approximately 15% during the IPO quiet period.

[Insert Figure 1 About Here]

Next, I explore whether identified rivals make strategic response out of the concern for increased product market competition. Utilizing Factiva's subject classification scheme, I specifically select press releases tagged as "product", "contract" or "marketing" in the NS (news subject) section as these are most related to firm's product market incentive.[7] I find that identified rivals initiate highly positive press release articles about their product market condition during the IPO quiet period compared to the pre-quiet period. Furthermore, the tone reverses in the post-quiet period. This result is consistent with the hypothesis that the disclosures of identified rivals are strategic in nature, and it also reflects identified rivals' incentives in preempting IPO firm in the product market competition. Cross-sectional tests suggest that the tone reversal is mainly driven by identified rivals experiencing their competitor's IPO withdrawal, a result consistent with identified rivals feeling less "threatened" and then normalizing their tone after the IPO firm announces withdrawal. To further rule out the possibility that the results are driven by some economy-wide factors, I decompose each press release into content as related to "Industry Competition" or "Macro Economy." The additional analysis of the disclosure tone along these two

[6] In Figure 1, Period 2 denotes the quiet period, and Period1 and Period3 represent the pre- and post-quiet period, respectively. Figure 1(a) plots the changes in word-count tone measure (based on Loughran and McDonald Dictionary) around the IPO quiet period, and Figure 1(b) plots the changes in sentiment score (another tone measure based on SentiWordNet) across the three time periods.
[7] The detailed definition of each news subject used in Factiva is described in the Data and research design section.

news dimensions shows that identified rivals use more positive language in describing their competitiveness within the industry during the IPO quiet period. However, this relation is not pronounced for news content on “Macro Economy”, which reinforces the product market incentive hypothesis.

Having found that identified rivals strategically adjust their disclosures during the quiet period, I then examine whether the strategic changes in disclosures are more likely to cause disruptions to the IPO process. I find that overall, IPO firms are more likely to withdraw their public listing plans when the disclosures initiated by the identified rivals become more positive during the quiet period. This evidence shows that the strategic disclosures initiated by identified rivals have real implications. If identified rivals intend to exploit the communication constraint imposed on the IPO firm through the quiet period rules, then their positive information will make the IPO firm look less appealing.

Finally, I consider how identified rivals benefit from their strategic disclosure activities. Using pairwise product fluidity to proxy for product market threat from the IPO firm,[8] I find that as the tone of identified rivals’ press release gets more positive during the quiet period, the product market threat from the IPO firm becomes less intense, and this effect does not exist for non-identified control firms. This result, on the one hand, confirms my assumption that firms not identified as the direct rivals by the IPO firm are not necessarily affected by the IPO case, and that is the reason their disclosure behavior is less likely to reduce the competitive threat from the IPO

[8] The data for pairwise product market fluidity is obtained from Hoberg-Phillips data library. The detailed description of how to calculate this product market fluidity data can be found in the data section in Hoberg and Phillips (2014, 2016). Pairwise product fluidity is well suited for the purpose of this analysis because it measures the cosine similarity between the identified rival and the IPO firm in the product related description in their 10-K filings. Traditional measures for product competition, such as the industry concentration, does not afford such a nuanced view on the pairwise competition between two industry rivals.

firm; on the other hand, this result is consistent with the argument that identified rivals have incentives to adjust the tone of their disclosures to preempt the product market competition in the first place.

This study contributes to several streams of literature. First, it builds on the strategic disclosure literature. Studies in this area show that firms alter their disclosure if doing so negatively affect other peer firms and help the disclosing firms gain strategic benefits (Ahern and Sosyura 2014; Kim et al. 2018; Aobdia and Cheng 2018). This study extends this literature by introducing a strategic benefit for rival firms related to disclosing information during the IPO quiet period, namely, to preempt the IPO's competitive effects.

This paper is also related to a large literature on information externalities. Starting from Lang and Stulz (1992), studies in this area usually take disclosure events, such as bankruptcy announcement, earnings announcement (Pandit et al. 2011) or restatement (Durnev and Mangen 2009; Gleason et al. 2008) as exogenous and examine the impact of these disclosure events on the stock market performance and operating decisions of other peer firms. More recently, some studies take an opposite approach. They don't assume that firms' disclosure decisions are exogenous; rather, they show that some disclosure decisions are made with the intention to take advantage of the externalities of these disclosure activities to gain strategic benefits (Aobdia and Cheng 2018; Kim et al. 2018). This study adds to this stream of literature by investigating how rival firms strategically exploit the externalities of their positive disclosure during the quiet period to affect the IPO process and post-IPO competition.

This paper also contributes to the emerging literature on IPO quiet period. Although IPO quiet period regulation has existed for decades, very few research has specifically examined the effectiveness and implications of this regulation (Bradley et al. 2003; Bradley et al. 2004;

Cedergren 2014). SEC initially imposed this gag order to ensure that investors' valuation of the IPO firm is not affected by biased information from the firm. However, in the wake of a few high-profile cases, practitioners and even some regulators start to question the desirability of this regulation. Some critics argue that imposing quiet period rules can create even greater information asymmetry between the large and retail investors.[9] This paper, in contrast, focuses on the unintended consequences arising from this quiet period rules on industry rivals' strategic disclosure and on IPO success. By showing that identified rivals modify their disclosure during the IPO quiet period to forestall the competitive effects from the IPO firms, this paper reveals a previously undocumented effect of quiet period regulation and adds fresh evidence to the debate on the relevance and implications of this regulation. As such, given the importance of public offering in facilitating technological innovation, job creation, and financing growth (Zweig 2010; Piwowar 2017), this study is also relevant and informative to regulators and practitioners.

The remainder of this paper proceeds as follows. Section 2.2 motivates the setting and develops hypotheses. Section 2.3 describes the dataset and the research design. Section 2.4 reports empirical tests and the results. Section 2.5 discusses an alternative explanation and presents the additional analysis. Section 2.6 concludes.

[9] After Facebook's botched debut, several lawmakers began to rethink the "informational disadvantage" that the quiet period rules could bring to average investors. As quiet period rules prohibit remarks from the IPO firm about its own prospects, small investors are kept uninformed of relevant analysis. Mary Schapiro, the former chairman of the Securities and Exchange Commission, noted in her letter to congressman Darrell Issa that the agency would review the gag order imposed on firms ahead of initial public offerings (Eaglesham and Demos 2012) (See https://www.wsj.com/articles/SB10000872396390444230504577613322734045592).

2.2 Research setting and hypothesis development

2.2.1 Research setting

The goal of this study is to investigate how industry rivals strategically preempt the competitive effects of their peer's IPO through adjusting their disclosure practices. The primary challenge is to identify a setting where the IPO firms are most vulnerable to the information released by industry rivals, because in such a setting, industry rivals have the strongest incentives and opportunities to change their disclosure behavior to gain strategic benefits. Motivated by this challenge, I examine identified rivals' disclosure behavior around their IPO peer's quiet period. This setting offers several desirable features.

First, quiet period creates an "information seesaw" between the IPO firm and its rivals. IPO firms are restrained in expressing positive opinions during this time period (Cedergren 2014), whereas public incumbents are free to communicate whatever information that can put themselves in a better light. According to the SEC communication rules, IPO firms can continue to disclose "regularly released factual business and forward-looking information" during quiet period.[10] However, for a private company that does not conduct regular public communication activities before its initial S-1 filing, any incidental information release, especially forward-looking information after its S-1 filing, is likely to be under heightened SEC scrutiny. The fact that SEC does not precisely define what types of communications are barred or allowed implies that the quiet period rules themselves are subject to interpretation. On top of that, a few high-profile "gun-jumping" cases highlight the serious consequences of violating the rules.[11] As such, in reality,

[10] SEC release No. 33-8591 addresses communication rules related to public offerings. In this document, SEC has specified that an issuer's release of new types of financial information or projections during the quiet period will likely constitute a violation of the rules.

[11] For example, online grocer Webvan Group Inc. had to delay its IPO in 1998 after its chief executive granted an interview to a reporter before the IPO, and the company disclosed material information through conference call without

companies going public generally tend to err on the side of caution and refrain from making too much comment, even if they fall under predicament from negative media coverage.[12]

Second, according to the SEC regulation, when an IPO firm files S-1 with the agency, it must disclose information related to its competition in the "Competition" section. In this section, the IPO firm specifically identifies which industry rivals are currently competing with the firm. This feature allows me to extract the names of these identified rivals and substantiate the link between the IPO's effects and the identified rival's strategic disclosure behavior. The fact that I focus on identified rivals, as opposed to firms that are only hypothetically competing with the IPO firm based on rough industry classification scheme ensures that these rivals have the strongest incentives to take measures to preempt the competitive effects from the IPOs.

Third, the filing date of initial registration statements (or the start of the IPO quiet period) when the identified rivals first know that they have been identified as the directly competing rivals by the IPO firm is largely independent of these identified rivals' control, providing a near-exogenous shock for identified rivals. Therefore, any adjustment shown in the identified rivals' disclosure behavior from before to after the S-1 filing date is less likely to be driven by other non-IPO related factors.

However, despite all these appealing features of this setting, one challenge still remains: The IPO cases are not isolated in time. Firms in the same industry may choose to file a registration statement (S-1) and announce the attempt of listing their stocks concurrently, which implies that

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making the same information available to the public. Salesforce.com was forced to delay its IPO after its chief executive Marc Benioff discussed the company's business and competitors on The *New York Times*. The SEC decided that the chief executive had violated the quiet period rules.

[12] For instance, SEC imposed "cooling off period" on Groupon's IPO, because the regulators had concern over the firm's performance metrics presented in its prospectus, however, when asked to comment on SEC's decision, the company declined and cited a quiet period (Wasserman 2011) (See https://mashable.com/2011/07/27/groupon-sec-ip/).

the competitive effects of one IPO case are likely confounded by other concurrent industry IPOs. To deal with this challenge, I adopt a similar selection approach employed by Hsu et al. (2010) by identifying the largest IPO per industry and year.[13] I use IPO offering amount as the measure of the size of an IPO in order to minimize the confounding effects from other same industry IPOs. Since large IPOs usually attract a lot of media attention, being identified as directly competing with the IPO firm means that these rival firms are being put "in the limelight", and they are more likely to be compared with the IPO firm during the entire IPO process, so these firms should have the strongest incentives to take measures to strategically respond to the IPO effects during the quiet period.

2.2.2 Hypothesis development

I first investigate whether identified rivals strategically change the tone of their disclosure during the IPO quiet period. Disclosure tone can be manipulated for strategic purposes. Managers can issue significantly more positive or negative news to manipulate the bidder or the target's stock price and then the cost of the deal during merger negotiation periods (Ahern and Sosyura 2014; Kim et al. 2018). Managers can also hurt rivals' product market competition by releasing more positive news during those rivals' labor renegotiations (Aobdia and Cheng 2018). Sometimes, managers are even willing to issue more negative news to deter new entrants (Burks et al. 2018). As shown by prior research, public listing in the stock market brings competitive advantages to the IPO candidates and the opposite outcomes to the industry incumbents (Hsu et al. 2011). Therefore, firms that are identified as directly competing with the IPO candidate should have the strongest incentives to respond to such a threat. But what could be their opportunity?

[13] As documented in prior literature, there are some data issues with the date of the IPO and its industry classification in SDC database, I follow Hsu et al. (2010) in validating this key information using Compustat, Nasdaq, and EDGAR. Industry is classified by the first two digits of SIC code.

As discussed earlier, managers of the IPO firm and its affiliated analysts are constrained in issuing forward-looking statements or other positive opinions about the firm during the quiet period, but industry rivals are not bound by this regulation. If identified rivals intend to preempt the competitive effects of the largest IPOs (Hsu et al. 2011; Spiegel and Tookes 2019), one should expect to see a significant increase in the positivity of tone of the identified rivals' communications, such as their press releases, during the IPO quiet period.

Some might argue that identified rivals could also release significantly negative disclosures with the aim of influencing investors' perception of the whole industry prospects and discouraging their enthusiasm for the new issuance. For example, Ma and Yu (2019) analyze earnings management of industry rivals when their peers file for IPOs, and they predict and find that industry rivals manage earnings downwards when their peers are engaged in the public listing process. In addition to the fact that the research questions of these two studies are essentially different, several other unique features of the research setting and design choices can further help reconcile our different predictions.

First, Ma and Yu (2019) use all 4,995 IPOs that went public in the U.S from 1991-2014. This approach mixes small and large IPOs together and implicitly assumes that large public incumbents will be "threatened" by small IPOs as they will be by large IPOs. As argued by Hsu et al. (2010), when examining the competitive effects on industry rivals, pooling all IPOs together is likely to result in the effects of one IPO being contaminated by other IPOs in the same industry. As such, to avoid the effects on rivals being contaminated by other IPOs, this study examines the largest IPOs per industry and year, and these IPOs are much more likely to cause competitive effects to industry incumbents than small IPOs.

Furthermore, Ma and Yu (2019) use the number of IPOs, and the total volume of IPO proceeds to proxy for the aggregate competitive IPO effects at the industry level. As documented by Spiegel and Tookes (2019), while some large IPOs might pose a big competitive threat to other industry incumbents, most IPO cases are driven by industry-wide trends of product commoditization. Therefore, the proxies they use for the competitive IPO effects can also be considered as good measures for the extent of the industry-wide trends. Since it is highly likely that the industry-wide trends drive more IPO attempts within the industry as well as the rivals' declining earnings performance and then strategic disclosure behavior, to rule out this alternative interpretation and to focus on rival's strategic behavior in response to a specific IPO case, I examine the competitive effects of IPOs at the firm level instead of the industry level.

Finally, unlike Ma and Yu (2019), which define industry rivals based on firms' 3-digit SIC code, I adopt a more nuanced approach: I define rivals as firms that are identified by the IPO firm as direct competitors in the IPO registration statement. Though limiting the potential sample size, this approach ensures that there is a direct competition relationship between the IPO firm and the sample rival firms. As argued previously, being identified as direct competitors signifies a stark increase in competition. It is reasonable to assume that investors or other stakeholders will constantly compare the IPO firm against these identified rivals in their decision making. Because in direct competing relationships, positive information about the identified rival likely puts the firm itself in a better light and consequently, the IPO firm in an unfavorable position. Thus, based on the above discussion, my first hypothesis is:

H1: The disclosure tone of press release articles initiated by identified rivals becomes more positive during the IPO quiet period compared to control firms.

Next, I try to investigate identified rivals' product market incentives behind their disclosure activities. Public offering recapitalizes the issuing firm, lowers its leverage, and provides it with more financial flexibility. Using this equity capital on product marketing or research and development, IPO firms can expand their productive capacity, enhance their product heterogeneity and capture larger market shares in the future (Spiegel and Tookes, 2019). Therefore, a major IPO could intensify the product market competition between the identified rivals and the IPO firm, and facilitate the product commoditization within the whole industry. This incentivizes the identified rivals to differentiate their product from industry peers and show better growth prospect through their product market related news articles. I label this as "product market incentive".[14] To investigate such motivation, I analyze the content of these firms' press release articles. Content analysis reveals the disclosing firms' incentives (Burks et al. 2018). To capture the theme of a whole press release article instead of focusing on a few content words, and to objectively classify the news subject, I utilize Factiva's subject classification schemes and select firm-initiated press releases that are classified as product market related. The content classification is described in detail in Section 3. I hypothesize the incentives for identified rivals as follows:

H2: The disclosure tone of product market related information becomes more positive during the IPO quiet period to enable identified rivals to differentiate themselves from others and enhance their product market competition.

Research on intra-industry information diffusion finds evidence that rival firms' disclosure contains information about the economic conditions of other firms (Roychowdhury et al. 2019;

[14] It is possible that the competition can extend to the capital market sphere. Prior studies show that institutional ownership and corporate disclosure are closely related (Healy et al. 1999; Bushee and Noe 2000; Ajinkya et al. 2005; Boone and White 2015; Bird and Karolyi 2016). In this setting, seeing the potential impact of IPO firm on identified rivals' product market competition, institutional investors might reduce their shareholdings in these rival firms. Therefore, to maintain their attractiveness to institutional investors, identified rivals may "talk up" capital market related news content. However, since institutional investors make their decisions based on their analysis on firms' product market performance, it may very well be the case that identified rivals' "capital market incentive" is dominated by their "product market incentive". Therefore, I only focus on the latter incentive in this study.

Lang and Stulz 1992; Gleason et al. 2008). Not only do managers of the other firms learn from their rivals' disclosure and adjust their own investment decisions (Durnev and Mangen 2019), but investors also keep track of these rival firms' disclosed information and react accordingly (Baranchuk and Rebello 2018; Thomas and Zhang 2008). The issue of information asymmetry in the capital raising process has been well documented in early research (Myers and Majluf 1984; Rock 1986; Benveniste and Spindt 1989). To get information across to potential investors, IPO firms undertake a series of activities, such as filing registration statements, and conducting roadshows and book-buildings. However, the quiet period regulation severely restricts the public communication of IPO firms, especially the communication on forward-looking information, the kind of information that is highly valued by potential investors. Therefore, investors should have incentives to compare the IPO firm with other public incumbents, especially those that are directly competing with the IPO firm, in order to get perspectives about whether the IPO candidate is going to perform well in the future and whether they should invest in the public offering.

By initiating more positive disclosures, identified rivals convey the message to the market that they are doing great in the product market sphere. Identified rivals' strategic disclosures during the IPO quiet period suggest to the market that the IPO firm faces intense competition from its direct rivals. And this message should inevitably raise investors' doubts about the IPO firm's future profitability and success, resulting in a higher likelihood of disruptions to the IPO process. Besides, if identified rivals' incentive to change their disclosure is to enhance their product market competition, one should observe a negative relationship between the strategic changes in disclosure tone and the product market threat from the IPO firm subsequent to the IPO quiet period. Thus, I test the following hypothesis:

H3a: The positive changes in identified rivals' disclosure tone during the quiet period increase the likelihood of disruption to the IPO process.

H3b: The positive changes in identified rivals' disclosure tone during the quiet period reduce the competitive threat from the IPO firm in the post-quiet period.

2.3 Data and research design

2.3.1 The IPO data

I obtain an initial sample of IPOs from the Securities Data Company (SDC) New Issue Database. Some key data used in this study, such as the filing date, withdrawal date or offering amount is corrected and augmented with data from Nasdaq website, EDGAR, and credible news agency such as Reuters and Business Wire. The start year of my IPO sample is 2001 because press release articles published before the year 2000 are incomplete on Factiva. In order to include every press release issued by the identified rivals and control firms around the initial IPO registration date, I begin the sample in 2001. I end the sample period in 2017 to ensure that data for post-IPO quiet period is available for some recent IPO cases. I first follow the IPO sample selection criteria applied in Boone et al. (2016),[15] and collect a total of 1,612 IPO events. I further exclude IPOs in the financial and utility industries due to their special features in the regulated industries.[16]

It is worth noting that firms can make several IPO registration statements before they finally go public. Some firms may choose to abort their IPO plan before they file a registration

[15] I apply the following criteria in selecting IPO events: the offering of common stock is made by a US-based private company; the stock is listed on a major US exchange (New York, Nasdaq, America stock exchange); the offer price is above $5. I also exclude American Depository Receipts, reverse leveraged buyouts, closed-end funds, limited partnerships, unit investment trusts, tracking stocks, two-tranche offerings, simultaneous international offerings, and IPOs of non-common shares.

[16] These two industries are highly regulated with great barriers to market entry. Many firms mention in their prospectus that they do not face direct competition in their major service area, or their competitors are owned by the same large investors. For example, please find the discussion on industry competition in American Water Works Company's IPO prospectus https://www.sec.gov/Archives/edgar/data/1410636/000119312508088989/d424b4.htm.

statement again several years later, but their registration statement, especially their description of the firm's current industry competition, remains largely unchanged in most IPO cases. This feature implies that firms that are identified in the IPO firms' prospectus as direct rivals usually already know about this IPO event and its implications if this is not the IPO firm's very first public listing attempt. Therefore, in order to ensure that being identified by the IPO case is unexpected, I focus on the initial IPO attempt; namely, I specifically examine the identified rivals' strategic disclosure behavior around the time at which they first know about the fact that the firm has been identified as a public rival in the IPO firm's initial registration statement. This restriction, coupled with the criteria of non-missing date for initial registration and withdrawal announcement, further reduces the sample size to 1,135 IPO events.

As I have briefly described in the "Research setting" section, private firms in the same industry may choose to enter the IPO process simultaneously or in proximity to take advantage of a favorable market condition. To study the changes in rival firms' disclosure behavior around an IPO event means that I need to compare these firms' disclosure behavior from the treatment period to the control period. Although it is very rare that one firm is identified as a direct rival by two different IPO firms in their prospectus around the same time, the fact that other same-industry IPOs may occur in either treatment or control periods and can then affect the rival firm's behavior makes it crucial to identify IPOs with the lowest likelihood of other IPOs contaminating the results. Therefore, I follow Hsu et al. (2010)'s "largest IPO volume" approach,[17] and there are 285 IPO events that satisfy this identification approach. Table 1 Panel A outlines the sample selection procedure for IPO events in detail. Panels B and C provide the year and industry composition of

[17] As argued in that study, this selection approach enables one to make the most use of the data without arbitrarily setting a cut-off value for the purpose of defining what a large IPO volume is.

the IPO sample, respectively. Except for years immediately after the financial crisis, the IPO sample is pretty much evenly distributed across all sample years. Consistent with other IPO studies, technology, life science, and trade & services firms account for most IPOs.

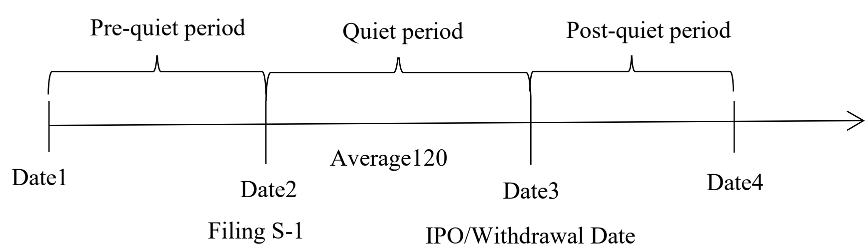
[Insert Table 1 About Here]

To examine identified rivals' disclosure behavior around the IPO quiet period, I first need to define the cut-off dates. Based on SEC guidelines, the quiet period begins when the initial registration statement is made effective and lasts for 40 days after the stock begins trading. However, that 40-day post-offering quiet period is hardly "quiet" anymore, because it is difficult for SEC to punish non-compliance once the firm gets public, but that is not the case with the pre-offering quiet period. Not only is SEC more vigilant to IPO firm's information release prior to the offering date, but the agency also has the power to enforce the communication rules and punish any non-compliance through delaying or even derailing the public offering. Indeed, prior research shows that there is a significant variation in the degree of IPO candidates' compliance with the quiet period rules after the offering date. Not a small number of firms release earnings announcements or even hold conference calls during this post-offering quiet period, and these firms are found to obtain more analyst coverage (Cedergen 2014). The lack of SEC enforcement on post-offering violation emboldens some IPO candidates to break the "quietness". Therefore, to provide a clean setting in which the IPO firms are strictly regulated in their information dissemination and thus creating opportunities for identified rivals to exploit this constraint, in this study, I focus on the pre-offering quiet period, which starts from the date when a company first files a registration statement (S-1) with the SEC and ends on the IPO offering or withdrawal date. In my sample, the median length of the IPO quiet period for all 1,135 IPO events is around 120 days. In order to facilitate the comparison of identified rival' disclosure behavior from before to during and post-quiet period,[18] I define the following periods.

(1) Pre-quiet period: the 120 days immediately preceding the day when the IPO firm files its initial security registration statement. This window spans t=-120 to t=-1 relative to the IPO firm's release of its initial S-1 filing.

(2) Quiet period: the period stretching from initial S-1 filing date to the IPO date or withdrawal date.

(3) Post-quiet period: the 120 days following the ending date of the quiet period, so the window spans t=+1 to t=+120 relative to the quiet period ending date.



Financial variables for the identified rivals are measured at the quarter end immediately preceding the start of each event period, and I collected all firm-initiated press releases issued during the period starting from Date1 to Date4.

[18] Because press release articles (around 56,000) are hand-collected from Factiva, the way I define the cut-off dates and then the length of each event period determined afterwards directly impact which press release articles should be collected, implying that changing the length of the event period will involve tremendous work in hand-collection, so it is almost infeasible to change the current event period for robustness test. I acknowledge that the length of the event period will, to some extent, affect the result, but I believe the effect does not constitute a big concern in this study. Because in this study, I focus on the changes in average disclosure tone of identified rivals' press release articles, instead of the total number of press release articles issued during each event period. The latter may be highly correlated with the number of days in each event period, but the former is highly unlikely to have the same issue.

2.3.2 Identified rivals, control firms, and firm-initiated press release articles

To collect information on these identified rivals, I read each of the 285 IPO prospectuses and collect the name of every identified rival from the "Competition" section.[19] After this procedure, I identify a total of 1,484 firms from these 285 prospectuses. 397 out of the 1,484 firms can be matched with a COMPUSTAT industrial record and are with no missing value for all control variables and textual variables. Table 2 Panel A describes the sample construction of the identified rivals.

To mitigate the concern that the changes in identified rivals' disclosure behavior are due to noise in the estimation, I generate a sample of control firms and implement an entropy balancing technique to match the identified rivals and control observations.[20] Table 2 Panel B presents the sample construction of control firms. I identify control firms as those operating in the same industry as the IPO firm but are not identified as the direct rivals by the IPO firm. Industry classification is based on the first 2-digit SIC code. Then, I restrict my control firm sample to those firms with non-missing value for control variables and textual variables for at least two consecutive event periods in order to analyze the changes in disclosure behavior. The final sample of control firms consists of 670 control firm instances in total. These 670 control firm instances correspond to 107 IPO events, and 267 identified rival instances. The identified rivals and control firms are matched on Size, ROA, and Tobin's Q.[21] For each identified rival and control firm, I obtain

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[19] In some cases, the IPO firm does not mention a specific name of its rival in the "Competition" section; rather, it offers some analyses on its industry competition when discussing other risk factors. In this scenario, I will search for the whole prospectus for information on the identity of its direct rivals.

[20] This matching procedure preserves the full identified rival sample and meanwhile, addresses some of the concerns that the changes in identified rivals' disclosure behavior around the IPO event are due to unobservable industry-wide factors (Hainmueller 2012; McMullin and Schonberger 2017; Bonsall and Miller 2017; Basu et al. 2018).

[21] It is worth mentioning that I am unable to identify prior literature that examines the likelihood that a specific firm will be identified as the direct rival by the IPO firm, but my interview with a portfolio manager who has tremendous institutional knowledge on this IPO setting suggests that IPO firms have incentives to show their relatively low valuation and high growth potential compared to other large publicly-traded incumbents. Therefore, the size,

financial data from COMPUSTAT, stock return data from CRSP, analyst forecast data from I/B/E/S.

In the main analysis of this study, I follow Ahern and Sosyura (2014) and Kim et al. (2018) and collect articles issued from the beginning of the pre-IPO quiet period through to the end of post-IPO quiet period from the top four press release distribution services: PR Newswire, Business Wire, Market Newswire and GlobeNewswire. Dow Jones News Services is used as a supplemental news source.[22] I utilize Factiva's Intelligent Indexing code to identify and machine-read the content of firm-initiated press release articles.[23] In order to make sure that a firm delivers substantive information through press articles to the public, I require that the press release selected for textual analysis to contain at least 50 words (WC field>50) and can be successfully parsed by Python. The details of the firm-initiated press release articles are reported in Table 2 Panel C.

[Insert Table 2 About Here]

2.3.3 Measures of disclosure tone and content

To investigate identified rival's strategic disclosure behavior, I construct two primary measures of disclosure tone. Following prior literature (e.g., Jiang et al. 2019; Bushee et al. 2018), I first use the standard dictionary method—Loughran and McDonald (2011) financial world

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profitability, and growth potential are likely to be the determinants of the likelihood of being identified as the rival in the IPO prospectus. In untabulated results, the entropy balancing procedure achieves covariate balance across the mean and variance of all these covariates.

[22] Previous research (Guest 2017) shows that articles published by the Dow Jones News Service usually include additional analyses relative to the press release initiated by the firm itself, a feature that could potentially leads to inaccurate empirical results if one mixes firm-initiated press release and other news coverage together. Therefore, I include articles from this channel only when no press release can be identified from the above-mentioned four major news wires for a specific firm, and the firm chooses to distribute its press release through Dow Jones News Services.

[23] To select firm-initiated press releases, I require that the company's name appears in the data field CT (contact) section of the press release. It is worth noting that although a majority of press releases issued by PR Newswire, Business Wire and Market Newswire have a separate CT (contact) section, press release articles released by GlobeNewswire usually do not contain this separate CT section, but a careful inspection suggests that most of the press releases distributed by GlobeNewswire are initiated by the firm itself instead of written by another research firm or news agency.

dictionaries to identify tone words. *Tone_netpositive(article)* is defined as the difference between the number of positive words and the number of negative words scaled by the total content word count of each press release article.[24] Depending on different regression specifications, I aggregate article level tone word count at daily level, such as variable *Tone_netpositive*, or at news subject-period level, such as *Market_netpositive*. Further details on the construction of key disclosure tone variables are provided in Appendix A.

My second measure of disclosure tone relies on an enhanced lexical resource—SentiWordNet to gauge the numerical scores of each term on its positive and negative sentiment information.[25] Each term in the press release is associated with two numerical scores ranging from 0 to 1, indicating its positive and negative connotation. *Sentiment_positivity/negativity(article)* is defined as the average of positivity/negativity scores of each term across the whole article, and the *Sentiment_netscore(article)* is constructed by taking the sum of positivity and negativity scores.[26] In line with different regression specifications, the sentiment tone variables are defined at daily level, such as variable *Sentiment_netscore* or at news subject-period level, such as *Market_netscore*. In Appendix B, I provide an example of identified rival's press releases and their tone value.

In addition to identifying the changes in disclosure tone of press release articles, to examine the product market incentives of identified rivals' strategic disclosure, I also analyze the content of their disclosure. Based on Factiva's subject classification scheme, I define the product market

[24] If there are negation words (e.g., not, no, none, despite, neither) within three words before a positive word, I also count the positive word as negative.
[25] This approach is widely used in opinion mining applications. It has a large corpus of POS-tagged (part-of-speech tagged) English words along with their sentiment. The advantage of this approach is that it marks up the positivity or negativity of a term based on its definition and its context, for example, its relationship with adjacent words in a phrase or sentence. Therefore, this approach nicely complements the bag of words approach that depends on manually built dictionaries.
[26] Sentiment_negativity is defined as the raw average sentiment score on negativity connotation multiplied by -1.

category as consisting of news on Marketing (C31), Products (C22) and, Contract (C33).[27] Table 3 Panel B reports the description for these subject codes on Factiva.

[Insert Table 3 About Here]

2.3.4 Summary statistics

Table 4, Panel A presents the descriptive statistics for the disclosure variables for all sample firms. Tone_netpostitive(article) and Sentiment_netscore(article) are defined at the article level, and these article level tone measures are then aggregated at the firm-day level, because firms, especially larger firms usually release more than one news article during a day. The mean values for *Tone_netpositive(article)* and *Sentiment_netscore(article)* (0.85 and 0.015, respectively) and their firm-day level counterparts (1.060 and 0.019 respectively) are positive, suggesting that firms are more likely to release overall positive information to the public. Table 4, Panel B reports the disclosure tone for identified rivals and matched firms along three event periods. The identified rival sample of 267 firms are matched with the group of 670 control firms through entropy balancing. The mean values of *Tone_netpositive(article)* and *Sentiment_netscore(article)* are displayed for each group during the three event periods. From the pre-quiet period to the quiet period, the identified rival group experiences an increase in *Tone_netpositive(article)* to 0.512, in contrast, the matched firm group's *Tone_netpositive(article)* only increases very modestly by 0.008. Further, the disclosure tone in the post-quiet period seems to revert to the pre-quiet period levels for the identified rivals, with the mean value for *Tone_netpositive(article)* decreasing to 0.467 and the *Sentiment_netscore(article)* to 0.013, which is even lower than the average tone for the pre-quiet period. However, this reversal is less obvious for matched control firms. The initial

[27] As discussed earlier, Factiva has set a fixed structure of Intelligent Indexing Field to organize its published news articles, one of the data fields is NS (news subject), which is used to keep track of the subjects of each press release.

increase and then reversal of the disclosure tone provide partial evidence for the first hypothesis that identified rivals have strategic incentives to initiate more positive information during the IPO quiet period compared to the matched control firms.

Table 4, Panel C shows the period average of daily level disclosure tone of news dimensions classified as "Industry Competition" and "Macro Economy" across both identified rivals and matched control firms. Overall, firms use much more positive language when they talk about their competitiveness within the industry than about macroeconomy. Besides, the increase in tone for "Industry Competition" related content is more pronounced than for "Macro Economy" related information. Panel D presents the period level disclosure characteristics for identified rivals based on product market related news subjects. The product market related content category includes news subject on marketing, product and contract, all directly related to the product market competition faced by identified rivals. Panel E displays the mean value of subject-tone proxies for each of the three event periods. The product market related news articles become much more positive in the quiet period compared to the pre-quiet period. For instance, the mean value of disclosure tone for news on Product (about product or service enhancements) increases from 8.916 to 15.750. Further, consistent with the tone reversal documented in Panel B, in the post-quiet period, the tone of product market related news drops back to the pre-quiet period level, suggesting that the increase in disclosure tone in the quiet period is strategic in nature, and is not driven by unobserved broad economic factors.

Table 4, Panel F presents descriptive statistics for relevant firm variables. The average *Logat_IPO* (natural logarithm of total assets) equals 18.880, if translated into dollar value, is similar to the figure in Hsu et al. (2010). However, the average value for *Logat* for identified rivals is greater than the corresponding figure for incumbent firms in Hsu et al. (2010), which, if taken natural logarithm, equals 18.365. A likely explanation for the difference is that my sample of rival firms includes only firms identified by the IPO firm as a direct rival, whereas Hsu et al. (2010) include all firms sharing the same first two-digit SIC code. It is highly likely that the IPO firm tends to compare itself against already established and highly valued companies in its registration statements to emphasize its own growth potential. Before entropy balancing, identified rivals and control firms are largely comparable in leverage, profitability, and growth potential, but identified rivals have higher analyst coverage and stock price than control firms, which may be due to the slightly larger size of identified rivals. *Product_fluidity*, the pairwise product market similarity between the IPO firm and the identified rivals, measures the product market threats from the IPO firm right after the quiet period ends. The mean value of Product_fluidity is 0.075, which is higher than the average pairwise fluidity score of 0.060 for all sample firms in Hoberg and Phillips's database, consistent with the fact that the IPO firm and the identified rivals are directly competing with each other in the product market sphere.

[Insert Table 4 About Here]

2.4 Empirical results

2.4.1 Disclosure of identified rivals around the IPO quiet period

I test whether the identified rivals release more positive news during the IPO quiet period, a time during which their competitor—the IPO firm faces strict regulation in its public communication (H1). The treatment sample—identified rivals is first matched with a control group consisting of the IPO firm's other industry peers that are not identified as the direct rivals. I then estimate the following difference-in-differences regression:

$$Disclosure\ Tone_{i,t}=\beta_0+\beta_1 During_{i,t}\times Identified_i+\beta_2 During+Controls_{i,t}+\varepsilon_i \qquad (1)$$

Where Disclosure tone is the firm-day level tone measure (*Tone_netpositive*, *Sentiment_netscore*) defined in Section 3.3. The choice of control variables follows prior literature (e.g., Bushee et al. 2010; Shroff et al. 2013; Aobdia and Cheng 2018). I control for the market-to-book value of assets (*Tobin's Q*), the number of analysts following the firm (*Analyst*), return of assets (*ROA*), the natural logarithm of company assets (*Logat*), the logarithm of market capitalization (*Logmktcap*), the total debt to assets ratio (*Leverage*), and the logarithm of stock price (*Logprice*). All these variables are measured at the prior quarter end immediately preceding the focal event period. In order to mitigate the effect of extreme observations, I winsorize all continuous control variables at the 1st and 99th percentiles.

During is an indicator variable that takes the value of one if the observation occurs during the IPO quiet period and zero if it occurs in the pre-quiet period. Identified is an indicator variable which is equal to one if firm i is an identified rival and zero otherwise. The variable of interest is During×Identified, the coefficient on this interaction term captures the incremental changes in the identified rivals' disclosure tone from pre-quiet period to quiet period relative to that of the matched control firms.

Table 5 Panel A presents the results of Model (1). The interaction term During×Identified is positive for both *Tone_netpositive* and *Sentiment_netscore* specification. The positive coefficient indicates that as a firm files its initial registration statement and enters IPO quiet period, its identified rivals are increasingly likely to disclose positive news during the IPO quiet period relative to the pre-quiet period. The mean of *Tone_netpositive* is 1.060. Thus, the estimated coefficient of 0.155 in the first regression suggests that identified rivals, on average, increase the tone of their press release by approximately 15% in the IPO quiet period. Similarly, in the fourth column, the coefficient on the interaction term equals 0.003. Compared with an average

Sentiment_netscore of 0.019, the net sentiment score of press release increases by approximately 16% in the IPO quiet period.

To determine whether the net tone increase is influenced by the noticeability and importance of identified rivals, I partition the sample identified rivals between those that are highly noticeable and those that are less noticeable, with the level of noticeability measured by the total number of direct rivals identified by the IPO firms.[28] A direct rival firm that is identified alone or along with very few other firms easily stands out and attracts investors' attention. These highly noticeable firms are more likely to be put on the opposite side of the IPO firm. Therefore, identified rivals that are highly noticeable may have stronger incentives to increase their disclosure tone than firms that are identified along with many other direct rivals. Column (2), (3) and column (5), (6) present the results of this analysis. The interaction term loads positively in both column (2) and (5), but not in column(3) and (6), suggesting that the identified rivals that are highly noticeable have stronger incentives to disclose positive information during the IPO quiet period because their disclosures are more likely to be taken into account by the market to gauge the competitive advantage of the firm relative to its IPO competitor. Thus, overall, the results in Table 5 Panel A suggest that identified rivals initiate more optimistic press releases at times when the IPO competitor enters quiet period, supporting the first hypothesis.

To provide further evidence about how the disclosure tone changes after the quiet period ends, I add to the model indicator variable *Post*, which equals one if the observation occurs in the post-quiet period, and the interaction term between Post and Identified, *Post*×*Identified*. I expect that *During*×*Identified* loads positively as what is reported in Panel A. If identified rivals intend

[28] Firms that are identified by an IPO firm whose total number of identified rivals are below the median are classified as "highly noticeable" rivals; otherwise, they belong to the "less noticeable" group.

to take advantage of the gag order and strategically release more positive news only during the IPO quiet period, then I expect that *Post*×*Identified* does not load as identified rivals likely revert to the normal disclosure policies once the IPO quiet period ends and the IPO firms are less constrained in their communication.

Table 5 Panel B presents the results of this analysis. Consistent with my expectation, I find a positive coefficient on *During*×*Identified* in the *Tone_netpositive* and *Sentiment_netscore* specification. Further, except for column (5), *Post*×*Identified* does not load in any other specification, suggesting that identified rivals disclose more positive information only during the IPO quiet period, and the disclosure tone reverts to the pre-quiet period level after the quiet period ends. These findings help address the alternative interpretation and suggest that the changes in identified rivals' disclosure behavior are not due to the industry-wide trends but result from the identified rivals' strategic incentives.

[Insert Table 5 About Here]

2.4.2 Analysis of the incentives for identified rivals' disclosure

A successful public offering gives the IPO firm easier access to public financing. With extra funding, the IPO firm can enhance its product differentiation, customer loyalty, and expand its business into new territories. To explore the product market incentives for the identified rivals' disclosures, I examine how identified rivals adjust the tone of their disclosed information based on the content categories of the information. Specifically, I estimate the following regression:

$$Subject\_Tone_{i,t}=\beta_0+\beta_1 During_{i,t}/Post_{i,t}+Controls_{i,t}+\varepsilon_i \qquad (2)$$

Controls are composed of the same variables as in Model (1), *During* and *Post* are defined in the same way as in previous regression. The dependent variable─Subject_net tone measures the identified rivals' period level disclosure tone for press release articles of specific news subjects. I run Model (2) separately on the subsample of news articles related to each subject, and the unit of observation is firm-period.

Table 6 presents the results of the identified rivals' product market incentives. Panel A focuses on the news subject of marketing. Consistent with my expectation, I find a positive coefficient on *During* in column (1) and (5), suggesting that during the IPO quiet period identified rivals disclose more positive information when they promote existing product or services. I also find evidence that, on average, the strategic tone increase does not extend to the post-IPO quiet period. Relative to the press release articles initiated during the IPO quiet period, news released in the post-quiet period is significantly less positive, evidenced by the negative coefficient on *Post* in the column (2) and (6), indicating that the adjustment of disclosure behavior is strategic and occurs only during the IPO quiet period. The mean of *Market_netpositive (netscore)* is 5.097 (0.082) for news released in pre-quiet period. Thus, the estimated coefficients suggest that the identified rivals on average increase the tone of their product marketing related press release by approximately 82% (70%) during the IPO quiet period. Similarly, the coefficient on *Post* equals -4.704 (-0.071) in the second (sixth) column. Compared with the average *Market_netpositive (netscore)* value of 9.06 (0.134) for the IPO quiet period, the disclosure tone for news on product or service promotion drops by approximately 51% (53%) after the quiet period ends.

If the changes in identified rivals' disclosure behavior are caused by their strategic incentives to deal with the competitive effects from a successful IPO event, then whether the IPO candidate successfully lists the stock or withdraws the IPO case should influence whether identified rivals continue to "paint a rosy picture" of themselves in the post-quiet period. Although on average, Identified rivals choose to "tone down" in the post-quiet period, those that still face intense competition from a large successful IPO firm may have strong incentives to maintain their strategic tone level, while those that have "threat" lifted from the IPO withdrawal might loosen up and reverse the disclosure policy back to normal.

To test this prediction, I partition the sample of identified rivals between those experiencing the IPO firm's successful public offering and those witnessing the IPO withdrawal. The results from this cross-sectional analysis are presented in column (3), (4) and column (7), (8). As expected, the reverse in disclosure tone occurs primarily for identified rivals whose competitor withdraws its IPO. Whereas, the insignificant coefficient of *Post* in the "completed IPO" subsample in column (4) and (8) indicates that identified rivals are more likely to maintain their strategic tone level in the post-quiet period as their competitor successfully completes the IPO. This finding is also corroborated by evidence from Hsu et al. (2010), which shows that public rivals experience negative stock price reactions to the completed IPOs and positive stock price reactions to the IPO withdrawals. Different from Hsu et al. (2010), my results on the post-quiet period tone changes take one step further and suggest that identified rivals not only passively respond to the IPO event, they also take strategic actions to deal with the competitive effects from the IPO candidate's successful public offering.

Panel B and Panel C present the results on the other two major news subjects related to identified rivals' product market incentives.[29] Panel B focuses on the subsample of press release articles on new product development and service enhancements, and Panel C on news about the firms' contractual relations. Consistent with the key findings from Panel A, results from these two

[29] I've also run some additional analyses on identified rivals "capital market incentive". Press release with news subjects on corporate funding (C17), ownership changes (C18), and financial performance (C15) is classified as capital market related. Overall, I get weak evidence from examining the word-count tone measure. The untabulated analysis suggests that the capital market incentive, on average, is less likely a primary driven force for identified rivals' strategic disclosure behavior.

panels show that identified rivals respond to the IPO events by initiating more positive news on subject of product and contract during the IPO quiet period, and such strategic tone level reverts back to normal in the post-quiet period. Moreover, the post-quiet period tone reversion is mainly driven by observations of identified rivals who witness a withdrawal of the IPO filing. Collectively, results in Table 6 lend support to H2 by suggesting that identified rivals strategically change their disclosure behavior because they have incentives to maintain their position in the product market competition.

[Insert Table 6 About Here]

2.4.3 Consequences of identified rivals' disclosure

In this subsection, I conduct a number of analyses to determine whether the IPO candidates are hurt by the identified rivals' disclosure behavior and whether the identified rivals themselves get benefits from their strategic actions.

2.4.3.1 Disruptions to the IPO process

To test if identified rivals' strategic disclosure behaviors increase the likelihood of disruptions to the IPO process, I focus on the probability of IPO withdrawal, and I estimate the following empirical model:

$$Withdraw=\beta_0+\beta_1 Tone\_Chg(Total\ News/Specific\ Subject)_{m,t}+Controls_{m,t}+\varepsilon_m \qquad (3)$$

The dependent variable, *Withdraw* is an indicator variable that equals one when the IPO is withdrawn or zero otherwise. The main variable of interest is the strategic tone change for all press releases or press release related to specific news subjects. *Tone_Chg(Total News)* is defined as the average changes in the tone of press releases across the IPO firm's identified rivals from the pre-quiet period to quiet period. *Tone_Chg (Specific Subject)* is the average changes in identified rivals' disclosure tone of the press release on either Marketing, Product, or Contract from the pre-quiet period to quiet period. Controls is a vector composed of *Logat_IPO*, the logarithm of IPO firm's total assets, *Leverage_IPO*, the ratio of IPO firm's total debt divided by total assets, *ROA_IPO*, the operating income divided by total assets, *LogCapex*, the logarithm of the firm's capital expenditure, *CashHoldings*, the IPO firm's cash and cash equivalent divided by total assets, *Reputation*, an indicator variable that equals to one if the ranking of an IPO firm's underwriter exceeds 8 according to Jay Ritter's IPO database. Detailed variable definitions are provided in Appendix A.

Table 7 presents the results on IPO withdrawal probability. The proxy for tone change in the first four columns is based on sentiment score, and in the rest of the columns the word count measure. Except for the coefficient of column (5) and (6), the proxy for tone or sentiment change is positive in all the other specifications and loads significantly positive. These results suggest that after controlling for the characteristics of the IPO firm, the strategic disclosure practices of the identified rivals during the IPO quiet period do affect how equity market evaluates the competitiveness of the IPO firm. For potential investors, the fact that the IPO candidate is surrounded by strong direct rivals means that the firm itself has to deliver much better performance to outcompete these public incumbents. The gap between the investors' expectations and the real value of the IPO firm may result in higher IPO withdrawal probability. For brevity, take as an example of the effect of the strategic changes in disclosure sentiment, the estimated coefficient of *Tone_Chg(Total News)* in column (1) suggests that for one standard deviation increase in the net sentiment of identified rivals' disclosure from the pre-quiet period to quiet period, the probability of IPO withdrawal increases by approximately 30.4%. Collectively, the results from Table 7 indicate that the strategic changes in identified rivals' disclosure practices do have negative implications on the IPO process.

[Insert Table 7 About Here]

2.4.3.2 Product market benefits

Results in previous sections show that identified rivals release more optimistic press release during the quiet period, and such strategic disclosure behavior harms the IPO firm. However, if the final goal of identified rivals is not only to influence the IPO process but also to deal with the competitive threats from the IPO firm, it is necessary to examine if identified rivals' strategic disclosure practice indeed helps to achieve this goal. I measure product market threat from the IPO firm by using pairwise product fluidity data from Hoberg-Phillips data library. The measure for product market threat─Product Fluidity is especially suited for this analysis because it measures the cosine similarity between the identified rival and the IPO firm in their 10-K product related description. Traditional measures for product competition, such as industry concentration does not afford such a nuanced view on the pairwise competition between two industry rivals. The control variables are composed of the same variables as in Model (1) and (3). Next, I estimate the following regression as:

$$Product\ Fluidity_{i,t}=\beta_0+\beta_1 Tone\_Chg_{i,t}+Controls_{m,t}\text{-}IPO+Controls_{i,t}\text{-}Rival+\varepsilon_i \quad (4)$$

For comparison, I estimated the model on the sample of identified rivals and matched control firms. If identified rivals' strategic disclosure behavior arises from their incentives to reduce the competitive threat from the IPO firm instead of being caused by some economy-wide trends, then I should observe a significantly negative relation between the *Tone_Chg* and *Product Fluidity* for the subsample of identified rivals and not the matched control firms. As predicted in

H3b, in Table 8, I find a significantly negative coefficient of *Tone_Chg* in both column(2) and (5), which suggests that identified rivals benefit from their strategic changes in disclosure during the IPO quiet period in the form of less product market threat posed by the IPO firm. Moreover, this coefficient is insignificant for the subsample of control firms, as is shown in column (3) and (6). Control firms are not directly competing with the IPO firm, so a potential successful IPO does not pose a serious threat to them as compared to the identified rivals. Therefore, it is not surprising to observe a muted effect of the changes in disclosure tone on the pairwise product market competition between the control and the IPO firm. However, since the data on pairwise product fluidity is available for only a small number of identified rivals, the results need to be interpreted with caution.

[Insert Table 8 About Here]

2.5 An alternative explanation and additional analysis

I also consider an alternative explanation for my results. For example, identified rivals could change their disclosure behavior out of the concern over economic trends that also affect the IPO firm's public listing decision. As reported by Spiegel and Tookes (2019), in most IPO events, the decline in industry rivals' post-IPO performance results from macroeconomic factors, only in around 8% of cases, the decline is due to the IPO firm being a more competitive force by going public. Therefore, the economic trends might explain identified rivals' strategic disclosure behavior during the IPO quiet period.

I note that there are four elements in my setting that help address this explanation. First, my research design focuses on the largest IPOs. Those 8% "competitive" IPO cases that are documented in Spiegel and Tookes (2019) to have caused performance reductions of industry rivals are more likely to be the largest IPOs as opposed to be small IPO cases. These IPOs enhance the competitive position of the IPO firm and pose a big threat to industry rivals, especially direct rivals.

Second, different from prior studies that define industry rivals by SIC codes, this study examines rivals that are specifically identified by the IPO firm in its initial registration statement. And I focus on the changes of disclosure tone in identified rivals' press releases from the pre-quiet period to quiet period, with the date of the initial registration as the cut-off date separating these two periods. These rival firms may feel the economy-wide trends of increased product commoditization, and therefore have strategic incentives to adjust their disclosure accordingly to distinguish themselves from others, but it is nearly impossible for them to know beforehand the exact date for the release of the IPO firm's initial registration statement, or in other words, they would have no prior knowledge in terms of the date on which they will be identified as the direct rivals by the IPO firm. As a result, the possibility that the IPO firm gets to be a stronger competitor poses a "competition shock" to the identified rivals. And in such a setting, the adjustments of identified rivals' disclosure behavior can be reasonably linked to the "shock" from the IPOs.

Third, disclosing information is not without cost, especially when the firm is facing more intense competition (Harris 1998; Botosan and Stanford 2005; Verrecchia and Weber 2006). My findings that identified rivals provide more positive information during the IPO quiet period and then reverse their disclosure tone in the post-quiet period are only consistent with their strategic incentives to preempt the heightened product market competition. Finally, in the scenarios where the increased product commoditization reduces the benefits of staying private and causes firms to go public, and meanwhile results in the industry rivals' declining performance and their strategic release of positive information, my argument for this study, that identified rivals adjust their disclosure behavior out of the consideration to preempt the product market competition, remains legitimate. Because if IPOs facilitate product commoditization, which in turn reduces customer loyalty, identified rivals should be more incentivized to take advantage of the quiet period regulation and initiate highly positive product market related news to differentiate themselves from the IPO firm and other industry peers. Thus, the findings of Spiegel and Tookes (2019) do not negate but instead provide extra theoretical support to my findings.

Nevertheless, to provide more robust evidence that identified rivals release more optimistic information to preempt industry competition as opposed to responding to some economy-wide shift, I decompose each press release into content as related to "Industry Competition" or "Macro Economy", and then I apply the following regression to analyze the changes of disclosure tone along these two different news dimensions. If identified rivals strategically adjust their disclosure behavior not as a response to economy-wide factors but just from an industry competition standpoint, I expect to observe the changes in disclosure tone to be more pronounced in "Industry Competition" than "Macro Economy" related news dimension. The model specification is the same as Model (1), except that the disclosure tone is measured on news content that is specifically classified as "Industry Competition" or "Macro Economy" related, instead of on the entire press release.[30]

$$\text{Tone\_News Dimension}_{i,t}=\beta_0+\beta_1\text{During}_{i,t}\times\text{Identified}_i+\beta_2\text{During}+\text{Controls}_{i,t}+\varepsilon_i \quad [5]$$

[Insert Table 9 About Here]

[30] Relying on the Business Category Dictionary developed by Kothari et al. (2009) and the Risk Category Dictionary developed by Campell et al. (2014), I form two key words lists— "Industry Competition" and "Macro Economy". Sentences containing key words defined in the two words lists are grouped together and defined as either "Industry Competition" or "Macro Economy" related, and then each group is parsed and analyzed for its specific tone level. However, to capture a complete context for the discussion along a specific news dimension, I also extract three sentences and five sentences before and after the sentence that contains the key words. I then group these sentences together and calculate the tone level. In untabulated analyses, I find that the results still hold. Appendix C presents the details.

Table 9 presents the results of this analysis. The increase in disclosure tone is more pronounced for news content on "Industry Competition", as evidenced by the significantly positive coefficients on *During*×*Identified* in four regressions. Whereas, identified rivals do not significantly adjust the disclosure tone when they describe news content on the macroeconomy. These results further mitigate the concern that some economy-wide factors are driving the findings, and they also complement the evidence from previous incentive analyses which focused on the "Product market related" press release articles.

2.6 Conclusion

Intensifying product market competition and encroaching on incumbents' market share, a large IPO is often considered as a frontal assault on the established public incumbents, yet prior research has made little investigation into whether and how public incumbents identify opportunities to preempt the IPO competitive effects. In this study, I fill this gap in the literature by examining the strategic disclosure of identified rivals in the quiet period, a time during which the IPO firm is restricted in their communication. Using data on firm-initiated press release articles around the quiet period, I show that the disclosure tone of identified rivals' press release becomes more positive during the quiet period compared with a matched control group of unidentified industry peers, and the tone of their disclosure reverts to normal level after the quiet period ends. To understand identified rivals' product market incentives behind their disclosure choices, I examine the content of their disclosed information, and I find a consistently significant positive change in the disclosure tone of product market related press release during the quiet period. Furthermore, the cross-sectional analyses suggest that identified rivals "tone down" in the post-quiet period only when the IPO is withdrawn. Additionally, the upward tone adjustments only exist when identified rivals talk about their industry competition instead of about some macroeconomic conditions. Taken together, this evidence highlights that identified rivals strategically increase the tone of their disclosure during the quiet period to preempt the IPO competitive effects and to strengthen their position in the product market competition.

My results also suggest that the strategic changes in the disclosure behavior of identified rivals during the quiet period have negative implications for the IPO firm but benefit the identified rivals themselves. The IPO firm is more likely to go through withdrawal and identified rivals who increase their disclosure tone during the quiet period face less product market threat from the IPO firm afterwards, an effect that is not found for unidentified industry peers. Overall, this study, the first to focus on rival firms' disclosure during the quiet period, contributes to an extensive literature on strategic disclosure and information externality. It extends this literature by introducing a strategic benefit related to disclosing information during the quiet period ─ preempting the IPO's competitive effects on rival firms. This study also contributes to the emerging literature on IPO quiet period by identifying an unintended effect of quiet-period rules on industry rivals' disclosure behavior. For regulators whose mission is to maintain fair markets and facilitate capital formation, the unexpected findings that identified rivals can take advantage of the quiet period rules to influence the IPO process and market competition should also be relevant to them.

2.7 References, figure, tables and appendices

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Figure 1

Identified rival's disclosure tone around the IPO quiet period

In the figure below, the x-axis represents period (Period 2 is the IPO quiet period, Period 1 is the pre-quiet period, and Period 3 is the post-quiet period) and the y-axis represents the period average of disclosure tone of identified rival's press releases. In Figure 1(a), the net disclosure tone is measured based on Loughran and McDonald Dictionary. In Figure 1(b), the net disclosure tone is measured based on SentiWordNet sentiment score. The sample consists of 1191 firm-period observations.

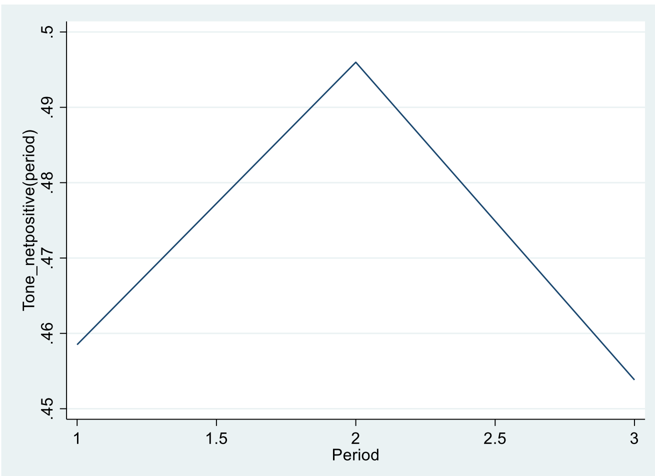

Figure 1(a) Word-count tone measure

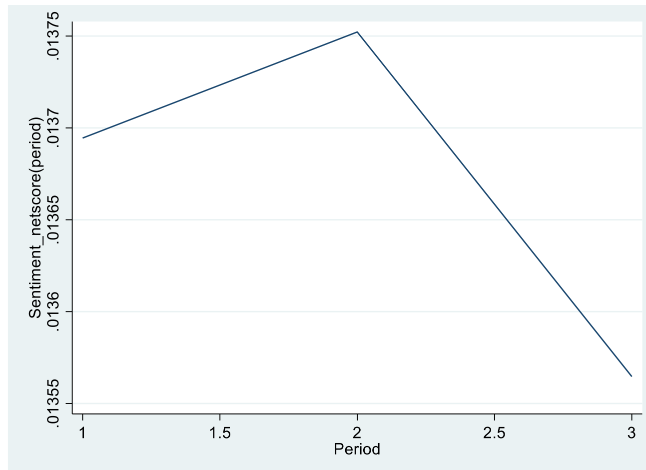

Figure 1(b) SentiWordNet sentiment score

Table 1: IPO sample and selection procedures

The IPO sample consists of 285 U.S. firms which file an initial registration statement from January 1, 2001 to December 31, 2017. The initial IPO sample is generated from the Securities Data Corporation (SDC) database, some key data used in this study is augmented and corrected using information from Nasdaq website, SEC EDGAR, and press release from Reuters and Business Wire. I exclude American Depository Receipts, reverse Leveraged buyouts, closed-end funds, limited partnerships, unit investment trusts, tracking stocks, two-tranche offerings, and simultaneous international offerings, and any IPO consisting of non-common shares or with offer price less than $5. I also eliminate firms in financial and utilities industries and firms with missing date for its initial registration statement. To identify IPOs with the lowest likelihood of other IPOs contaminating the results, I apply Hsu, Reed and Rocholl (2010)'s approach and focus on IPOs with the largest offering amount in the SIC 2-digit industry in a given year. Panel A provides details on the sample construction of the IPO sample. Panel B provides the yearly distribution of the sample, based on the year of initial filing date. Panel C provides the industry composition of the sample, based on the first 2-digit SIC code.

Panel A: IPO sample construction

Data Attribution Process	No. of IPO cases
Number of IPO events from year 2001-2017 (from SDC New Issues Database, initial IPO selection criteria follows Boone, Floros and Johnson (2016)).	1,612

Continued

Exclude:	
IPO events in financial and utility industries (SIC 4900-4999, 6000-6999)	(382)
IPO events with missing initial registration statement or the timing of the initial registration or withdraw statement is not available in EDGAR	(20)
IPO events of which the initial registration statement is earlier than January 1st 2001 in EDGAR	(20)
IPO events which are not related to the initial efforts in security registration	(55)
Total number of IPO events	1,135
Select:	
IPO events with the largest offering amount within SIC 2-digit industry in a giving year (Information on IPO offering amount is obtained from Nasdaq website, firm's own S-1 filing, and credible press sources, such as Reuters or Business Wire)	285

Panel B: IPO sample of filing year of initial registration statement

Year of initial registration statement	Frequency	Percent pf subsample
2001	17	5.96
2002	19	6.67
2003	11	3.86
2004	27	9.47
2005	25	8.77
2006	22	7.72
2007	18	6.32
2008	18	6.32
2009	12	4.21
2010	19	6.67
2011	22	7.72
2012	10	3.51
2013	15	5.26
2014	10	3.51
2015	17	5.96
2016	11	3.86
2017	12	4.21
Total	285	100

Panel C: Industry composition of IPO sample

Industry	Frequency	Percent of subsample	Industry	Frequency	Percent of subsample
Agricultural Production	4	1.40	Local & Interurban Passenger Transit	1	0.35
Forestry	1	0.35	Trucking & Warehousing	5	1.75
Metal, Mining	2	0.70	Water Transportation	3	1.05
Coal Mining	3	1.05	Transportation by Air	5	1.75
Oil & Gas Extraction	13	4.56	Pipelines, Except Natural Gas	1	0.35
General Building Contractors	4	1.40	Transportation Services	5	1.75
Heavy Construction, Except Building	1	0.35	Communications	12	4.21
Special Trade Contractors	2	0.70	Wholesale Trade – Durable Goods	10	3.51
Food & Kindred Products	11	3.86	Wholesale Trade – Nondurable Goods	4	1.40
Tobacco Products	1	0.35	Building Materials & Gardening Supplies	1	0.35
Apparel & Other Textile Products	1	0.35	General Merchandise Stores	1	0.35
Lumber & Wood Products	1	0.35	Food Stores	3	1.05
Furniture & Fixtures	2	0.70	Automative Dealers & Service Stations	1	0.35
Paper & Allied Products	3	1.05	Apparel & Accessory Stores	4	1.40
Printing & Publishing	1	0.35	Furniture & Homefurnishings Stores	2	0.70
Chemical & Allied Products	17	5.96	Eating & Drinking Places	9	3.16
Petroleum & Coal Products	6	2.11	Miscellaneous Retail	11	3.86
Rubber & Miscellaneous Plastics Products	2	0.70	Hotels & Other Lodging Places	1	0.35
Stone, Clay, & Glass Products	1	0.35	Personal Services	1	0.35
Primary Metal Industries	3	1.05	Business Services	17	5.96
Fabricated Metal Products	6	2.11	Auto Repair, Services, & Parking	3	1.05
Industrial Machinery & Equipment	15	5.26	Motion Pictures	5	1.75
Electronic & Other Electric Equipment	17	5.96	Amusement & Recreation Services	6	2.11
Transportation Equipment	11	3.86	Health Services	15	5.26
Instruments & Related Products	15	5.26	Educational Services	4	1.40
Miscellaneous Manufacturing Industries	3	1.05	Engineering & Management Services	9	3.16
Total	285	100			

Table 2: Identified rivals, control firms, and firm-initiated press release articles

This table reports the sample construction of identified rivals (Panel A), control firms (Panel B), and firm-initiated press release articles (Panel C). Identified rivals are defined as the firms identified by the IPO firm in its initial registration statement as the direct rivals. Control firms are firms that are operating in the same industry (industry classification is based on first 2-digit SIC code) but are not identified as rivals in the IPO firm's initial registration statement. Press release articles are hand-collected from Factiva. To focus on the strategic disclosure behavior of the identified rivals, I require that the press release articles selected are initiated by the firm itself, instead of by external news agencies. Also, to make sure that the press release articles contain substantive content, I require that the press release articles selected contain at least 50 words. (WC field>50).

Panel A: Sample construction of identified rivals

Data Attribution Process	No. of Identified rival instances
Firms that are identified as directly competing rivals by IPO firm in the initial registration statement (related to the largest 285 IPO case)	1,484
Exclude:	
Identified rivals whose name cannot be manually matched to a company in the COMPUSTAT industrial file	(655)
Identified rivals with missing data for control variables	(439)
Total number of identified rival instances for further press articles search	400
Identified rivals with no press release issued During any one of the three pre-defined event periods	(3)
Final sample:	
Total number of identified rival instances	397
Total number of IPO events corresponding to the 397 identified rival instance	163
Total number of identified rival-period observations	1,191

Panel B: Sample construction of control firms

Data Attribution Process	No. of matched firm instances
Control firm instances whose SIC-2 digit is the same as that of IPO firms from COMPUSTAT Industrial record	11,246
Exclude:	
Control firm instances with missing quarterly data for control variables	(10,471)
Total number of control firm instances for further press articles search	775
Control firm instances with no press release issued during any one of the three pre-defined event periods	(105)
Final sample	
Total number of entropy matching firm instances	670
Total number of entropy matching firm-period observations	1,993
Total number of identified rival instances corresponding to the 670 entropy matching firm instances	267
Total number of IPO events corresponding to the 670 identified rival instance	107

Panel C: Sample of firm-initiated press release articles

This Panel shows the details of firm-initiated press release articles for identified rivals and entropy matching firms. Press release articles are hand-collected from Factiva. To focus on the strategic disclosure behavior of the identified rivals, I require that the press release articles selected are initiated by the firm itself, instead of by external news agencies. Also, to make sure that the press release articles contain substantive content, I require that the press release articles selected contain at least 50 words. (WC field>50).

Press Articles:	Identified rivals	Entropy matching firms
News Sources	Business Wire, PR News Wire, Marketwire, Globe Newswire	
Number of firm-initiated press releases	30,381	26,046
Number of days in the sample	4,467	4,050
Number of firm instances	397	670
Number of firm period observations	1,191	1,993
Number of firm-initiated press releases for difference-in-differences analysis	46,941	
Number of firm-days with at least one article for difference-in-differences analysis	37,594	
Total number of firm-period observations for difference-in-differences analysis	2,794	

Table 3: Factiva subject code and description

This table shows the detailed definition of three news subjects that are classified as related to identified rivals' product market incentives.

Factiva NS	Descriptor	Description
Product Market Incentive		
C31	Marketing	Promoting and pricing of products or services. Brand development. Public, customer and investor relations.
C22	Product	Introduction, preview, or announcement of a new product or service. Includes product or service enhancements, improvements and new versions. Does not include products still in the early developmental stages or the opening of new facilities such as factories or retail stores
C33	Contract	All contractual agreements involving companies.

Table 4: Descriptive statistics

Panel A: Descriptive statistics of disclosure tone for the entire sample of firms

VARIABLES	N	Mean	SD	P25	P50	P75
Firm-day Level (Loughran & McDonald Dictionary):						
Tone_netpositive	37,594	1.060	1.874	0.000	0.902	1.841
Tone_positive	37,594	1.871	1.772	0.875	1.493	2.346
Tone_negative	37,594	0.811	1.060	0.129	0.498	1.110
Firm-day Level (SentiWordNet score):						
Sentiment_netscore	37,594	0.019	0.018	0.009	0.015	0.023
Sentiment_positivity	37,594	0.037	0.026	0.026	0.031	0.039
Sentiment_negativity	37,594	-0.019	0.013	-0.022	-0.016	-0.012
Article Level (Loughran & McDonald Dictionary):						
Tone_netpositive(article)	46,941	0.850	1.348	0.000	0.855	1.661
Tone_positive(article)	46,941	1.501	0.964	0.831	1.364	2.031
Tone_negative(article)	46,941	0.651	0.811	0.000	0.408	0.927
Article Level (SentiWordNet score):						
Sentiment_netscore(article)	46,941	0.015	0.009	0.009	0.014	0.020
Sentiment_positivity(article)	46,941	0.030	0.008	0.025	0.029	0.034
Sentiment_negativity(article)	46,941	-0.015	0.006	-0.019	-0.015	-0.011

Panel B: Comparison of disclosure tone by event period

Period Average	Identified rivals	Matched firms
	Mean	Mean
Tone_netpositive (article) (Loughran & McDonald Dictionary)		
Pre-quiet period	0.479	0.392
Quiet period	0.512	0.400
Post-quiet period	0.467	0.373
Sentiment_netscore (article) (SentiWordNet score)		
Pre-quiet period	0.014	0.012
Quiet period	0.014	0.012
Post-quiet period	0.013	0.012

Panel C: Disclosure Tone by two news dimensions and event period

Period Average	Loughran & McDonald Dictionary		SentiWordNet	
	Industry Competition	Macro Economy	Industry Competition	Macro Economy
Identified rivals				
Pre-quiet period	1.517	0.983	0.012	0.006
Quiet period	1.629	1.032	0.012	0.008
Post-quiet period	1.506	0.892	0.011	0.007
Matched firms				
Pre-quiet period	1.044	0.640	0.009	0.003
Quiet period	1.062	0.609	0.008	0.003
Post-quiet period	1.154	0.592	0.010	0.004

Panel D: Disclosure Tone (Identified rival by content categories at period level)

VARIABLES	N	Mean	SD	P25	P50	P75
Product market related (Marketing, Product, Contract)						
Loughran & McDonald Dictionary						
Market_netpositive	664	6.569	15.02	0.352	2.321	7.029
Product_netpositive	626	11.600	29.910	0.874	2.793	8.951
Contract_netpositive	544	7.139	14.330	0.914	2.457	6.648
SentiWordNet						
Market_netscore	664	0.098	0.204	0.019	0.043	0.100
Product_netscore	626	0.166	0.390	0.018	0.045	0.117
Contract_netscore	544	0.117	0.269	0.015	0.033	0.093

Panel E: Comparison of identified rival's disclosure tone by event period and news subject

Content	Product market related		
	Market	Contract	Product
Content_netpositive (Loughran & McDonald Dictionary):			
Pre-quiet period	5.097	5.464	8.916
Quiet period	9.066	8.803	15.75
Post-quiet period	5.216	6.919	9.731
Content_netscore (SentiWordNet score)			
Pre-quiet period	0.082	0.091	0.138
Quiet period	0.134	0.146	0.220
Post-quiet period	0.074	0.109	0.132

Panel F: Descriptive statistics of firm characteristics for the entire sample of firms

VARIABLES	N	Mean	SD	P25	P50	P75
Characteristics of Identified rivals:						
Logmktcap	1,191	22.520	2.117	22.560	21.000	24.120
Leverage	1,191	0.522	0.255	0.548	0.370	0.658
ROA	1,191	0.006	0.057	0.014	0.005	0.024
Tobin's Q	1,191	2.314	2.044	1.688	1.260	2.531
Logat	1,191	22.460	2.248	22.420	20.880	24.270
Analyst	1,191	15.320	9.868	15.000	7.000	22.000
Logprice	1,191	3.438	0.975	3.556	2.903	4.052
Characteristics of Matched firms:						
Logmktcap	1,993	20.690	1.779	20.620	19.450	21.810
Leverage	1,993	0.431	0.251	0.409	0.240	0.584
ROA	1,993	0.007	0.064	0.013	-0.002	0.028
Tobin's Q	1,993	2.330	2.580	1.667	1.169	2.623
Logat	1,993	20.600	1.857	20.530	19.320	21.700
Analyst	1,993	9.212	8.272	7.000	3.000	13.000
Logprice	1,993	2.800	1.036	2.901	2.128	3.542
Characteristics of IPO firms:						
Reputation	163	0.798	0.403	1.000	1.000	1.000
Logat_IPO	163	18.880	2.145	19.180	17.320	20.400
Leverage_IPO	163	1.346	3.531	0.686	0.441	0.977
ROA_IPO	163	-0.090	1.063	-0.003	-0.182	0.039
LogCapex	163	0.668	3.724	0.034	0.015	0.144
CashHoldings	163	0.200	0.264	0.075	0.022	0.265
withdraw	163	0.528	0.501	0.000	1.000	1.000
Offer Price	79	15.600	6.891	11.000	15.000	19.000
Product market threat from IPO firm (pairwise)						
Product Fluidity	236	0.075	0.062	0.030	0.060	0.108

Table 5: Changes in identified rival disclosure tone

Panel A presents the results from examining the changes in the tone of identified rival's press articles from pre-quiet period to During quiet period compared to that of the matched firms. During is an indicator variable equal to one (zero) if the article falls within the quiet period defined as starting from the filing date of initial registration statement to the issue/withdrawal date (120-day window immediately preceding the initial filing date). During×Identified is the interaction term between variable During and Identified (An indicator variable equal to one (zero) if the article is issued by the identified rival (matched firm)). All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Disclosure tone change from pre-quiet period to quiet period

Variable	**Tone_netpositive(Loughran & McDonald)**			**Sentiment_netscore (SentiWordNet)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Highly noticeable	Less noticeable	Total	Highly noticeable	Less noticeable
During×Identified	0.155*	0.340*	-0.056	0.003***	0.002**	-0.001
	(1.942)	(1.867)	(-0.896)	(2.826)	(2.293)	(-1.224)
During	-0.111	-0.145	0.020	-0.002	-0.001	-0.000
	(-1.094)	(-1.039)	(0.534)	(-1.539)	(-1.159)	(-0.250)
Logmktcap	0.001	0.259*	-0.084**	0.001	0.003*	-0.001**
	(0.018)	(1.843)	(-2.244)	(1.385)	(2.041)	(-2.088)
Logat	0.209***	0.008	-0.025	0.002**	-0.003	-0.002
	(3.311)	(0.014)	(-0.065)	(2.112)	(-0.343)	(-0.673)
Tobin's Q	0.088	0.337***	-0.044	0.000	0.002*	-0.001
	(1.429)	(3.510)	(-0.505)	(0.485)	(1.893)	(-1.446)
Leverage	-0.034	-3.232*	-0.654	-0.005	-0.041*	-0.016
	(-0.125)	(-1.921)	(-0.472)	(-1.392)	(-1.733)	(-0.797)
Logprice	-0.072	-0.394	-0.012	-0.002	-0.007**	0.001
	(-0.613)	(-0.896)	(-0.062)	(-1.383)	(-2.090)	(0.693)
ROA	1.148	0.918	1.866***	0.017	-0.021	-0.000
	(0.814)	(0.776)	(2.832)	(1.342)	(-0.872)	(-0.004)
Analyst	0.001	0.032	-0.006	0.000	0.000	0.000
	(0.120)	(0.656)	(-1.418)	(1.459)	(1.223)	(0.818)
Constant	-3.641***	-2.929	4.296	-0.038***	0.057	0.102
	(-2.960)	(-0.220)	(0.477)	(-2.698)	(0.349)	(1.027)
F-Value	30.600	3.960	6.910	58.640	4.680	80.710
Prob>F	(0.000)	(0.003)	(0.006)	(0.000)	(0.000)	(0.000)
Observations	28099	5361	22738	28099	5361	22738
Adjusted R^2	0.097	0.263	0.192	0.148	0.260	0.320
Firm FE	YES	YES	YES	YES	YES	YES

Panel B presents results from examining the changes in the tone of identified rival's press articles from pre-quiet period to During quiet period and from pre-quiet period to post-quiet period compared to that of the matched firms. The newly added variable Post×Identified is the interaction term between Identified and Post (an indicator variable equal to one if the article falls within the 120-day window immediately after issue/withdrawal date or zero otherwise. All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel B: Disclosure tone change from pre-quiet period to during and post-quiet period

Variable	**Tone_netpositive (Loughran & McDonald)**			**Sentiment_netscore (SentiWordNet)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Highly noticeable	Less noticeable	Total	Highly noticeable	Less noticeable
During×Identified	0.169*	0.270	-0.032	0.003**	0.002**	-0.000
	(1.993)	(1.605)	(-0.516)	(2.602)	(2.711)	(-0.870)
Post×Identified	0.077	0.130	-0.251	0.002	0.002**	-0.002
	(0.547)	(1.068)	(-1.540)	(1.255)	(2.220)	(-0.997)
During	-0.125	-0.114	0.008	-0.002	-0.001	-0.000
	(-1.243)	(-0.861)	(0.195)	(-1.600)	(-1.132)	(-0.400)
Post	-0.105	-0.091	0.085	-0.002*	-0.001**	-0.001
	(-0.703)	(-1.266)	(0.857)	(-1.688)	(-2.158)	(-1.584)
Logmktcap	0.015	0.230**	-0.079**	0.001**	0.002**	-0.001
	(0.335)	(2.145)	(-2.227)	(2.098)	(2.372)	(-1.383)
Logat	0.220***	0.096	0.083	0.002**	-0.003	-0.001
	(3.593)	(0.221)	(0.356)	(2.361)	(-0.586)	(-0.414)
Tobin's Q	0.102	0.248***	-0.018	0.000	0.001	-0.001
	(1.599)	(2.812)	(-0.303)	(0.611)	(1.560)	(-1.486)
Leverage	-0.112	-2.145**	-0.308	-0.005	-0.024**	-0.011
	(-0.357)	(-2.314)	(-0.290)	(-1.230)	(-2.441)	(-0.734)
Logprice	-0.101	-0.344	-0.055	-0.002	-0.005**	-0.000
	(-0.811)	(-1.416)	(-0.522)	(-1.510)	(-2.425)	(-0.021)
ROA	0.758	-0.339	1.608***	0.008	-0.003	-0.007
	(0.513)	(-0.295)	(2.957)	(0.605)	(-0.247)	(-1.364)
Analyst	-0.001	0.024	-0.004	0.000	0.000*	0.000
	(-0.153)	(0.927)	(-1.362)	(1.223)	(1.963)	(0.799)
Constant	-4.049***	-4.784	1.525	-0.038***	0.050	0.060
	(-3.111)	(-0.452)	(0.261)	(-2.884)	(0.546)	(0.989)
F Value	11.510	7.930	32.160	16.120	3.630	151.000
Prob>F	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
Observations	37594	7614	29980	37594	7614	29980
Adjusted R^2	0.096	0.262	0.191	0.141	0.269	0.300
Firm FE	YES	YES	YES	YES	YES	YES

Table 6: Product market incentive and the changes and reversal of disclosure tone

This table presents the results from examining the changes in the tone of identified rival's press articles from the pre-quiet period to quiet period (column(1) and (5)) and the reversal of tone from quiet period to post-quiet period (column(2-4) and column(6-8)) for product market related news. The dependent variables are period level net tone measure of press releases classified as product market related. Product market related content consists of content on marketing (Panel A), product (Panel B) and contract (Panel C). The unit of analysis in each column is a firm-period. All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Pane A: Press release on Marketing

	Market_netpositive (Loughran & McDonald)				Market_netscore (SentiWordNet)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-During	During-Post			Pre-During	During-Post		
Variable		Total	IPO withdrawal	IPO success		Total	IPO withdrawal	IPO success
During	4.221**				0.057***			
	(-2.504)				(2.722)			
Post		-4.704**	-7.346**	-2.151		-0.071***	-0.113***	-0.023
		(-2.536)	(-2.598)	(-1.291)		(-3.027)	(-3.056)	(-1.251)
F Value	3.300	6.010	39.870	12.070	4.580	5.830	35.920	9.850
Prob>F	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	455	449	250	199	455	449	250	199
Adjusted R^2	0.100	0.106	0.193	0.12	0.067	0.075	0.145	0.078
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Pane B: Press release on Product

Variable	Product_netpositive (Loughran & McDonald)				Product_netscore (SentiWordNet)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-During	During-Post			Pre-During	During-Post		
		Total	IPO withdrawal	IPO success		Total	IPO withdrawal	IPO success
During	7.670**				0.092**			
	(2.399)				(2.145)			
Post		-7.830**	-12.236**	-1.590		-0.111**	-0.175**	-0.024
		(-2.196)	(-2.190)	(-0.554)		(-2.230)	(-2.399)	(-0.609)
F Value	16.360	22.140	1.670	251.770	5.080	8.980	3.210	434.850
Prob>F	(0.000)	(0.000)	(0.146)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)
Observations	431	418	236	182	431	418	236	182
Adjusted R^2	0.211	0.200	0.249	0.217	0.168	0.159	0.181	0.191
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Pane C: Press release on Contract

Variable	Contract_netpositive (Loughran & McDonald)				Contract_netscore (SentiWordNet)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-During	During-Post			Pre-During	During-Post		
		Total	IPO withdrawal	IPO success		Total	IPO withdrawal	IPO success
During	4.025***				0.065***			
	(3.123)				(2.749)			
Post		-2.838**	-5.970***	0.996		-0.050**	-0.106***	0.023
		(-2.706)	(-3.870)	(1.080)		(-2.153)	(-2.771)	(1.225)
F Value	10.530	6.480	13.710	115.770	4.620	8.250	4.810	85.740
Prob>F	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	379	366	208	158	379	366	208	158
Adjusted R^2	0.087	0.105	0.109	0.072	0.066	0.068	0.020	0.131
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: The impact of identified rival's strategic disclosure on the IPO firm's withdrawal probability

This table presents the results from examining the impact of identified rival's strategic disclosure on the likelihood of an announced IPO being withdrawn. The independent variable of tone measure is based on SentiWordNet Score (from column (1) to column (4)) and Loughran & McDonald Dictionary (column (5) to column (8). Column (1) and (5) present results related to the tone change from all press releases. The rest of the columns are about the changes in tone of press releases on specific "product market incentive" related news subject. The unit of analysis in each column is an announced IPO. All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Dependent Variable: Withdraw	**SentiWordNet Score**				**Loughran & McDonald Dictionary tone measure**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total News	Market	Product	Contract	Total News	Market	Product	Contract
Tone_Chg	35.100*	2.293**	1.778**	2.302**	-0.305*	0.018	0.017*	0.031**
	(1.736)	(2.016)	(2.171)	(1.991)	(-1.714)	(1.593)	(1.931)	(2.041)
Logat_IPO	-0.070	-0.089	-0.096	-0.095	-0.067	-0.103	-0.094	-0.107
	(-0.653)	(-0.803)	(-0.853)	(-0.862)	(-0.629)	(-0.940)	(-0.843)	(-0.972)
Leverage_IPO	0.059	0.055	0.051	0.050	0.032	0.053	0.053	0.048
	(0.960)	(0.902)	(0.829)	(0.791)	(0.486)	(0.862)	(0.867)	(0.771)
ROA_IPO	0.080	0.072	0.115	0.148	0.158	0.114	0.117	0.151
	(0.343)	(0.266)	(0.435)	(0.605)	(0.627)	(0.445)	(0.461)	(0.615)
LogCapex	-0.021	-0.014	-0.010	-0.016	-0.020	-0.017	-0.011	-0.016
	(-0.353)	(-0.245)	(-0.172)	(-0.269)	(-0.349)	(-0.290)	(-0.179)	(-0.281)
CashHoldings	-2.243***	-2.251***	-2.192***	-2.152***	-2.021**	-2.220***	-2.185***	-2.157***
	(-2.806)	(-2.810)	(-2.740)	(-2.685)	(-2.536)	(-2.792)	(-2.739)	(-2.690)
Reputation	0.934*	0.957*	0.987*	0.928*	0.899*	1.019*	0.991*	1.029*
	(1.794)	(1.782)	(1.806)	(1.738)	(1.733)	(1.907)	(1.831)	(1.916)
Constant	1.069	1.258	1.379	1.442	1.066	1.534	1.340	1.595
	(0.563)	(0.645)	(0.697)	(0.744)	(0.565)	(0.795)	(0.686)	(0.822)
Chi Square	16.130	20.250	21.690	19.100	16.020	17.120	19.480	19.420
Prob>Chi Square	(0.024)	(0.005)	(0.003)	(0.008)	(0.025)	(0.017)	(0.007)	(0.007)
Observations	163	163	163	163	163	163	163	163
Pseudo R^2	0.072	0.090	0.096	0.085	0.071	0.076	0.086	0.086

Table 8: Product market benefits of disclosure for identified rivals

This table presents the results from examining the effect of rival (both identified rival and matched control firms)'s strategic disclosure on product market threat from the IPO firm (proxied by pairwise product similarity). The unit of analysis in each column is a rival firm. Pair-wise product fluidity measures the cosine similarity between the identified rival and the IPO firm in the product related description in their 10-K filings. The detailed description of product market fluidity data can be found from Hoberg-Phillips Data Library. All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a one-tailed t-test for main variables of interest and a two-tailed t-test for other control variables.

Dependent Variable: Product Fluidity	**SentiWordNet Score**			**Loughran & McDonald Dictionary tone measure**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Identified rival	Control firm	Total	Identified rival	Control firm
Tone_Chg	-1.164**	-1.351*	-0.032	-0.002	-0.017**	0.002
	(-1.997)	(-1.432)	(-0.050)	(-0.441)	(-1.720)	(0.478)
Logat_IPO	0.003	0.004	0.002	0.003	0.005	0.002
	(1.097)	(0.878)	(0.741)	(1.348)	(1.205)	(0.723)
ROA_IPO	0.008**	0.006	0.012**	0.008**	0.005	0.012**
	(2.406)	(1.287)	(2.234)	(2.396)	(1.066)	(2.265)
LogCapex	0.000	0.000	0.000	0.000	-0.000	0.000
	(0.045)	(0.069)	(0.429)	(0.003)	(-0.280)	(0.438)
CashHoldings	-0.001	0.027	-0.018	-0.004	0.041	-0.020
	(-0.056)	(0.650)	(-0.702)	(-0.164)	(0.950)	(-0.771)
Logmktcap	-0.026**	-0.022	-0.019*	-0.024**	-0.025	-0.018*
	(-2.545)	(-0.954)	(-1.867)	(-2.292)	(-1.070)	(-1.857)
Logat	0.018*	0.006	0.014	0.015	0.008	0.014
	(1.810)	(0.256)	(1.536)	(1.576)	(0.347)	(1.532)
Tobin's Q	0.006	0.008	0.005	0.005	0.008	0.005
	(1.546)	(0.857)	(1.334)	(1.319)	(0.885)	(1.352)
Logprice	0.012*	0.013	0.000	0.012*	0.013	-0.000
	(1.873)	(1.214)	(0.041)	(1.845)	(1.190)	(-0.023)
ROA	-0.112	-0.681***	0.102	-0.141	-0.722***	0.104
	(-1.177)	(-2.982)	(1.162)	(-1.482)	(-3.218)	(1.199)
Constant	0.170***	0.333***	0.128*	0.154**	0.325***	0.128*
	(2.663)	(2.813)	(1.762)	(2.404)	(2.774)	(1.776)
F Value	2.200	3.400	1.550	1.790	3.530	2.940
Prob>F	(0.019)	(0.001)	(0.127)	(0.064)	(0.001)	(0.001)
Observations	236	73	163	236	73	163
Adjusted R^2	0.049	0.250	0.033	0.032	0.260	0.034

Table 9: Disclosure tone and two news dimensions

This table presents the results from examining the disclosure tone along two news dimensions "Industry Competition" and "Macro Economy" in identified rival's press articles from pre-quiet period to During quiet period or from pre-quiet period to post-quiet period compared to that of the matched firms. The details of the decomposition of the content of each press article into the two news dimensions are presented in Appendix C. Dependent variable Tone_News Dimension (Industry Competition or Macro Economy) is defined as the firm-daily aggregation of the article level net tone measure for all the sentences classified as related to either news dimension. The tone measure is based on Loughran & McDonald Dictionary (from column (1) to column (4)) and SentiWordNet Score (column (5) to column (8). All variables are defined in the Variable Appendix. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Dependent Variable: Tone_News Dimension	**Loughran & McDonald Dictionary tone measure**				**SentiWordNet Score**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Industry Competition	Macro Economy	Industry Competition	Macro Economy	Industry Competition	Macro Economy	Industry Competition	Macro Economy
During×Identified	0.514**	-0.108	0.563**	-0.086	0.003***	0.002	0.003***	0.002*
	(2.261)	(-0.552)	(2.178)	(-0.399)	(4.756)	(1.529)	(4.198)	(1.784)
During	-0.155	0.049	-0.192	0.046	-0.001**	0.001**	-0.001**	0.001
	(-1.445)	(0.479)	(-1.659)	(0.367)	(-2.479)	(2.197)	(-2.406)	(1.177)
Post×Identified			0.148	-0.102			0.001	0.001
			(0.606)	(-0.529)			(1.512)	(0.725)
Post			-0.033	0.024			-0.001**	0.000
			(-0.251)	(0.152)			(-2.076)	(0.206)
Logmktcap	0.413*	0.037	0.314*	0.044	0.001	0.001	0.001	0.001***
	(1.840)	(0.719)	(1.978)	(0.687)	(1.082)	(1.597)	(1.641)	(3.112)
Logat	-0.456***	-0.184	-0.445**	0.001	-0.007***	-0.001	-0.006***	-0.001
	(-2.785)	(-0.414)	(-2.535)	(0.004)	(-4.119)	(-0.450)	(-3.532)	(-0.617)
Tobin's Q	-0.126	-0.025	-0.174*	0.013	-0.001***	-0.001	-0.002***	-0.001**
	(-1.214)	(-0.225)	(-1.693)	(0.142)	(-3.195)	(-1.270)	(-3.806)	(-2.202)
Leverage	1.605	0.917	0.834	0.766	0.013*	0.027***	0.006	0.018**
	(1.364)	(0.728)	(0.598)	(0.971)	(1.757)	(3.238)	(0.743)	(2.433)
Logprice	-0.846***	-0.489	-0.384**	-0.449	-0.002	-0.001	-0.000	-0.001
	(-4.163)	(-0.854)	(-2.095)	(-1.068)	(-0.725)	(-0.322)	(-0.102)	(-0.503)
ROA	-2.718	6.104	-0.188	5.302	-0.052**	-0.025*	-0.027**	-0.006
	(-1.587)	(1.526)	(-0.266)	(1.632)	(-2.408)	(-1.910)	(-2.211)	(-0.621)
Analyst	0.122***	0.027*	0.108***	0.028***	0.001***	0.000***	0.001***	0.000***
	(3.813)	(1.937)	(3.212)	(3.583)	(3.485)	(4.496)	(3.173)	(4.127)
Constant	2.830	5.059	3.946	0.404	0.125**	-0.004	0.102**	-0.007
	(0.555)	(0.593)	(0.943)	(0.065)	(2.690)	(-0.071)	(2.391)	(-0.169)
F Value	382.070	17.020	171.750	30.450	322.100	74.950	363.450	40.830
Prob>F	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	27969	27969	37428	37428	27993	27993	37456	37456
Adjusted R^2	0.259	0.224	0.253	0.224	0.234	0.172	0.233	0.167
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

Appendix A. Variable Definitions

This table provides a detailed description of the procedures used to calculate each variable in this paper. The data are obtained from COMPUSTAT, CRSP, SDC Platinum, Factiva, Hoberg-Phillips Data Library, Nasdaq, and firms' financial filings available on EDGAR. All continuous control variables are winsorized at 1% and 99% of the distribution.

Disclosure Tone Variables

Variable	**Definition**
Tone_positive/negative (article)	A variable defined as the number of positive/negative words divided by the number of total content words for each press release and multiplied by 100. This variable measures tone at the article level. Words are categorized as positive, negative using the word list available on Bill McDonald's website (Loughran and McDonald, 2011) (L&M Dictionary)
Tone_netpositive (article)	A variable defined as the difference between the number of positive and negative words divided by the number of total content words for each press release and multiplied by 100. This variable measures net tone at the article level.
Sentiment_positivity/ Negativity (article)	Positivity/negativity score, obtained through using SentiWordNet, a lexical resource for sentiment classification and opinion mining applications available through NLTK. Score for positivity/negativity is at the article level.
Sentiment_netscore (article)	A variable defined as the sum of Sentiment_positivity and Sentiment_negativity for each press release, this netscore measures the sentiment at the article level.
Tone_positive /negative/netpositive	A variable defined as the firm-daily aggregation of the article level tone measure.
Sentiment_positive /negative/netpositive	A variable defined as the firm-daily aggregation of the article level sentiment score.
Market_netpositive/ netscore	A variable defined as the firm-period aggregation of the article level net tone measure or net sentiment score for all the articles with "C31—Marketing" in its "Subject Code" (NS).
Product_netpositive/ netscore	A variable defined as the firm-period aggregation of the article level net tone measure or net sentiment score for all the articles with "C22—Product" in its "Subject Code" (NS).
Contract_netpositive netscore	A variable defined as the firm-period aggregation of the article level net tone measure or net sentiment score for all the articles with "C33—Contract" in its "Subject Code" (NS).
Tone_Industry Competition (L&M Dictionary)	A variable defined as the firm-daily aggregation of the difference between the number of positive and negative words divided by the number of total content words for sentences classified as related to "Industry Competition" dimension and then multiplied by 100. The key words list for category "Industry Competition" is presented in the Appendix E.
Tone_Industry Competition (SentiWordNET)	A variable defined as the firm-daily aggregation of the sum of positivity and negativity sentiment score for sentences classified as related to "Industry Competition" dimension.
Tone_Macro Economy (L&M Dictionary)	A variable defined as the firm-daily aggregation of the difference between the number of positive and negative words divided by the number of total content words for sentences classified as related to "Macro Economy" dimension and then multiplied by 100. The key words list for category "Industry Competition" is presented in the Appendix E.
Tone_Macro Economy (SentiWordNET)	A variable defined as the firm-daily aggregation of the sum of positivity and negativity sentiment score for sentences classified as related to "Macro Economy" dimension.

Continued

Variable	Definition
Tone_Chg(Total news/Subject)	A variable defined as the net changes in firm-period level net tone measure or net sentiment score from pre-quiet period to quiet period for all news subject or for press releases on the subject "Marketing", "Product" or "Contract".

All Other Variables

Variable	Definition
During	An indicator variable equal to one (zero) if the firm-day falls within the IPO firm's quiet period, which starts from the initial registration statement date and ends on the issue/withdraw date (pre-quiet period and post-quiet period; the former is defined as the 120-calender day window ending right before the start of initial registration statement date; the latter is defined as the 120-calender day window starting right after the end of the quiet period).
Post	An indicator variable equal to one (zero) if the firm-day falls within the 120-calender-day window starting right after the end of the quiet period and stretching 120 days forward relative to that date (quiet period and pre-quiet period; the definition is same as above)
Identified	An indicator variable equal to one if the firm is identified rival (identified specifically as a directly competing rival in IPO firm's initial registration statement) and zero if the firm is a matched firm. An industry matched firm is defined based on the 2-digit SIC.
Logmktcap	A variable defined as the natural logarithm of identified rival or matched firm's market value of equity, measured as the quarter ending immediately prior to the start of the specified time period.
Leverage	A variable defined as identified rival or matched firm's debt (short and long term) divided by the sum of the firm's debt and shareholder's equity, measured at the quarter ending immediately prior to the start of the specified time period
ROA	A variable defined as identified rival or matched firm's net income divided by assets measured at the quarter ending immediately prior to the start of the specified time period
Tobin's Q	A variable defined as market value of the identified rival or matched firm's assets (assets less book equity plus market value of equity) divided by the book value of the assets, measured at the quarter ending immediately prior to the start of the specified time period.
Logat	A variable defined as the natural logarithm of the identified rival or matched firm's total assets immediately prior to the start of the specified time period.
Analyst	A variable defined as the number of analysts with earnings estimates in the I/B/E/S summary file immediately prior to the start of the specified time period to proxy for investors' demand for corporate disclosure.
Logprice	A variable defined as the natural logarithm of stock price, measured at the date immediately prior to the start of the specified time period.
Reputation	A dummy variable equal to one if an IPO firm's underwriter ranking exceeds 8. Source: Jay Ritter's website.
Logat_IPO	A variable defined as the natural logarithm of IPO firm's most recent total assets disclosed in its initial registration statement. Source: EDGAR.

Continued

Variable	Definition
Leverage_IPO	A variable defined as IPO firm's most recent total liability divided by total assets disclosed in its initial registration statement. Source: EDGAR.
ROA_IPO	A variable defined as IPO firm's most recent net income divided by total assets disclosed in its initial registration statement. Source: EDGAR.
LogCapex	A variable defined as the natural logarithm of IPO firm's most recent capital expenditure disclosed in its initial registration statement. Source: EDGAR.
CashHoldings	A variable defined as IPO firm's most recent cash or cash equivalent scaled by total assets disclosed in its initial registration statement. Source: EDGAR.
IPO Withdraw	A dummy variable equal to one if the IPO is withdrawn by the IPO firm.
Offer Price	A variable defined as the offering price at initial public offering. Source: Nasdaq.
Product_fluidity	A variable defined as the pairwise product fluidity between the IPO firm and identified rival/matched firms measured for the year after the year of IPO offering or withdrawal. Source: Hoberg-Phillips Data Library.

Appendix B. Illustrative evidence of identified rival's press release

This appendix provides an example of an IPO firm's description of its competition in the initial registration filing, and one of its rivals' disclosure activities around the IPO quiet period.

C.1 Excerpt from WCI Communities initial registration filing released on September 6th, 2001.

COMPTITION

The homebuilding industry and real estate development is highly competitive. In each of our business components, we compete against numerous developers and others in the real estate business in and near the areas where our communities are located. Some of our principal competitors include Toll Brothers, Inc., ***Lennar Corporation****, Pulte Corporation, Centex Corporation and Bonita Bay Properties. We, therefore, may be competing for investment opportunities, financing, available land, raw materials and skilled labor with entities that possess greater financial, marketing and other resources. Competition generally may increase the bargaining power of property owners seeking to sell, and industry competition may be increased by future consolidation in the real estate development industry.*

C.2 Example of press release and article level disclosure tone

The table lists the article level disclosure tone of three press release articles initiated by Lennar Corporation. The three examples show the leading paragraph of three press releases, corresponding to each of the three records.

Time period	Company	Total words	News_date	Positive	Negative	Content_words	Senti_pos	Senti_neg
Pre-quiet period	LENNAR CORP	554 words	1-Jun-01	5	3	493	0.020537525	-0.013438134
Quiet period	LENNAR CORP	801 words	12-Dec-01	17	3	744	0.039650538	-0.014112903
Post-quiet period	LENNAR CORP	432 words	21-Jun-02	1	1	383	0.021214099	-0.013381201

Example 1: Lennar Title Companies Unite Under The North American Title Banner (Pre-quiet period)
Source: PR Newswire
Publication Date: 1 June 2001
Text: MIAMI, June 1 /PRNewswire/ -- Lennar Corporation (NYSE: LEN), one of the nation's leading homebuilders and providers of financial services, announced today that it is combining its affiliated title agencies and title insurance companies under the North American Title banner. This combination places North American Title among the largest title service providers in the nation, with operations from coast to coast.

Example 2: Lennar to Commemorate Building 500,000th Home (Quiet period)
Source: PR Newswire
Publication Date: 12 December 2001
Text: MIAMI, Dec. 12 /PRNewswire/ -- Lennar Corporation (NYSE: LEN), one of America's largest homebuilders, announced today that it is delivering its 500,000th home on December 21st in a commemorative project with Habitat For Humanity and The Special Olympics organizations. Stuart Miller, President and CEO, stated, "The Lennar Family of Builders is pleased to have achieved this very exciting company milestone. For 47 years we have been committed to three simple goals -- helping American families realize their dream of home ownership, delivering responsible returns to our shareholders, and giving back to our community. Thus, we feel it only fitting that to commemorate this special moment, we once again partner with Habitat For Humanity and The Special Olympics to deliver our 500,000th home to a very deserving family."

Example 3: Lennar Commences Fortress Tender Offer (Post_quiet period)
Source: PR Newswire
Publication Date: 21 June 2002
Text: MIAMI, June 21 /PRNewswire-FirstCall/ -- Lennar Corporation (NYSE: LEN) announced today that its wholly-owned subsidiary, FG Acquisition Corporation, has begun a tender offer in which it is seeking all the shares of The Fortress Group, Inc. (Nasdaq: FRTG) which it does not already own for $3.68 per share in cash. The tender offer will expire at 5:00 p.m. New York City time, on July 22, 2002 unless it is extended.

Appendix C. Content decomposition and key words list

Decomposing press release

I first tag each sentence as "Industry Competition" or "Macro Economy" if a sentence includes any key word in the key words lists. I then combine these sentences together and form two groups. For robustness test, I also try to extract not only that specific "key word" sentence, but also three or five sentences before and after that sentence in order to capture the complete context of firm's discussion on these two topics. The process for tone analysis is the same as what has been described in Section 3 Measure of disclosure tone. Key words lists are developed based on Kothari et al. (2009) and Campbell et al. (2014) business content and risk categories.

Industry Competition		Macro Economy	
Compete	Proindustrialization	Aggregate demand	Fiscal policy
Competed	Quasi-industrial	Aggregate supply	GDP
Competes	Quasi-industrially	Asian crisis	General business risks
Competing	Regulatory compliance	Bad times	General conditions
Competings	Regulatory environment	Balance of payments	Gini Coefficient
Competition	Rival	Bank run	Global
Competitions	Rivaled	Business cycle	Globalisation
Competitive	Rivaling	Consumer confidence	Globalization
Competitiveness	Rivalry	Consumer confidence	GNP
Competitor	Rivals	Consumer prices index	Good times
Competitors	Seasonal	Consumer spending	Government policy
Competitory	Sectorial	Consumption	Gross National Income
Differentiation	Semi-industrial	Contractionary Policy	Inflation
Dominant	Semi-industrialized	Currency collapse	Macroeconomic
Downstream	Semi-industrially	Currency fluctuation	Macroeconomics
Entrants	Subsector	Cyclical	Macroeconomist
Industrial	Substitutes	Deflation	Macros
Industrialization	Substitutes	Deflationary	Macroscale
Industrially	The market	Deregulation	Market movement
Industrialness	Unindustrial	Domestic	Marketplace
Industrious	Unindustrialized	Economic boom	Monetary policy
Industry condition	Upstream	Economic contraction	Monetary system
Industrywide	Value chain	Economic cycle	Money supply
Innovation	Win-win	Economic downturn	Operating environment
Line of business	Zero-sum	Economic expansion	Overseas market
Market demand	Business conditions	Economic growth	Political climate
Market power	Proindustrial	Economic shocks	Political instability
Market supply	Preindustrial	Economic slowdown	Protectionism
Monopolistic	Price pressure	Economic trend	Recession
Monopoly	Pricing power	Economic uncertain	Reflationary
Nonindustrial	Prisoner's dilemma	Economic uncertainties	Regulatory environment
Nonindustrialization		Economic uncertainty	Retail Price Index
Nonindustrialized		Economic upturn	Sarbanes-Oxley
Nonindustrially		Economic condition	SARS
Oligopoly		Economic crisis	Stagflation
Overindustrialization		Economy	Tariff
Overindustrialize		Employment	Terrorism
Porter's		Exchange rate	Trade deficit
Porter's Five Forces		Exchange rates	World Trade Organisation
		Expansionary Policy	WTO
		Federal reserve	National Income
		Financial crisis	Unemployment

Chapter 3: Capitalizing on Information Externalities: IPO Firms' Peer Choice

[With] the IPO now complete, investors can begin to look at Facebook and value it just like any other company. That is what we aim to do in this article. We will be comparing Facebook to several of its peers to see if a case can be made for investing in the stock. We chose 3 peers in the technology sector: Google (NASDAQ:GOOG), because it is seen as Facebook's primary competitor in the social networking space. Apple (NASDAQ:AAPL), because it is seen as the standard against which to compare high-growth companies to. And LinkedIn (LNKD), because the company is arguably the public company whose business most closely resembles that of Facebook. For the record, all of our financial figures presented in this article, unless otherwise noted, are taken either from the most recent 10-Q filings of Apple, Google, and LinkedIn, or Facebook's final prospectus filed with the SEC. *(Helix Investment Research, Valuing Facebook against its peers: Can a case be made for the stock?, published on Seeking Alpha on May 20, 2012)*

3.1 Introduction

I examine Initial Public Offering (IPO) firms' choice of peer firms in their registration statement (S-1). According to Securities & Exchange Commission's (SEC) regulations, firms intending to engage in an IPO need to describe their market conditions and business operations when filing a registration statement. Specifically, they need to identify which industry peers they are directly competing with. These identified peers are assumed to face similar economic forces and are comparable to IPO firms with respect to product market competition and growth opportunities. Consequently, institutional investors typically select these firms for their comparable valuation models (Kim and Ritter, 1999). Information about private firm that is going public is typically scarce. Therefore, the information environment of peer firms could affect the overall amount of information investors gather in their attempt to value the IPO firm. I hypothesize that to facilitate their valuation, IPO firms will identify industry peers with better information environment in their registration statements, with the information externalities of these peers having a real economic effect on the IPO price formation process. When firms have a shorter history of public disclosure, the externalities of peer disclosure reduce the information asymmetry between managers and investors (Shroff et al., 2017).

However, there are several reasons why the peer information environment may not be positively associated with IPO firms' peer choice. For example, while for valuation purposes investors derive more information from peers, they also compare the economic viability of peers against that of the IPO firm. To the extent that a lower information asymmetry reduces the risk of investment and enables investors to better gauge the present value of IPO firms' future cash flows, identifying peer firms with a higher quality information environment may put the IPO firms themselves in an unfavorable position. Moreover, by clearly identifying peer firms with a solid market position, IPO firms expose their relative disadvantages and the potential threat from industry incumbents to the public. Thus, it is still unclear if and how IPO firms consider the information environment of the firms they select as peers. More specifically, I examine whether IPO firms take advantage of this peer effect in their choice of peer firms and how such peer effect influences the price setting process.

Focusing on a large sample of IPOs that take place between 2001 and 2017, I hand-collect data about industry peers that are identified in initial registration statements. Using this unique data set, I test the hypothesis of whether IPO firms tend to identify peers with a better information environment. A principal benefit of this setting is that to successfully list their firm's shares on the stock market, managers have strong incentives to reduce the information asymmetry between themselves and potential investors. Beyond increasing the production of firm-specific information through public disclosure in a registration statement, IPO firms can tap into peer information externalities. Since these peer firms have been public for a while, their information environment could greatly complement the limited amount of available information about the IPO firm. Thus, there is an incentive to identify the “right” peers. Additionally, since an IPO firm’s decision to go public and its timing of filing initial registration statement are largely out of the control of identified peer firms, it is almost impossible for these peer firms to plan ahead and change their disclosure accordingly just to suit the interests of IPO firms. Hence, in this setting, reverse causality is less likely to be an issue.

Instead of focusing on a specific disclosure channel while ignoring all the other possible aspects of financial reporting, I follow prior literature in recognizing the multi-faceted nature of an information environment (Hilary, 2006; Baik et al., 2017; Balakrishnan et al., 2019). Hence, I use several summary measures as well as construct a composite one from these measures to capture the quality of peer information environment. I initially focus on the relation between peer information environment and peer choice by IPO firms. If an IPO firm intends to reduce the information uncertainty associated with its forthcoming public issue, one possible strategy would be to select peer firms with better information environment. Information about these peer firms reveals common economic forces and provides context to assess the business conditions of the IPO firm at a time when investors are expected to put more weight on peer information due to the lack of firm information before the IPO. I find that IPO firms tend to identify peers with a higher quality information environment. Specifically, a one standard deviation increase in the composite proxy for the quality of peer information environment increases the likelihood of being identified as direct industry peers by 40%. The significance of the effects of peer information environment holds across the four different measures.

It is possible that alternative explanations drive the results. For instance, IPO firms may tend to select large and publicly-traded industry peers in order to highlight their firms’ relatively low valuation and high growth potential, with these selected peers usually having a longer history of public disclosure and a better information environment. I attempt to address this issue by including numerous control variables and by conducting cross-sectional tests that lend further support to this prediction.

Specifically, I examine whether the relation between peer information environment and peer selection varies systematically with the IPO firm's information uncertainty and the proprietary cost of peer firm disclosure. First, I investigate whether the relation is increasing in IPO firms' information uncertainty. I proxy for the level of information uncertainty using (i) the age of the IPO firm (Kim and Ritter, 1999), (ii) the presence of venture capital investors' backing (Boone et al., 2016), (iii) the specificity of the description of the use of proceeds (Leone et al., 2007), and (iv) the underwriter' reputation (Loughran and Ritter, 2004; Carter and Manaster, 1990) . Consistent with my prediction that peer information environment makes up for lacking firm information at the time of the share issue, I find that IPO firms are more likely to select peers with a higher quality information environment when they face greater information uncertainty. Second, prior research suggests that potential competitive threats increase the cost of corporate disclosure, and that firms operating in fiercely competitive environment are usually less forthcoming in their information release (Guo et al., 2004). The results show that the relation between peer information environment and peer selection is much weaker for IPO firms operating in the biotech industry. This finding suggests that, compared to non-biotech firms, firms in the biotech sector are inherently more concerned with preserving proprietary information, so peer information environment is expected to play less of a role in IPO firms' peer choice as the amount of relevant peer information should be limited.

I then turn to the real implication tests. First, if peer information environment matters, I expect that rich peer information facilitates the IPO price setting process. Prior research shows that

IPO firms have strong incentives to influence the market's perception of their shares, their goal being to sell shares at a higher price (Teoh et al., 1998). In this regard, extant research finds that information release about the IPO firm itself, such as the intended use of IPO proceeds (Leon et al., 2007), or the receipt of a SEC comment letter (Li and Liu, 2017), can influence the perceived information risk and the final offering price. However, it is less clear how IPO firms can take advantage of the externalities of a richer peer information environment to raise their offering price. By examining the difference between the IPO offering price and the initial filing price, I find that a higher quality peer information environment leads to a higher likelihood of upward offering price revision.

Second, I investigate the effect of the peer information environment on the number of amendment filings IPO firms make before the offering date. Since IPO firms have to take longer time and exert more efforts to file additional amendments to satisfy investors' demand for more information (Li and Liu, 2017), selecting peers with more transparent information can fill the information gap and reduce investors' uncertainty regarding the value of the IPO firm. Consistent with this prediction, I find that a richer peer information environment significantly reduces the number of amendment filings made to the IPO firms' initial registration statement.

I also examine analyst coverage in the post-offering period. Prior research finds that information environment is positively associated with analyst coverage (Fernandes and Ferreira, 2008; Frankel and Li, 2004). As analysts gather more information about the IPO firm from other comparable and transparent industry peers, their forecasts and recommendations are to be more accurate. They are also more likely to be motivated by higher trading commissions generated by investors who trade on the additional information. In line with this thought, I find that peer information environment leads to a substantial increase in analyst coverage subsequent to the IPO offering.

This research, which is the first to employ a unique hand-collected data set of identified peers in IPO firms' registration statements, contributes to the literature in the following ways. First, it relates to the spillover effects of peer disclosure. Prior research shows that peer information such as earnings announcements (Foster, 1981; Pandit et al., 2011), bankruptcy announcements (Lang and Stulz, 1992), or restatements (Durnev and Mangen, 2009; Gleason et al., 2008) has externalities on industry peers or peers along the supply chains. These disclosure events not only have immediate wealth effects, but also affect peers' financing and investment decisions. However, early studies usually take a firm's disclosure events as exogenous without questioning whether it is possible for some firms to take advantage of the spillover effects of their disclosure to influence other related peers. For this question, a few recent studies show that the answer is affirmative. Firms intentionally exploit the externalities of their disclosure to gain benefits in merger negotiations (Kim et al., 2018) or during their competitor's labor dispute (Aobdia and Cheng, 2018). This paper builds on prior research by examining an important setting that has been under explored so far. Specifically, I hypothesize and show that peer information externalities substitute for firm information at the IPO time, compensating for limited firm-specific information. Hence, firms can tap into a richer information environment through peer selection to facilitate IPO valuation. The evidence extends Shroff et al. (2017) who show that the importance of peer information environment can act as a substitute for firm-specific information and lower the cost of capital. However, their measure of peer information is at the industry level, so even if IPO firms now know the effects of peer information, it would still be difficult for them to act on this finding. In contrast, I focus on the information environment of identified peers, i.e., peers that are selected by the IPO firm itself. Moreover, Shroff et al. (2017) focus on a single measure (bid-ask spread) and do not explore whether and how an IPO firm can actively use this externality feature to gain benefits.

This paper is also related to a nascent stream of literature that examines the selection of peers. Using comparable firm multiples is a standard practice adopted widely by investment bankers in the pricing of IPOs (Kim and Ritter, 1999). Beyond this specific IPO setting, peers are used by analysts to assist their earnings forecasts and stock recommendations (e.g., De Franco et al., 2015), by board of directors in setting executive compensation (Vaan et al., 2019; Albuquerque et al., 2013), and by investors in their portfolio construction through analysis of financial statement comparability (Kim et al., 2016; De Franco et al., 2011). Peer firm selection is rooted in the assumption that there is a higher-level comparability between peer firms and the focal firm, but prior studies show that I cannot ignore the strategic incentives involved on the part of decision makers in their peer firm selection. This study adds to this stream of literature by showing that peer selection does matter in IPO price setting process.

The remainder of this paper proceeds as follows. Section 3.2 motivates the setting and develops hypotheses. Section 3.3 describes the research design. Section 3.4 presents data and sample selection. Section 3.5 reports empirical tests and the results. Section 3.6 concludes.

3.2 Background and hypothesis development

3.2.1 Background

The goal of this study is to investigate if IPO firms select peers on the basis of information externalities and to facilitate their price setting process. Conducting a successful initial public offering brings numerous benefits for a private firm, such as access to a large pool of capital, lower financing costs, market recognition, and greater visibility among suppliers, customers and talent (e.g., Butler et al., 2017; Kutsuna et al., 2016; Chemmanur and He, 2011; Hsu et al., 2010). However, one of the most challenging issues faced by every IPO firm is stock market valuation. As private firms are not required to make public disclosures before their initial public offering, it is extremely difficult for potential investors to forecast the firms' future cash flows and to ascertain a fair value for the IPO firm. Both IPO firms and the investment community have made their own attempt to address this issue.

Prior literature documents that investment banks often use comparable firm multiples together with financial information analysis to value IPO firms (Paleari et al., 2014; Roosenboom, 2012; Kim and Ritter, 1999). They start out by screening for public companies that operate in the same sector and have operating models similar to the IPO firm, with the assumption that comparable firms tend to be valued with relative consistency by the capital market. Then they identify key industry-specific operating metrics such as number of subscribers, number of scientists, or traditional operating metrics like revenues, EBITDA, or net income to derive market value multiples. Once calculated, they apply the multiple to the IPO firm's metrics with adjustments to derive the IPO firm's value. In terms of which comparable firms to choose, the real-life Renaissance capital case documented in Kim and Ritter (1999) suggests that investment firms tend to choose comparable firms based on peer firms identified in the registration statement as direct competitors of the IPO firm. Of course, notably, underwriters have strategic incentives to choose comparable firms in a manner that help rationalize their valuation of the IPO firms while simultaneously presenting IPO firms as undervalued to attract investors' attention. However, for potential investors who consider buying into the shares, peer firms identified as major competitors are expected to be the most comparable in terms of the extensive amount of public information which they indirectly provide about the IPO firm's future prospects.

As to the IPO firms, prior studies show that IPO firms can lower uncertainty through content disclosure in their prospectus (Crain et al., 2017; Leone et al., 2007; Loughran and McDonald, 2013). For instance, IPO firms tend to discuss more about their competitive environment when there is greater uncertainty about firm value (Crain et al., 2017). And IPO firms providing specific use-of-proceeds disclosures experience less underpricing, as higher-level specificity lowers the information uncertainty and assists investors in obtaining a more accurate price estimate (Leone et al., 2017). Except for prospectus disclosures, IPO firms can also adjust investors' perception through CEO's presentations on the roadshows. The value of the shares is positively related to investors' perception of the management, and this relation is more pronounced as more uncertain language is used in prospectus disclosures (Blankespoor et al., 2017). Such evidence suggests that IPO firms have incentives to disclose information in a manner that mitigates uncertainty. Considering that investors base their selection of comparable firms on IPO firms' peer choice and that IPO firms have strong incentives to bridge the information gap, it is worth examining whether IPO firms take advantage of information externalities and select peers with high-quality information environment to reduce perceived uncertainties related to their share issue.

3.2.2 Hypothesis development

3.2.2.1 Peer information environment and IPO firms' peer firm choice

I draw on extant literature and formulate hypotheses based on the following arguments. First, information asymmetry between IPO firms and potential investors create frictions in the IPO process. For instance, Beatty and Ritter (1986) find that the underpricing of an initial public offering is positively related to the information uncertainty investors perceive of its value.

Relatedly, Rock (1986) shows that to avoid informed investors from bidding for 'mispriced' securities, IPO firms need to compensate for investors' information seeking cost and price their shares at a discount. Built up on this theoretical argument, most recent studies provide empirical evidence showing that IPO firms and underwriters can limit underpricing through more transparent and informative public disclosure. For example, they can attain a more accurate offer price and less underpricing by providing customized earnings metrics (Brown et al., 2020), specific description of proceed usage (Leone et al., 2007), or a less industry standard component in the prospectus (Hanley and Hoberg, 2010), all of which suggest that IPO firms have incentives to resolve information frictions and lower the financing costs.

The second argument underlying my hypothesis is that peer information bridges the information gap and reduces the cost of capital for IPO firms. Starting from Foster (1981), a long-standing literature on intra-industry information transfers shows that the externalities of peer disclosure have capital market effects (Han and Wild, 1990; Gleason et al., 2008; Arif and De George, 2017). To the extent that firms face similar economic forces and industry dynamics, peer disclosure is informative about other firms' future prospects, therefore, it affects their stock price, cost of capital, and investment decisions (e.g., Roychowdhury et al., 2019; Baranchuk and Rebello, 2018; Badertscher et al., 2013; Durnev and Mangen, 2009). Shroff et al. (2017) find that the externalities of peer information are time varying, with peer information playing a greater role in mitigating information asymmetry when firm information is scarce such as when there is a first debt or equity issue by a firm.

Thus, based on the above discussion, my main hypothesis is as follows:

H1: IPO firms tend to choose peers with higher quality information environment.

My predictions notwithstanding, it remains an empirical question as to whether IPO firms select peers with a higher level of information transparency. First, there is evidence that IPOs can reshape the competitive environment of an industry and cause negative implications on incumbents' product market competition (e.g., Hsu, Reed, and Rocholl, 2010; Chemmanur and He, 2011). A fiercely competitive environment then increases the competitive cost of corporate disclosure, discouraging peer firms or even some IPO firms from increasing information transparency and reducing information asymmetry (Boone et al., 2016; Guo et al., 2004). Thus, it may very well be the case that peer firms, sensing competitive threat from the upcoming initial public offering, shield proprietary information from potential rivals as well as the capital markets. It is unlikely that peer information environment would become a determinant of IPO firm's peer firm choice if peer firms choose to protect their proprietary information and maintain low corporate transparency. Second, I assume that peer information can compensate for the lack of firm information and expand the amount of information available for investors in pricing the new issuance. However, it is also conceivable that investors would compare the IPO firm on a continuous basis with its peers that have established disclosure channels and that exhibit a less uncertain information environment. The relatively higher uncertainty increases the risk premium investors request for holding the shares, thus implying that they will only accept the offering at a price discount.

3.2.2.2 Implications of peer information environment on IPO price formation and post-IPO analyst coverage

I explore whether a high-quality peer information environment facilitates IPO price formation. Prior research documents that publicly observable information is related to the changes in valuation from the initial filing price to the final offering price. On average, IPO firms with strong operating performance or more informative disclosure content experience a more positive price revision (e.g., Willenborg, Wu, and Yang, 2015; Leone et al., 2007; Hanley and Hoberg, 2010). In contrast, public information indicating higher uncertainty about the value of a firm's shares or its potential prospects is associated with downward price revision (Li and Liu, 2018; Crain et al., 2017). The lack of a transparent information environment due to the shorter history of public disclosure is a major driving force for IPO firms' high financing costs. Although IPO firms can disclose more proprietary information to lower their cost of capital, such an action may generate significant proprietary costs (Boone et al., 2016). Given IPO firms' incentive to reduce information asymmetry, extra peer information can change investors' perception about the overall uncertainty associated with the IPO firm and its industry, which could drive up market demand for the shares and then a higher offering price. I present the second hypothesis as follows:

H2: IPO firms that select peers with a higher quality information environment are more likely to have upward price revision.

We also investigate whether a better peer information environment leads to a high post-offering analyst following. Prior literature shows that firms initiating more voluntary disclosure experienced an increase in analyst following (Botosan and Harris, 2000; Healy et al., 1999; Lang and Lundholm, 1996). Analysts trade off the costs and benefits of gathering information. Under this current setting, as analysts derive high-quality information from peer firms, they incur relatively lower information gathering costs. In the meantime, they also reap the greater benefits associated with covering the newly issued IPO firms which attract a lot investor interest and with little historical coverage. Therefore, as peer information enhances the informativeness of IPO firm disclosure and complements analysts' private information in their decision on earnings forecast and stock recommendations about the IPO firm, we should expect to observe a higher analyst following (Giraldo, 2011). Moreover, higher analyst following is also associated with firms with more trading volume (Alford and Berger, 1999; O'Brien and Bhushan, 1990). As potential investors acquire and trade on extra information coming from peer firms, analysts may also feel incentivized to initiate coverage to earn higher trading commissions. We present our third hypothesis as follows:

H3: IPO firms that select peers with a higher quality information environment are more likely to experience higher analyst following immediately after the initial public offering.

3.3 Research design

3.3.1 Identification of peers

3.3.1.1 Model

I use a unique hand-collected data set to examine the IPO firms' peer firm choice. The goal of my investigation is the possible relation between peer information environment and peer firm choice. Therefore, in the logit specification, I test for the effect of peer information environment after controlling for numerous factors that could potentially determine the peer firm choice.

$$PeerIdentify_{i,k}=\beta_0+\beta_1 PeerInfo_{i,k}+\beta_m Controls_{i,k}+\varepsilon_{i.k} \qquad [1]$$

In model 1, $PeerIdentify_{i,k}$ is an indicator variable that equals one if firm k is identified by an IPO firm i in its initial registration statement as a direct peer and zero otherwise. The treatment sample for this test includes peers identified by IPO firms in their registration statements. To estimate the model, I require a sample of control firms that are not identified by IPO firms. Following De Franco et al (2015), I randomly match each selected peer k with a firm with available data from the universe of COMPUSTAT in the same two-digit industry as the IPO firm i but which is not identified as a peer by the IPO firm in the registration statement. By construction, I have an equal number of identified and non-identified peers in the sample.

3.3.1.2 Peer information environment

PeerInfo refers to a peer firm's information environment. Recognizing the multiple dimensions of an information environment (Hilary, 2006; Baik et al., 2017; Balakrishnan et al., 2019), I use summary measures as well as construct a composite rank measure to capture the quality of a peer firm's information environment. I consider the following four widely used summary measures: analyst following, analyst forecast accuracy, bid-ask spread, and trading volume. I use these four measures to capture the extent of information uncertainty as well as the quality of information flows that are otherwise difficult to measure using individual disclosure channels.

I use analyst following (*AnalyFollow*) as my first proxy for information environment (Shroff et al., 2017; Muslu et al., 2015). I measure analyst following as the natural logarithm of the number of analysts providing earnings per share estimates for the peer firm. Analysts are an important financial intermediary in capital markets. They get access to managers, form recommendation and forecasts about the firm, and convey information to investors through their research output. Higher analyst following indicates a larger quantity of information production and a wider market scrutiny over corporate disclosure, and therefore, a better information environment. Since firms with a large analyst following typically exhibit better information environment, I predict that peers with a large analyst following are more likely to be identified by IPO firms.

Analyst forecast accuracy (*AfError*) is my second proxy for information environment. Analyst forecast accuracy reflects underlying information uncertainty about a firm's financial condition. Following Balakrishnan et al. (2019), I measure analyst forecast error as the absolute value of the difference between the median analyst estimate of earnings forecasts issued immediately before the fiscal year-end and the actual earnings for that fiscal year, scaled by the price at the end of the previous year. Since large analyst forecast errors are usually associated with less transparent information environment, I predict that peers with smaller analyst forecast errors are more likely to be identified by IPO firms.

My third proxy for information environment is the bid-ask spread (*Spread*), which is widely used as an information asymmetry measure. Following Baik et al. (2017), I measure spread as the yearly mean of the difference between daily bid and ask price divided by the average of the bid and ask price. Since a smaller bid-ask spread is usually associated with a more transparent information environment, I predict that peers with smaller a bid-ask spread are more likely to be identified by IPO firms.

My fourth proxy is trading volume (*TradVol*). Prior research shows that poor transparency could lower trading volume (Miller, 2010; Leuz and Verrecchia, 2000; Diamond and Verrecchia, 1991). In other words, low trading prevents investors from extracting relevant information as to who initiates trades and thus undermines a firm's information environment. I predict that peers with higher trading volume are more likely to be selected by IPO firms. I measure trading volume as the natural logarithm of the average daily volume of stock traded over the year before the filing of the IPO initial registration statement.

Since each of these four proxies represents a unique aspect of firm's information environment, to capture the multi-dimensional property of information environment, I follow Anderson et al. (2009) and Baik et al. (2017) and create a composite index of information environment (*Info_rank*) based on the above four proxies. I first rank the four information environment proxies into deciles. Firms with the highest quality information environment are ranked higher with a value of 10, whereas, firms with the poorest information environment have a value of 1. I then sum the four rankings and divide the sum by 40. The final value of *Info_rank* ranges between 1 to 0.1. It is worth noting that since analyst forecast errors and bid-ask spread are inversely related to information environment, when turning the value of these two measures into a ranking number, I specify that firms with the highest value of analyst forecast errors and bid-ask spread are ranked lowest in information environment. Therefore, the composite measure, *Info_rank*, captures the four different dimensions of information environment, and is predicted to be positively related to the dependent variable, *PeerIdentify*.

3.3.1.3 Control variables and cross-sectional factors

Control is a set of control variables expected to influence IPO firms' peer choice. To the best of my knowledge, no prior studies have specifically examined an IPO firm's peer choice. But based on Kim and Ritter's (1999) observation that investment firms sometimes choose comparable firms from those peers identified in the prospectus, IPO firms aiming to achieve a higher valuation are more likely to identify peers with higher valuation multiples because it gives the impression that the IPO firm is highly discounted and therefore becomes attractive to potential investors (Paleari et al., 2014). This observation is also confirmed by my interview with a portfolio manager who suggests that IPO firms have incentives to show their relatively low valuation and high growth potential compared to other large publicly traded incumbents. Therefore, firm size, profitability, and growth potential are likely to be the determinants of IPO firms' peer choice. *Size* is the natural logarithm of total assets measured at the year-end immediately preceding the filing date (year t-1) of initial registration statement. *Leverage* is total long-term debt divided by total assets at the end of year t-1. *Cash* is the natural logarithm of total cash and cash equivalent at the end of year t-1. *AssetTurover* is total revenue divided by total assets in year t-1. Profitability is earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total revenues in year t-1. *ROA* is measured as income before extraordinary items divided by total assets in year t-1. *Logprice* is the natural logarithm of stock price at the end of year t-1. *MTB* is the market value of assets divided by book value of assets. Market value of assets is defined as the book value of assets minus book value of equity plus the market value of equity.

I examine whether IPO firms have incentives to identify peers with high-quality information environment and make use of the externalities of such information transparency to facilitate the IPO process. Therefore, the strength of the relation between peer information environment and peer firm choice should vary with IPO firms' own information environment. For instance, if an IPO firm has existed for a long time and is very well-known to the public, then I expect that the firm is likely to be perceived as more transparent to potential investors. However, since IPO firms do not need to disclose publicly prior to its initial public offering, it is difficult to evaluate IPO firms' information environment using the above-mentioned measures such as analyst following or forecast accuracy.

Therefore, motivated by prior studies on IPO firms' informational attributes and its implications (Kim and Ritter, 1999; Boone et al., 2016; Leone et al., 2007, Loughran and Ritter, 2004), I put forward five indicator variables to further substantiate the relation between IPO firms' information needs and their peer choice. These cross-sectional variables are *Young*, *VC_backing*, *Specific*, *Underwriter,* and *Biotech*. *Young* has a value of one if the IPO firm's age at the time of their initial public offering is below the sample median and zero otherwise. *VC_Backing* equals one if the IPO firm is backed by a venture capitalist and zero otherwise. *Specific* is an indicator variable proxy for the specificity of IPO firms' disclosure of their use of proceeds. Although SEC mandates the disclosure of intended use of proceeds in the IPO registration statement, an IPO firm can decide on its own the extent of specificity of such disclosure. Firms trying to reduce the uncertainty related to the IPO pricing may disclose in more detail how they want to use proceeds, such as for “Investment” or “Research and product development”, otherwise they would often put in words as “general corporation purposes”. As documented in Leone et al (2007), greater use-of-proceeds disclosure specificity reduces the information asymmetry and resolves the ex-ante uncertainty about the value of the IPO firm. I define *Specific* using a ready-to-use data item from SDC, if the data item “primary use of proceeds” in SDC has a value other than a “general corporation purposes”, then *Specific* equals one and zero otherwise. *Underwriter* is defined based on the highest ranking of lead underwriters for an IPO firm. Underwriters classified as having high prestige have a ranking of 8 or above, otherwise, they belong to the low prestige group.

Except for IPO firms’ informational attribute, the proprietary cost of peer firm disclosure could also affect the strength of the relation between peer information environment and IPO firms’ peer choice. For firms in certain industries, the proprietary cost could be too high to justify a truly transparent information environment, which means that IPO firms are not likely to gain a lot of benefits from the ripple effects of identified peers’ information transparency. Motivated by Guo et al. (2004), who argue that the biotech industry is characterized by fierce competition and high disclosure cost, I include an indicator variable *Biotech* which equals one if the IPO firm is in the biotech industry to proxy for the level of proprietary cost arising from disclosure.

3.3.2 IPO price formation process and post-offering analyst following

Next, I test whether the peer information environment affects the IPO price formation process using the following model:

$$OfferPrice\_up/down_i=\gamma_0+\gamma_1 AverageInfo\_rank_i+\gamma_m Controls_i+\varepsilon_i \qquad [2]$$

where *AverageInfo_rank* is measured at the IPO firm level and reflects the average ranking number of identified peers’ *Info_rank*. To examine the impact of peer information environment on price formation during the entire IPO process, I use signed price change to reflect the direction of changes in IPO offer price from the initial IPO filing date to the final issue date (Li and Liu, 2018). *OfferPrice_up* is an indicator variable equal to one for IPO firms that have their final offer price exceeding the mid-point of the initial filing price range and zero otherwise. Similarly, *OfferPrice_down* equals one if the IPO firm's offering price is lower than what has been proposed on the initial filing date. I control for some financial factors that are shown to influence IPO price formation, such as the IPO firm's size, leverage, amount of cash, and return of assets (Lee and Masulis, 2009; Benveniste et al., 2003). These variables are measured at the end of the year immediately preceding the IPO firm's initial registration filing, and they are similarly defined to those employed in model [1]. I further control for the four cross-sectional factors mentioned above as these relate to the IPO firm's information environment. Except for the direction of price change, the number of amendments (*Namend*) that IPO firms file to the initial registration statements also reflects the IPO price formation process, the greater the number the more efforts and time IPO firms take in order to go public (Li and Liu, 2018). Therefore, I also provide additional evidence through replacing *OfferPrice_up/down* with *Namend* in model [2]. Note that all variables used in the study are defined in the Appendix A.

And then I test whether the peer information environment affects the post-IPO analyst following using the following model:

$$AnalyCoverage_i = \eta_0 + \eta_1 AverageInfo\_rank_i + \eta_m Controls_i + \varepsilon_i \qquad [3]$$

The independent and control variables are the same as those included in model [2]. The dependent variable *AnalyCoverage* is defined as the number of analysts who issue earnings forecasts immediately after the IPO offering date.

3.4 Data, sample selection, and descriptive statistics

I collect a total of 1,612 IPO events from 2001-2017 from SDC. The initial IPO sample selection criteria are in line with what is presented in Chapter 2. To extract information of identified peers, I focus on an IPO firm's initial registration statement as opposed to its final prospectus because IPO firms' description of their industry peers is rarely changed. Since the timing of filing the initial registration statement and being identified as an industry peer is largely out of the control of the peer firm, by focusing on this initial registration statement, I address the concern that the relation I observe between peer information environment and peer firm choice could be driven by reverse causality. Namely, some peer firms adjust their corporate disclosure to attract IPO firms' attention and get identified by them. This restriction, coupled with the criteria of non-missing date for initial registration statement and withdrawal announcement, further reduces the sample size to 1,135 IPO events.

I read each of the 1,135 initial registration statements and hand-collect the name of every identified peer from the "Competition" section. I then link these extracted firm names with COMPUSTAT records. After this procedure, I identify a total of 4,585 public peer instances, which relate to 897 IPO cases. For each peer identified in IPO firms' initial registration statement, I collect financial information from CRSP and COMPUSTAT, and analyst coverage information from IBES. I also collect information for a sample of non-identified peers within the same industry as the IPO firm (based on the first two digit SIC code).[31] The sample is further reduced by the requirement of independent and control variables for the identified peers and the non-identified control group which I select through the random matching process. The final sample comprises

[31] Further robustness tests show that the tenor of the main results remains unchanged if I require the control firm and IPO firm share the first three digit or four digit SIC code.

3,359 identified peer observations and an equal number of control firm observations, which together relate to 844 IPO cases. To mitigate the influence of outliers, all continuous variables are winsorized at the top and bottom 1%. Table 1 Panel A describes the sample construction of the IPO firms and their identified peers. Panel B and C provide the year and industry composition of the IPO sample, respectively. Except for years immediately after the financial crisis, the IPO sample is pretty much evenly distributed across all sample years. Consistent with other IPO studies, technology, life science, and trade & services firms account for most IPOs.

[Insert Table 1 about here]

I compare the characteristics of identified peers and the control group generated through random matching procedure. Table 2, Panel A presents descriptive statistics for relevant firm variables. I find that identified peers and control firms are similar in terms of market to book value, asset turnover rate, and leverage. However, identified peers seem to be more profitable, bigger in size, and have a better information environment overall, consistent with observations that IPO firms tend to compare themselves with more mature firms to show their low valuation and future growth potential. As to IPO firms, after I exclude firms with unavailable data for major variables, I am left with 285 IPO firms for the implication analyses. The average IPO firm *Size* (natural logarithm of total assets) equals 3.595, which is way smaller than that for identified peers and control firms, showing that compared to established peer firms, IPO firms are usually small in size. In addition, IPO firms have higher leverage ratio, lower return on assets and lower cash holdings. Apart from financial characteristics, I notice that around 84% of the sample IPO firms are backed by venture capitalists, and around half of the sample firms are biotech firms. The mean value of *Specific*, an indicator variable showing whether an IPO firm has specific use-of-proceed disclosure, is 0.498, a percentage relatively lower than that reported in Leone et al. (2007). A likely explanation for the difference is that biotech IPOs take up a higher proportion in the sample. These firms are usually small in size, face greater industry competition and are more likely to incur high proprietary cost if they disclose detailed proceeds usage. Overall, these statistics suggest that small and privately owned firms, prior to their initial public offerings, may lack the resources to engage in effective information dissemination to reduce the uncertainties related to the value of the new share issue.

Table 2, Panel B, presents descriptive statistics for the number of peers per IPO firm identified in the initial registration statement. For the final sample of 844 IPO firms, the average firm has around 6.0 identified peers with available data to perform the analyses. It is also worth mentioning that there is a considerable variation in the number of identified peers per IPO initial registration statement. Specifically, the 25th percentile equals 4 identified peers whereas the 95th percentile equals 12 peer firms.

The correlation matrix in Table 3 shows that the pairwise correlations are not greater than 0.5, suggesting multicollinearity is not likely an issue.

[Insert Table 2, 3 about here]

3.5 Results

This section describes the empirical results of the main tests. The first subsection provides analyses of the relation between peer information environment and IPO firms' peer choice. I next report cross-sectional analyses in which I consider the effects of IPO firms' own informational attributes. I further examine the implications of peer information environment on the IPO price formation process.

3.5.1 Peer information environment and IPO firms' peer choice

3.5.1.1 Regression results

Table 4 shows the logit estimation results of model (1). *PeerInfo* in model (1) represents four summary measures (*AnalystFollow, Spread, AfError and TradVol*) and one composite measure (*Info_rank*) that proxy for peer information environment. Each of the five columns in Table 4 presents the relation between one *PeerInfo* measure and the dependent variable *PeerIdentify*. All logit regressions include control for IPO firm fixed effects and appear to be well-specified. Overall, results are consistent with hypothesis 1. In column (1), the coefficient for *AnalyFollow* is 0.371 ($p < 0.01$), which suggests that IPO firms select peers with a higher analyst following. In column (2), the coefficient for *Spread* is -19.357 ($p < 0.01$), which indicates that IPO firms select peers with a lower bid-ask spread. In column (3), the coefficient for *AfError* is also negative at -1.163 ($p < 0.05$), which implies that IPO firms select peers with smaller analyst earnings forecast errors. In column (4), the coefficient for *TradVol* is 0.289 ($p < 0.01$), which indicates that IPO firms choose peers with higher trading volume. Column (5) shows results of the logit regression with the composite rank measure of information environment. The coefficient for *Info_rank* is 1.66 ($p < 0.01$), which implies that IPO firms tend to choose peers with a higher quality information environment.

Regarding economic significance of the result, I find that a one standard deviation increase in the composite measure, *Info_rank*, increases the likelihood of being identified as direct industry peers by 40%. With respect to control variables, firm size, leverage, cash holdings, asset turnover rate, market to book value, and stock price are all statistically significant. The sign of these control variables is quite consistent across all five model specifications.

Although alternative explanations might exist, for instance, it is possible that the relation I observe could be due to the fundamental difference between the identified peers and non-identified control firms that are not captured in the model. I believe that the inclusion of numerous control variables, IPO firm fixed effects, as well as the use of five different proxies for information environment can address some of the concerns. Nevertheless, to provide more comfort on this issue, I further conduct a few robustness and cross-sectional tests.

[Insert Table 4 about here]

3.5.1.2 Robustness tests

I first test the sensitivity of the main regression results to the selection of sample control firms. In main regression analyses, control firms with the same first two-digit SIC code are randomly matched with identified peers. For robustness, I tighten the matching requirement by selecting control firms from the same SIC three-digit or four-digit industry as the IPO firm, and I rerun the random matching process. Panels A of Table 5 presents the results of the analyses with the three-digit matching procedure while Panel B of Table shows results of the analyses with the four-digit matching procedure. Across almost every specification in Panels A and B, the coefficient of the proxy for information environment is significantly different from zero and with the same sign as in the main regression analyses (the only exception is for the coefficient *AfError* in column (3) of Panel B which is negative but not statistically significant). Focusing on column (5) in each Panel, the coefficient for *Info_rank* is 1.451 ($p < 0.01$) in Panel A and 1.524 ($p < 0.01$) in Panel B, which is consistent with the hypothesis that IPO firms tend to select peers with a higher quality information environment.

Next, I consider the possibility that the relationship between the peer information environment and peer firm choice that I observe depends on the time period over which I measure independent variables. In main regression analyses, I measure the peer information environment over the year immediately prior to the filing of IPO registration statement. However, the quality of information environment is not static. Managers can increase the level of voluntary disclosure to attract investors, or they can reduce total information production to avoid market scrutiny or proprietary costs. It is highly unlikely that peer firms first successfully predict the detailed timeline of first-time issuers' public offering schedule and then adjust their information disclosure accordingly to present themselves as an established and competitive peer to the IPO firm. However, to rule out such a possibility and ensure the robustness of the measurement of independent variables, I compute independent variables as the three-year average as opposed to over only one year right before the filing of initial registration statement. Panel C presents results from this analysis. I find that the relationship between IPO firm's peer choice and peer information environment remains qualitatively unchanged.

[Insert Table 5 about here]

3.5.2 Cross-sectional analysis: IPO firms' information attributes and competitive disclosure costs

Table 6 presents the results of the cross-sectional analyses. Panel A tabulates the results relating to the IPO firm's information attributes, proxied by IPO firms' age, venture capitalist backing, the specificity of its use-of-proceed description, and the lead underwriter's prestige. For ease of exposition, I only present results using the composite information environment measure — *Info_rank*. IPO firms that are younger (1.826 > 1.402, P=0.070), without venture capital backing (2.757 > 1.240, P=0.001), disclose only general information about their proceeds usage (1.805 > 1.471, P=0.032), and are underwritten by investment banks of low prestige (1.945>1.538, P=0.021) tend to select peers with a higher quality information environment than their counterparts that are older, with venture capital backing, specific disclosure and highly ranked lead underwriters. These results are consistent with the evidence provided in Shroff et al. (2017), who show that the effects of peer information are more important when the amount of firm information is much more limited.

In untabulated analyses, I find that for IPO firms that initially exhibit a higher quality information environment, a one standard deviation increase in peer *Info_rank* translates into an approximate 30%-39% increase in likelihood that firm k is identified as a peer. Whereas, for IPO firms with lower quality firm information, a standard deviation increase in peer *Info_rank* leads to 43%-66% change in the likelihood that peer firm k is identified. I conclude that IPO firms are more likely to identify peers with high-quality information environment when they have relatively limited firm information and therefore are more likely to benefit more from peer firm disclosure.

Panel B shows the results of tests that examine whether the relation between peer information environment and IPO firms' peer choice is mitigated by proprietary cost concerns. As the biotech industry is widely regarded as a very competitive industry characterized by high disclosure costs and high level of survival threat posed by new entrants, I classified sample firms into biotech and non-biotech firms. The coefficients of four *PeerInfo* variables as well as for the summary indicator *Info_ran*k are not significant for firms in the biotech industry. In comparison, for non-biotech IPOs, the coefficients for the four *PeerInfo* proxy variables are statistically significant in the hypothesized direction, as is the coefficient for *Info_rank*. The chow test results show that the difference in coefficient for each information environment measure across biotech and non-biotech firms are statistically significant, suggesting that peer information becomes less important in IPO firm's peer choice as proprietary concern rises and negatively affect the extent of information conveyed by the peer firms.

Taken together, cross-sectional analyses provide further support for the main regression analysis—that is, IPO firms' peer choice is more likely to be driven by the quality of peer information if IPO firms can benefit from such peer effects. Specifically, IPO firms that are low in their firm information production and those that can count on a more transparent peer disclosure are more likely to choose peers with higher quality information environment.

[Insert Table 6 about here]

3.5.3 Peer information environment and IPO price formation

The uncertainty surrounding an IPO valuation increases the information risk and potentially discourages investors from purchasing the newly issued shares (Merton, 1987). To boost market demand, IPO firms may revise the estimated issue price downward and thus charge a lower offering price. However, by doing so, their cost of capital financing increases. What I have documented so far provides evidence that private firms with a poor information environment and that lack disclosure channels can opt for an alternative approach, i.e., capitalize on the externalities of selected peers' information environment, thus enhancing their own information environment. In doing so, such IPO firms can assist investors to better evaluate their value and their industry. In this section, I investigate whether such alternative approach has real implications on the price formation process.

Table 7 shows the results of these analyses. In Panel A, I compare the effects of average peer information environment on IPO firms' price revision across identified peers and non-identified control firms. I find that identified peers' high-quality information environment leads to an upward offering price revision by the IPO firm, evidenced by the significantly positive coefficient of *Info_rank* in column (1) (0.506; $p < 0.01$). Such effect is asymmetric, as results in column (2) show that peer information is not highly associated with downward offering price revision. To explore whether these results are driven by some mechanical relations, I test the same model on non-identified control firms. I find that for IPO firms, the information environment of non-identified control firms does not matter to their IPO price formation. This result is largely expected. Since these firms are not intentionally identified by IPO firms in their registration statement, the transparency of their disclosure is not expected to have externalities on the IPO firms' price formation.

I also explore how peer information relates to the attempts IPO firms make in conveying additional information through amendments. IPO firms usually make several amendment filings to the initial registration statement. As one Reuters reporter commented on the amended IPO filings, "they fill in critical details on the pricing of the offering, which shows how much interest the IPO is garnering among the investing public".[32] The number of amendments reflects IPO firms' efforts in narrowing the information gap between managers and investors (Li and Liu, 2018; Bradley and Jordan, 2002). If peer information can act as a substitute for IPO firm information, then I expect high-quality peer information to lower the number of IPO amendment filings. As shown in Panel B, the coefficient for *Info_rank* is significantly negative in both columns (1) (-1.860; $p < 0.10$), suggesting that identified peers' information transparency has spillover effects that reduce information asymmetry between managers and investors during the IPO process. Similar to price revision, this peer effect on the number of amendment filings is not significant for non-identified control firms. The chow test statistics formally show that identified peer's information environment has significant impact on IPO firms' price formation, and the same effect is not found on non-identified control firms.

[32] This comment is from the book "Show me the money: Writing business and Economics stories for mass communication" where Reuter reporter Karey Wutkowki offered tips to readers on SEC filings.

It is worth noting that the final sample size of the analyses in this part is relatively small due to the data availability issue for some IPO sample firms.

[Insert Table 7 about here]

3.5.4 Peer information environment and post-IPO analyst coverage

An enhanced information environment is often associated with added analyst coverage (Fernandes and Ferreira, 2008; Frankel and Li, 2004). On the one hand, analysts need more reliable information to help them make earnings forecasts or issue stock recommendations. On the other hand, as investors gather more information from peer disclosure to complement the limited amount of information they have about the IPO firm, they are more likely to get into active trading activities. Firms with higher trading volume often receive more analyst coverage (Bradley et al., 2006), as one main source of revenue for analysts is trading commissions. Therefore, it is worth examining whether peer information environment leads to substantial analyst coverage in the post-offering period.

Table 8 shows the results of this analysis. I compare the effects of average peer information environment on post-offering analyst coverage for IPO firms across identified peers and non-identified control firms. I find that identified peers' high-quality information environment leads to a more substantial analyst coverage immediately after the IPO offering. The coefficient is significantly positive for the composite measure *Avg_Info_rank* (4.219; $p<0.01$) and for the other three individual information environment proxies. However, the effect is much weaker for non-identified control firms. Together, these results suggest that identified peers' disclosed information can enhance IPO firm's information environment, leading to a higher analyst following.

[Insert Table 8 about here]

3.6 Conclusion

In this paper, I study whether peer information environment affects IPO firms' peer choice and its implications on the IPO process. I predict that IPO firms tend to choose peers with a high-quality information environment, and that peer information facilitates price formation. Using a unique hand-collected data set of IPO firms' identified peers, I test which peers IPO firms identify in their initial registration statement. By doing so, my analyses focus on IPO firms' attempt in utilizing peer information to make up for scarce firm information when they issue public capital for the first time.

I find that IPO firms identify peers with a better information environment. Further, this peer effect becomes more important when IPO firms themselves have scarcer firm information and when peer information is more forthcoming. Specifically, I find that IPO firms that are younger, not backed by venture capitalists, or not specific in disclosing their proceeds usage focus on the peer information environment more in their peer choice. Plus, such effect is also more pronounced for non-biotech IPO firms. I next investigate whether peer information has real implications on the IPO process. Results show that high-quality peer information is associated with upward offering price revision and reduces the IPO firms' amendment filings. In summary, the evidence suggests that there is an improvement in IPO firms' information environment if IPO firms take advantage of the externalities of transparent peer information. I acknowledge that I cannot completely rule out alternative explanations. For instance, unobserved firm characteristics that influence IPO firms' peer choice are not fully controlled for in my models. It is also possible that IPO firms' peer choice is mainly driven by their incentives to present themselves as having more growth opportunities in comparison with highly-established and mature industry players, and these industry players normally have longer disclosure history and are widely covered by financial intermediaries and the public media. Moreover, facing greater competitive threats from an IPO firm, identified peers might take advantage of the quiet period regulation to influence investors' perception about the IPO firm, essentially leaving the firm more vulnerable rather than more attractive. These findings should be interpreted with such limitations in mind.

These findings contribute to the literature on the externalities of corporate disclosure (Shroff et al., 2017; Leuz and Wysocki, 2016). Although numerous studies document the relation between IPO firms' information dissemination and cost of capital financing, none of them examine how can IPO firms actively use peer information to make up for the lack of firm information at the time of their capital issuance. To the best of my knowledge, This is the first study to provide empirical evidence that by identifying peers with high-quality information environment, IPO firms can tap into the externalities of peers' information transparency to facilitate price formation and speed up the filing process.

3.7 References, tables and appendices

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Table 1: IPO firm, identified peer and selection procedures

The IPO sample consists of 844 U.S. firms which file an initial registration statement from January 1, 2001 to December 31, 2017. The initial IPO sample is generated from the Securities Data Corporation (SDC) database, some key data used in this study is augmented and corrected using information from Nasdaq website, SEC EDGAR, and press release from Reuters and Business Wire. I exclude American Depository Receipts, reverse Leveraged buyouts, closed-end funds, limited partnerships, unit investment trusts, tracking stocks, two-tranche offerings, and simultaneous international offerings, and any IPO consisting of non-common shares or with offer price less than $5. I also eliminate firms in financial and utilities industries and firms with missing date for its initial registration statement. Panel A provides details on the sample construction of the IPO sample and identified peers. Panel B provides the yearly distribution of the sample, based on the year of initial filing date. Panel C provides the industry composition of the sample, based on the first 2-digit SIC code.

Panel A: Sample construction of IPO firm and identified peers

Data Attribution Process	No. of IPO cases
Number of IPO events from year 2001-2017 (from SDC New Issues Database, initial IPO selection criteria follows Boone, Floros and Johnson (2016)).	1,612
Exclude:	
IPO events in financial and utility industries (SIC 4900-4999, 6000-6999)	(382)
IPO events with missing initial registration statement or the timing of the initial registration or withdraw statement is not available in EDGAR	(20)
IPO events of which the initial registration statement is earlier than January 1st 2001 in EDGAR	(20)
IPO events which are not related to the initial efforts in security registration	(55)
Total number of IPO events	1,135
The number of identified peer instances extracted with record in Compustat	4,585
The number of identified peer instances with non-missing observations	3,359
The number of IPO events corresponding to the sample of identified peers	844

Panel B: IPO sample of filing year of initial registration statement

Year of initial registration statement	Frequency	Percent pf subsample
2001	25	2.96
2002	31	3.67
2003	28	3.32
2004	81	9.60
2005	62	7.35
2006	67	7.94
2007	79	9.36
2008	33	3.91
2009	17	2.01
2010	44	5.21
2011	41	4.86
2012	19	2.25
2013	74	8.77
2014	93	11.02
2015	70	8.29
2016	42	4.98
2017	38	4.50
Total	844	100

Panel C: Industry composition of IPO sample

Industry	Frequency	Percent of subsample	Industry	Frequency	Percent of subsample
Agricultural Production	4	0.47	Trucking & Warehousing	1	0.12
Metal, Mining	2	0.24	Water Transportation	2	0.24
Coal Mining	1	0.12	Transportation by Air	2	0.24
Oil & Gas Extraction	11	1.30	Transportation Services	3	0.36
General Building Contractors	2	0.24	Communications	24	2.84
Special Trade Contractors	1	0.12	Wholesale Trade – Durable Goods	13	1.54
Food & Kindred Products	11	1.30	Wholesale Trade – Nondurable Goods	3	0.36
Tobacco Products	1	0.12	General Merchandise Stores	1	0.12
Lumber & Wood Products	1	0.12	Food Stores	2	0.24
Furniture & Fixtures	1	0.12	Apparel & Accessory Stores	4	0.47
Paper & Allied Products	3	0.36	Furniture & Homefurnishings Stores	2	0.24
Printing & Publishing	1	0.12	Eating & Drinking Places	4	0.47
Chemical & Allied Products	332	39.34	Miscellaneous Retail	16	1.90
Petroleum & Coal Products	3	0.36	Business Services	147	17.42
Rubber & Miscellaneous Plastics Products	2	0.24	Auto Repair, Services, & Parking	1	0.12
Stone, Clay, & Glass Products	1	0.12	Motion Pictures	3	0.36
Primary Metal Industries	4	0.47	Amusement & Recreation Services	3	0.36
Fabricated Metal Products	4	0.47	Health Services	22	2.61
Industrial Machinery & Equipment	31	3.67	Educational Services	1	0.12
Electronic & Other Electric Equipment	56	6.64	Engineering & Management Services	10	1.18
Transportation Equipment	8	0.95			
Instruments & Related Products	98	11.61			
Miscellaneous Manufacturing Industries	2	0.24			
Total	844	100			

Table 2: Descriptive statistics

Panel A: Firm characteristics

Variables	N	Mean	SD	P25	P50	P75
Characteristics of Identified peers:						
Logprice	3,359	3.436	1.051	2.939	3.623	4.074
MTB	3,359	2.516	1.804	1.322	2.020	3.132
ROA	3,359	-0.004	0.225	0.005	0.056	0.101
Profitability	3,359	-1.642	14.380	0.075	0.228	0.318
AssetTurnover	3,359	0.699	0.550	0.400	0.583	0.847
Cash	3,359	7.018	2.247	5.253	7.259	8.852
Leverage	3,359	0.169	0.163	0.035	0.143	0.241
Size	3,359	8.803	2.465	6.914	9.415	10.867
AnalyFollow	3,359	2.393	0.923	1.792	2.708	3.091
Spread	3,359	0.002	0.005	0.000	0.001	0.002
TradVol	3,359	14.450	1.689	13.374	14.525	15.631
AfError	3,359	0.008	0.041	0.000	0.001	0.004
Info_rank	3,359	0.664	0.211	0.525	0.700	0.850
Characteristics of Control firms:						
Logprice	3,359	2.467	1.326	1.571	2.676	3.467
MTB	3,359	2.591	2.052	1.293	1.899	3.074
ROA	3,359	-0.139	0.362	-0.231	0.014	0.072
Profitability	3,359	-4.835	23.758	-0.121	0.091	0.197
AssetTurnover	3,359	0.765	0.667	0.318	0.633	1.021
Cash	3,359	4.295	1.950	3.089	4.239	5.507
Leverage	3,359	0.161	0.210	0.000	0.073	0.264
Size	3,359	5.983	2.117	4.410	5.784	7.359
AnalyFollow	3,359	1.441	0.990	0.693	1.386	2.197
Spread	3,359	0.007	0.011	0.001	0.003	0.008
TradVol	3,359	12.582	1.558	11.583	12.598	13.615
AfError	3,359	0.029	0.084	0.001	0.004	0.015
Info_rank	3,359	0.427	0.209	0.250	0.400	0.575

Characteristics of IPO firms:						
Implication analyses						
Size	285	3.595	1.603	2.948	3.734	4.408
Leverage	285	0.297	0.926	0.000	0.037	0.278
Cash	285	2.703	1.675	2.161	2.948	3.738
ROA	285	-1.072	2.465	-0.987	-0.432	-0.142
AvgInfo_rank	285	0.707	0.143	0.625	0.718	0.809
OfferPrice_up	285	0.291	0.455	0.000	0.000	1.000
OfferPrice_down	285	0.361	0.481	0.000	0.000	1.000
Amendment	284	4.018	2.525	2.000	4.000	5.000
ln(AnalyCoverage)	385	1.631	0.558	1.386	1.609	1.946
Cross-sectional factors						
Age	558	20.547	17.046	13.000	18.000	22.000
VC_back	551	0.760	0.427	1.000	1.000	1.000
Specific	596	0.411	0.492	0.000	0.000	1.000
Underwriter	836	7.818	1.842	7.500	8.750	9.000
BioTech	844	0.383	0.486	0.000	0.000	1.000

Panel B: Number of identified peers per IPO registration statement

Mean	SD	Percentiles						
		1st	5th	25th	Median	75th	95th	99th
6.0	3.5	1.0	2.0	4.0	5.0	8.0	12.0	17.0

Table 3: Correlation Matrix

This table shows the correlation matrix of variables in main regression analysis. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	PeerIdentify	1.000													
(2)	AnalyFollow	0.445***	1.000												
(3)	AfError	-0.151***	-0.314***	1.000											
(4)	TradVol	0.498***	0.760***	-0.169***	1.000										
(5)	Spread	-0.272***	-0.540***	0.391***	-0.515***	1.000									
(6)	Info_rank	0.492***	0.895***	-0.342***	0.839***	-0.596***	1.000								
(7)	Size	0.523***	0.657***	-0.26***	0.723***	-0.488***	0.776***	1.000							
(8)	Leverage	0.021*	0.114***	-0.007	0.131***	-0.066***	0.106***	0.173***	1.000						
(9)	Cash	0.543***	0.665***	-0.243***	0.765***	-0.515***	0.771***	0.889***	0.048***	1.000					
(10)	AssetTurnover	-0.054***	-0.040***	-0.048***	-0.142***	0.073***	-0.048***	0.022*	-0.070***	-0.132***	1.000				
(11)	Profitability	0.081***	0.131***	-0.098***	0.079***	-0.103***	0.147***	0.222***	0.061***	0.144***	0.199***	1.000			
(12)	ROA	0.220***	0.388***	-0.322***	0.245***	-0.384***	0.447***	0.565***	-0.008	0.435***	0.303***	0.378***	1.000		
(13)	MTB	-0.019	0.096***	-0.036***	0.058***	-0.064***	0.069***	-0.282***	-0.045***	-0.113***	-0.116***	-0.169***	-0.278***	1.000	
(14)	Logprice	0.375***	0.601***	-0.360***	0.396***	-0.586***	0.682***	0.702***	0.044***	0.640***	0.088***	0.203***	0.628***	0.078***	1.000

Table 4: Peer information environment and IPO firms' peer choice

This table presents the results from examining the effects of peer information environment on IPO firms' peer choice. PeerIdentify is an indicator variable equal to one (zero) if the firm is identified as a direct competitor in an IPO firm's initial registration statement (control firm). Identified peers are hand-collected from IPO firms' initial registration statement and are randomly matched to non-identified industry peers which share the same first two-digit SIC code with the IPO firm. All variables are defined in the Variable Appendix. All specifications include IPO firm fixed effects. The T value are reported below the coefficient estimates in parentheses and are calculated based on standard error clustered by industry. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**PeerIdentify**	**PeerIdentify**	**PeerIdentify**	**PeerIdentify**	**PeerIdentify**
PeerInfo					
AnalyFollow	0.317***				
	(7.140)				
Spread		-19.357***			
		(-2.939)			
AfError			-1.163**		
			(-1.977)		
TradVol				0.289***	
				(9.025)	
Info_rank					1.660***
					(6.728)
Size	0.307***	0.357***	0.351***	0.201***	0.264***
	(8.154)	(9.591)	(9.502)	(4.937)	(6.754)
Leverage	-0.824***	-0.769***	-0.718***	-0.811***	-0.758***
	(-4.628)	(-4.350)	(-4.085)	(-4.545)	(-4.280)
Cash	0.359***	0.377***	0.390***	0.319***	0.363***
	(10.080)	(10.599)	(11.080)	(8.802)	(10.206)
AssetTurnover	-0.164**	-0.186***	-0.196***	-0.146**	-0.161**
	(-2.271)	(-2.606)	(-2.764)	(-2.015)	(-2.240)
Profitability	0.001	0.001	0.002	0.001	0.001
	(0.829)	(0.899)	(0.912)	(0.785)	(0.870)
ROA	-0.833***	-0.867***	-0.833***	-0.840***	-0.863***
	(-5.161)	(-5.322)	(-5.169)	(-5.210)	(-5.372)
MTB	0.114***	0.149***	0.151***	0.059**	0.101***
	(5.242)	(7.158)	(7.272)	(2.516)	(4.536)
Logprice	-0.118**	-0.120**	-0.090*	0.093*	-0.109**
	(-2.518)	(-2.476)	(-1.932)	(1.845)	(-2.351)
Observations	6,718	6,718	6,718	6,718	6,718
Number of id_ipo	844	844	844	844	844
IPO_Firm FE	YES	YES	YES	YES	YES
Pseudo R^2	0.356	0.351	0.350	0.361	0.355
Prob>chi2	0.000	0.000	0.000	0.000	0.000

Table 5: Robustness tests

This table presents the results of robustness tests where I examine the sensitivity of our main regression results to the selection of control firms and the way I measure independent variables. In Panel A (B), I randomly match control firms in the same SIC three (four)-digit industry as the IPO firm. In Panel C, I measure independent variable as the average information environment over three years preceding the filing of IPO registration statement. All variables are defined in the Variable Appendix. All specifications include IPO firm fixed effects. The T value are reported below the coefficient estimates in parentheses and are calculated based on standard error clustered by industry. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Randomly match control firms in the same SIC three-digit industry as the IPO firm

VARIABLES	(1) **PeerIdentify**	(2) **PeerIdentify**	(3) **PeerIdentify**	(4) **PeerIdentify**	(5) **PeerIdentify**
PeerInfo					
AnalyFollow	0.331***				
	(7.196)				
Spread		-18.768***			
		(-2.883)			
AfError			-0.967*		
			(-1.717)		
TradVol				0.251***	
				(7.635)	
Info_rank					1.451***
					(5.587)
Size	0.460***	0.515***	0.510***	0.381***	0.433***
	(11.408)	(12.930)	(12.860)	(8.809)	(10.344)
Leverage	-0.605***	-0.540***	-0.484***	-0.621***	-0.548***
	(-3.353)	(-3.003)	(-2.709)	(-3.426)	(-3.047)
Cash	0.193***	0.213***	0.227***	0.161***	0.203***
	(4.912)	(5.447)	(5.845)	(4.022)	(5.188)
AssetTurnover	0.181**	0.162**	0.143*	0.199**	0.169**
	(2.250)	(2.025)	(1.801)	(2.478)	(2.109)
Profitability	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.243)	(-0.212)	(-0.328)	(-0.175)	(-0.166)
ROA	-0.697***	-0.722***	-0.702***	-0.704***	-0.721***
	(-4.698)	(-4.836)	(-4.728)	(-4.770)	(-4.889)
MTB	0.060***	0.092***	0.094***	0.026	0.060***
	(2.915)	(4.646)	(4.768)	(1.188)	(2.837)
Logprice	-0.076	-0.081*	-0.048	0.107**	-0.065
	(-1.599)	(-1.660)	(-1.022)	(2.085)	(-1.373)
Observations	6,626	6,626	6,626	6,626	6,626
Number of id_ipo	832	832	832	832	832
IPO_Firm FE	YES	YES	YES	YES	YES
Pseudo R^2	0.383	0.377	0.376	0.384	0.380
Prob>chi2	0.000	0.000	0.000	0.000	0.000

Panel B: Randomly match control firms in the same SIC four-digit industry as the IPO firm

VARIABLES	(1) PeerIdentify	(2) PeerIdentify	(3) PeerIdentify	(4) PeerIdentify	(5) PeerIdentify
PeerInfo					
AnalyFollow	0.287***				
	(5.718)				
Spread		-26.249***			
		(-3.483)			
AfError			-0.031		
			(-0.055)		
TradVol				0.255***	
				(7.337)	
Info_rank					1.524***
					(5.442)
Size	0.541***	0.588***	0.582***	0.447***	0.502***
	(12.453)	(13.673)	(13.592)	(9.638)	(11.145)
Leverage	-0.608***	-0.574***	-0.502***	-0.627***	-0.557***
	(-3.340)	(-3.167)	(-2.788)	(-3.441)	(-3.078)
Cash	0.177***	0.196***	0.213***	0.149***	0.183***
	(4.164)	(4.664)	(5.106)	(3.463)	(4.317)
AssetTurnover	0.202**	0.192**	0.184**	0.217**	0.201**
	(2.258)	(2.148)	(2.071)	(2.419)	(2.253)
Profitability	0.001	0.000	0.000	0.000	0.001
	(0.417)	(0.305)	(0.232)	(0.315)	(0.378)
ROA	-0.534***	-0.604***	-0.536***	-0.555***	-0.566***
	(-3.337)	(-3.742)	(-3.370)	(-3.491)	(-3.562)
MTB	0.062***	0.087***	0.092***	0.021	0.053**
	(2.882)	(4.194)	(4.438)	(0.926)	(2.390)
Logprice	-0.113**	-0.134***	-0.080	0.075	-0.104**
	(-2.255)	(-2.584)	(-1.619)	(1.388)	(-2.099)
Observations	6,352	6,352	6,352	6,352	6,352
Number of id_ipo	802	802	802	802	802
IPO_Firm FE	YES	YES	YES	YES	YES
Pseudo R-squared	0.415	0.412	0.410	0.418	0.415
Prob>chi2	0.000	0.000	0.000	0.000	0.000

Panel C: Three-year average peer information environment

VARIABLES	(1) PeerIdentify	(2) PeerIdentify	(3) PeerIdentify	(4) PeerIdentify	(5) PeerIdentify
PeerInfo					
AnalyFollow	0.352***				
	(7.252)				
Spread		-21.618***			
		(-3.234)			
AfError			-0.755		
			(-1.262)		
TradVol				0.288***	
				(8.484)	
Info_rank					1.785***
					(6.847)
Size	0.312***	0.371***	0.365***	0.210***	0.274***
	(7.767)	(9.367)	(9.263)	(4.826)	(6.588)
Leverage	-1.092***	-0.998***	-0.946***	-1.045***	-1.004***
	(-5.443)	(-5.030)	(-4.792)	(-5.210)	(-5.033)
Cash	0.348***	0.366***	0.383***	0.310***	0.353***
	(9.132)	(9.663)	(10.229)	(8.021)	(9.293)
AssetTurnover	-0.166**	-0.187**	-0.197***	-0.153**	-0.162**
	(-2.236)	(-2.557)	(-2.700)	(-2.058)	(-2.185)
Profitability	0.000	0.000	0.000	0.001	0.000
	(0.258)	(0.341)	(0.246)	(0.453)	(0.243)
ROA	-0.991***	-0.996***	-0.944***	-1.001***	-1.037***
	(-5.905)	(-5.891)	(-5.657)	(-5.958)	(-6.192)
MTB	0.109***	0.153***	0.158***	0.058**	0.097***
	(4.730)	(7.040)	(7.294)	(2.314)	(4.090)
Logprice	-0.073	-0.085	-0.045	0.146***	-0.080
	(-1.437)	(-1.626)	(-0.883)	(2.669)	(-1.571)
Observations	6,718	6,718	6,718	6,718	6,718
Number of id_ipo	844	844	844	844	844
IPO_Firm FE	YES	YES	YES	YES	YES
Pseudo R-squared	0.359	0.353	0.352	0.361	0.358
Prob>chi2	0.000	0.000	0.000	0.000	0.000

Table 6: Cross-sectional tests

This table presents the results of cross-sectional analyses where I examine the role of two conditional factors, IPO firms' information attributes and proprietary concern within the industry in influencing the relationship between peer information environment and IPO firms' peer choice. In Panel A, I focus on the IPO firms' information attributes, proxied by firm age, venture capitalist backing, specificity of proceed related disclosure and underwriter prestige. In Panel B, I measure the level of proprietary concern using industry classification, firms that operating in bio-tech sector are assumed to be more concerned about the proprietary cost of their disclosure than other firms. Variables are defined in the Variable Appendix. All specifications include IPO firm fixed effects. The T value are reported below the coefficient estimates in parentheses and are calculated based on standard error clustered by industry. *, **, *** in the regression results indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cross-sectional tests conditional on IPO firms' information attributes

Dependent Variable: Peer_identify	**Firm age**		**Venture capital backing**		**Specificity of proceed usage**		**Underwriter Prestige**	
	Young	Old	Non_VC	VC	General	Specific	Low	High
Info_rank	1.826***	1.402***	2.757***	1.240***	1.805***	1.471***	1.945***	1.538***
	(4.031)	(3.138)	(4.141)	(3.385)	(4.602)	(3.071)	(4.062)	(5.271)
Size	0.144*	0.308***	0.273**	0.194***	0.324***	0.163**	0.152**	0.319***
	(1.937)	(4.549)	(2.458)	(3.297)	(5.190)	(2.089)	(2.054)	(6.856)
Leverage	-1.422***	-0.678**	-1.152**	-1.083***	-0.966***	-0.781**	-1.290***	-0.540***
	(-4.581)	(-2.176)	(-2.190)	(-4.372)	(-3.485)	(-2.254)	(-3.733)	(-2.583)
Cash	0.569***	0.347***	0.183**	0.558***	0.336***	0.458***	0.393***	0.344***
	(7.728)	(5.651)	(2.021)	(9.611)	(6.067)	(6.323)	(5.821)	(8.172)
AssetTurnover	-0.433***	-0.277**	-0.220	-0.429***	-0.192	-0.186	-0.137	-0.200**
	(-2.906)	(-2.115)	(-1.381)	(-3.399)	(-1.608)	(-1.341)	(-1.048)	(-2.303)
Profitability	0.000	0.004	-0.001	0.002	0.000	0.010**	-0.001	0.003
	(0.214)	(1.225)	(-0.281)	(0.896)	(0.178)	(2.163)	(-0.377)	(1.406)
ROA	-0.459*	-0.832***	-0.280	-0.719***	-1.095***	-0.279	-0.838***	-0.883***
	(-1.697)	(-2.784)	(-0.663)	(-3.110)	(-4.376)	(-0.878)	(-2.853)	(-4.557)
MTB	0.102***	0.151***	0.047	0.132***	0.065*	0.162***	0.101**	0.105***
	(2.830)	(3.708)	(0.720)	(4.335)	(1.818)	(4.080)	(2.407)	(3.978)
Logprice	-0.249***	-0.107	-0.280**	-0.168**	-0.144**	-0.158*	-0.086	-0.120**
	(-3.235)	(-1.215)	(-2.399)	(-2.484)	(-1.994)	(-1.862)	(-0.986)	(-2.148)
Observations	2,404	2,048	890	3,462	2,852	1,914	1,780	4,884
NO. id_ipo	291	267	132	419	351	245	232	604
IPO_Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.402	0.354	0.287	0.404	0.369	0.356	0.310	0.377
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Chow Test for the equality of coefficients:

Cross-sectional	Young-Old	NonVC-VC	General-Specific	Low-High prestige
Chi2	15.840*	27.800***	18.300**	19.490**
Prob>chi2	0.070	0.001	0.032	0.0213
Chi2(10)	44.030	37.750	13.640	27.020***
Prob>chi2	0.000	0.000	0.189	0.0026

Panel B: Cross-sectional tests conditional on the disclosure cost of the IPO firm industry

Dependent Variable: Peer_identify	(1) **Nonbio**	(2) **Bio**	(3) **Nonbio**	(4) **Bio**	(7) **Nonbio**	(8) **Bio**	(5) **Nonbio**	(6) **Bio**	(9) **Nonbio**	(10) **Bio**
AnalyFollow	0.444***	0.099								
	(7.252)	(1.452)								
Spread			-35.819***	8.500						
			(-3.698)	(0.937)						
AfError					-2.202**	-0.271				
					(-2.296)	(-0.357)				
TradVol							0.412***	0.040		
							(9.621)	(0.772)		
Info_rank									2.622***	0.317
									(7.728)	(0.837)
Size	0.445***	0.178***	0.540***	0.181***	0.540***	0.186***	0.290***	0.165**	0.390***	0.169***
	(8.300)	(2.880)	(10.358)	(2.938)	(10.408)	(3.018)	(4.997)	(2.479)	(7.045)	(2.608)
Leverage	-0.454	-1.004***	-0.470*	-0.925***	-0.409	-0.956***	-0.378	-0.982***	-0.338	-0.978***
	(-1.623)	(-4.197)	(-1.699)	(-3.884)	(-1.486)	(-4.047)	(-1.337)	(-4.108)	(-1.205)	(-4.107)
Cash	0.197***	0.580***	0.205***	0.605***	0.220***	0.595***	0.148***	0.584***	0.195***	0.588***
	(4.441)	(8.490)	(4.683)	(8.831)	(5.049)	(8.791)	(3.278)	(8.452)	(4.395)	(8.643)
AssetTurnover	0.206**	-1.054***	0.174**	-1.080***	0.165**	-1.069***	0.210**	-1.050***	0.225***	-1.059***
	(2.400)	(-6.033)	(2.059)	(-6.183)	(1.963)	(-6.126)	(2.435)	(-5.957)	(2.604)	(-6.059)
Profitability	-0.007	0.003*	-0.008	0.003*	-0.008	0.003*	-0.006	0.003*	-0.007	0.003*
	(-1.028)	(1.833)	(-1.187)	(1.836)	(-1.190)	(1.858)	(-0.987)	(1.835)	(-1.121)	(1.855)
ROA	-0.902***	-0.359	-1.061***	-0.301	-1.004***	-0.343	-0.851***	-0.353	-0.933***	-0.354
	(-3.351)	(-1.559)	(-3.849)	(-1.300)	(-3.714)	(-1.492)	(-3.152)	(-1.534)	(-3.498)	(-1.537)
MTB	0.151***	0.116***	0.217***	0.128***	0.221***	0.126***	0.053	0.115***	0.121***	0.117***
	(4.222)	(4.030)	(6.385)	(4.591)	(6.552)	(4.506)	(1.365)	(3.631)	(3.270)	(3.927)
Logprice	-0.125*	-0.100	-0.152**	-0.074	-0.091	-0.091	0.160**	-0.062	-0.136**	-0.091
	(-1.935)	(-1.411)	(-2.265)	(-1.036)	(-1.422)	(-1.291)	(2.317)	(-0.795)	(-2.117)	(-1.289)
Observations	3,600	3,118	3,600	3,118	3,600	3,118	3,600	3,118	3,600	3,118
NO. id_ipo	521	323	521	323	521	323	521	323	521	323
IPO_Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.370	0.404	0.360	0.374	0.357	0.374	0.381	0.372	0.372	0.374
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Chow Test for the equality of coefficients:

PeerInfo	AnalyFollow	Spread	AfError	TradVol	Info_rank
	Bio-NonBio	Bio-Nonbio	Bio-Nonbio	Bio-Nonbio	Bio-Nonbio
Chi2	107.870***	111.100***	105.400***	117.580***	118.780***
Prob>chi2	0.000	0.000	0.000	0.000	0.000
Chi2(10)	113.790	118.700	117.470	123.680	121.590
Prob>chi2	0.000	0.000	0.000	0.000	0.000

Table 7: Peer information environment and IPO process

This table presents the results from examining peers' information environment on IPO price formation process. I compare the results for identified peers to those of control firms. I focus on signed price change in Panel A and the number of amendment filings in Panel B. All variables are defined in the Variable Appendix. The T value are reported below the coefficient estimates in parentheses and are calculated based on standard error clustered by industry. *, **, *** in the regression results indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Peer information environment and IPO price revision

	Identified peers		Control firms	
	(1)	(2)	(3)	(4)
Dependent Variable:	**OfferPrice_up**	**OfferPrice_down**	**OfferPrice_up**	**OfferPrice_down**
Avg_info_rank	0.506***	-0.225	0.302	-0.193
	(4.056)	(-1.179)	(1.416)	(-1.063)
Size	0.077*	-0.081*	0.069*	-0.078
	(1.952)	(-1.773)	(1.702)	(-1.633)
Leverage	-0.025	0.045	-0.032	0.049
	(-1.044)	(1.129)	(-1.656)	(1.312)
Cash	0.027	-0.024	0.035	-0.027
	(0.846)	(-0.693)	(1.112)	(-0.781)
ROA	-0.027**	0.043***	-0.029*	0.044***
	(-2.085)	(3.016)	(-1.894)	(3.200)
VC_Back	0.107	-0.061	0.112*	-0.063
	(1.633)	(-0.613)	(1.717)	(-0.640)
Biotech	-0.159***	0.093	-0.198***	0.107
	(-2.706)	(1.244)	(-3.094)	(1.294)
Age	-0.002	0.005***	-0.002	0.006***
	(-0.908)	(2.784)	(-1.382)	(3.158)
Specific	0.160***	-0.071	0.152***	-0.067
	(3.181)	(-1.082)	(2.904)	(-1.041)
Underwriter_rank	0.003	0.011	0.004	0.011
	(0.180)	(0.454)	(0.202)	(0.458)
Constant	-0.518***	0.767***	-0.259	0.679***
	(-2.943)	(3.457)	(-1.313)	(3.407)
Observations	285	285	285	285
R-squared	0.219	0.103	0.206	0.103
F test	11.870	5.173	13.725	5.930
Prob>F	0.000	0.000	0.000	0.000
Adjusted R-squared	0.190	0.071	0.177	0.070

Chow Test for the equality of coefficients:

	OfferPrice_up	OfferPrice_down
	Identified-Control	Identified-Control
F test	1.880*	0.290
Prob>F	0.0578	0.9862

Panel B: Peer information environment and the number of IPO amendments

	Identified peers (1)	Control firms (2)
Dependent Variable:	**Namends**	**Namends**
Avg_info_rank	-1.860*	-1.908
	(-1.813)	(-1.644)
Size	0.570**	0.601**
	(2.253)	(2.327)
Leverage	0.022	0.063
	(0.230)	(0.669)
Cash	-0.392**	-0.427**
	(-2.146)	(-2.308)
ROA	-0.014	-0.004
	(-0.181)	(-0.050)
VC_Back	0.563	0.542
	(1.255)	(1.112)
Biotech	-0.687*	-0.584
	(-1.724)	(-1.404)
Age	0.010	0.011
	(0.468)	(0.520)
Specific	-1.113***	-1.081***
	(-3.312)	(-3.253)
Underwriter_rank	-0.404***	-0.400***
	(-2.852)	(-2.895)
Constant	7.863***	7.289***
	(5.368)	(6.255)
Observations	284	284
R-squared	0.158	0.160
F test	4.683	5.317
Prob>F	0.000	0.000
Adjusted R-squared	0.128	0.129

Chow Test for the equality of coefficients:

	Identified-Control
F test	1.990**
Prob>F	0.043

Table 8: Peer information environment and post-IPO analyst coverage

This table presents the results from examining peers' information environment on post-IPO analyst coverage. I compare the results for identified peers to those of control firms. Analyst coverage is defined as the number of analysts issuing earnings per share forecast immediate after the IPO offering date. All variables are defined in the Variable Appendix. The T value are reported below the coefficient estimates in parentheses and are calculated based on standard error clustered by industry. *, **, *** in the regression results indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: AnalyCoverage	Identified peers					Control firms				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Avg_Info_rank	4.219***					2.704*				
	(3.745)					(1.938)				
Avg_Analyfollow		1.030***					0.490*			
		(4.111)					(1.671)			
Avg_Spread			-79.407**					-27.013		
			(-2.276)					(-1.018)		
Avg_Traddvol				0.628***					0.348*	
				(4.175)					(1.807)	
Avg_AfError					-3.706					-2.845
					(-1.186)					(-1.156)
Size	1.217***	1.236***	1.199***	1.199***	1.226***	1.206***	1.207***	1.209***	1.217***	1.223***
	(4.700)	(4.725)	(4.507)	(4.638)	(4.596)	(4.513)	(4.524)	(4.459)	(4.531)	(4.597)
Roa	-0.279**	-0.303***	-0.297**	-0.292**	-0.314**	-0.309**	-0.309**	-0.308**	-0.312**	-0.315***
	(-2.508)	(-2.626)	(-2.481)	(-2.596)	(-2.600)	(-2.617)	(-2.564)	(-2.518)	(-2.589)	(-2.666)
VC_Back	1.140*	1.206*	1.337**	1.074*	1.447**	1.478**	1.436**	1.414**	1.483**	1.487**
	(1.837)	(1.901)	(2.048)	(1.708)	(2.244)	(2.257)	(2.211)	(2.114)	(2.265)	(2.290)
Biotech	-1.607***	-1.400***	-1.899***	-1.614***	-1.882***	-1.884***	-1.872***	-1.946***	-2.043***	-1.894***
	(-5.546)	(-5.048)	(-6.143)	(-5.921)	(-6.117)	(-6.217)	(-6.201)	(-6.338)	(-6.606)	(-6.046)
Underwriter_rank	0.278**	0.281**	0.294**	0.285**	0.309**	0.303**	0.307**	0.312**	0.311**	0.308**
	(2.226)	(2.313)	(2.340)	(2.308)	(2.422)	(2.418)	(2.409)	(2.451)	(2.475)	(2.391)
Underpricing	-0.391	-0.357	-0.367	-0.453	-0.349	-0.291	-0.313	-0.345	-0.331	-0.336
	(-1.282)	(-1.189)	(-1.192)	(-1.456)	(-1.126)	(-0.938)	(-1.012)	(-1.101)	(-1.066)	(-1.072)
Constant	-4.057***	-3.999***	-1.112	-10.254***	-1.614	-2.712**	-2.275*	-1.350	-5.975**	-1.569
	(-2.774)	(-2.846)	(-0.916)	(-3.819)	(-1.382)	(-2.055)	(-1.834)	(-1.051)	(-2.336)	(-1.366)
Observations	385	385	385	385	385	385	385	385	385	385
R-squared	0.328	0.330	0.311	0.338	0.306	0.314	0.311	0.308	0.313	0.306
F test	14.471	15.588	12.933	16.486	13.419	12.381	12.619	13.240	12.742	12.225
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-squared	0.316	0.318	0.298	0.326	0.293	0.301	0.298	0.295	0.300	0.294

Chow Test for the equality of coefficients
(Comprenhensive measure peer Info_rank):

	Identified-Control
F test	1.940*
Prob>F	0.061

Variable Appendix

This table provides a detailed description of the definitions for each variable used in the analyses. The data is obtained either through COMPUSTAT, CRSP, SDC Platinum, I/B/E/S, or the EDGAR. All continuous variables are winsorized at 1% and 99% of the distribution. The variables are listed according to alphabetical order.

Variable	Definition
AfError	A variable measured as the absolute value of the difference between the median analyst estimate of forecasts issued immediately before the fiscal year-end and the actual earnings for that fiscal year, scaled by the stock price at the end of the previous year.
Age	A variable defined as the number of years from founding or incorporation.
AnalyCoverage	The number of analysts providing earnings per share estimates for the IPO firm immediately after the IPO offering date.
AnalyFollow	The number of analysts providing earnings per share estimates for a firm during the fiscal year preceding the filing date of initial registration statement.
AssetTurnover	A variable defined as total revenue divided by total assets, measured at the fiscal year-end immediately preceding the filing date of initial registration statement.
AvgInfo_rank	A variable defined as the average info_rank across all identified peers or nonidentified control firms.
Biotech	An indicator variable that equals one if the IPO firm operates in biotech industry. The biotech industry in this study consists of firms with four-digit Standard Industrial Classfication (SIC) codes 8731and 2830-2836.
Cash	A variable defined as the natural logarithm of firm's cash or cash equivalent at the fiscal year-end immediately preceding the filing date of initial registration statement.
Info_rank	A composite index of information environment, measured by ranking the four individual proxies for information environment (AnalyFollow, Spread, TradVol, and AfError) into deciles in which firms with the highest information environment have a value of 10. The four individual rankings are then summed and divided by 40. The value of this composite measure ranges from 0.1 to 1.
Leverage	The ratio of long-term debt to total assets as of the fiscal year preceding the filing date of initial registration statement.
Logprice	A variable defined as the natural logarithm of a firm's stock price, measured at the fiscal year-end immediately preceding the filing date of initial registration statement.
MTB	A variable defined as market value of a firm's assets (assets less book equity plus market value of equity) divided by the book value of the assets, measured at the fiscal year-end immediately preceding the filing date of initial registration statement.
Namend	A variable defined as the number of amendments issued to initial registration statements during the IPO waiting period.
OfferPrice_down	An indicator variable equals one if final offer price is lower than the initial file price, where initial file price is the middle high and low prices in the initial IPO filing, and zero otherwise.
OfferPrice_up	An indicator variable equals one if final offer price is higher than the initial file price, where initial file price is the middle high and low prices in the initial IPO filing, and zero otherwise.

Continued

Variable	Definition
PeerIdentify	A dummy variable equals one if a firm is an identified peer and zero otherwise.
Profitability	The ratio of earnings before interest, taxes, depreciation, and amortization to sales. It is measure as the fiscal year-end preceding the filing date of initial registration statement.
ROA	A variable defined as a firm's income before extraordinary items divided by assets, measured at the fiscal year-end immediately preceding the filing date of initial registration statement.
Size	The natural logarithm of a firm total assets as of the fiscal year preceding the filing date of initial registration statement.
Specific	An indicator variable that equals zero if the data item "Primary Use of Proceeds" in SDC contains only "General corporate purposes" and one other wise.
Spread	A variable measured as the stock's average of daily bid-ask spread computed as the ask price minus the bid price divided by the average of the bid and ask prices over the fiscal year preceding the filing date of initial registration statement.
TradVol	A variable defined as the natural logarithm of the stock's average daily trading volume over the fiscal year preceding the filing date of initial registration statement.
Underwriter	A variable defined as the highest ranking of lead underwriters for an IPO firm. The underwriter prestige rankings are on a 0 to 9 scale, and are retrieved from Jay Ritter's IPO data base.
VC_back	An indicator variable that equals one if the IPO firm is backed by venture capitalists and zero other wise.

Chapter 4: Economic Links and the Wealth Effects of Layoff Announcement along the Supply Chain

4.1 Introduction

Ever since the first wave of corporate layoff took place in 1980s, employee layoff has become an integral part of organizational life (Budros, 1999). Few firms, even if prominent market players can live through the rapidly changing global economy and product demand without experiencing the "pain" of corporate layoff. Over the past three decades, nearly all Fortune 1000 firms have been reported by Wall Street Journal to conduct permanent layoff of employees, and this phenomenon of employee downsizing has fundamentally reshaped U.S. economy. The corporate strategy also attracts substantial discussion among academics. A key focus in previous research is the antecedent and impact of the layoff announcements. Factors such as pressure from globalization and industry deregulation to those such as financial condition and governance mechanism all relate to firms' layoff decisions (Datta, Guthrie, Basuil and Pandey, 2010). In terms of the short-term stock market reaction of layoff announcement, previous research presents quite mixed results and shows that investor's sentiment to layoff news changes overtime, with the stock market reactions becoming less negative over the past several decades (Chalos and Chen, 2002; Farber and Hallock, 2009). The empirical results of long-term financial consequences of corporate layoff are inconclusive either. Although firms adopt this strategy to increase their ability to compete, not all firms manage to accomplish this goal. Firms that solely rely on employee layoff do not have better performance than the average companies (Cascio, Young and Morris, 1997). In fact, several hidden costs like being distracted from normal revenue-generating activities, low morale of survivors, employee retraining costs and damaged corporate reputation could all possibly eat up any visible cost savings from this layoff strategy and fill more uncertainties into the firm's post-layoff operation.

While numerous empirical studies exist on the reason and consequences of corporate layoff decision, the attempts of examining this decision in a broader context by studying the impact of corporate layoff on other economically linked entities are still scarce. Firms cannot operate in isolation. In current economy, information and resources transfer rapidly through interfirm linkages. The 2008 financial crisis and the most recent global trade dispute demonstrate that corporate operations are closely intertwined along supply chain. No matter if two firms operate in the same industry or exist as supply chain partners, one firm's decision such as M&A, bankruptcy or corporate layoff is going to have value implications for other economically related firms. Existing research has examined the extent to which bankruptcy or earnings announcement has valuation consequences for firms in the supply chain (Hertzel, Li, Officer and Rodgers, 2008; Pandit, Wasley and Zach, 2010), but offers little evidence on the information externality of corporate layoff on announcing firms' suppliers. Considering the increasing prevalence and importance of layoff strategy to corporate restructuring, the unsettled dispute over its effectiveness to corporate growth, and the closely intertwined economic relations between supply chain partners, it is essential to examine systematically whether the layoff announcement of one party affects the valuation and operating performance of its supply chain partners.

This paper shows that, for the time period of 2004-2017, suppliers experience an overall negative information externality at the time of their major customers' layoff announcements. Furthermore, suppliers exhibit declines in investments and slight improvement in profitability in the subsequent years after their major customers announce the layoff news. This evidence is consistent with the notion that information externalities are pervasive in the economy, and it also suggests corporate layoffs have significant spillover effects on firms' supply chain partners. Thus, by providing insight into the nature and extent of the overall wealth effects associated with corporate layoffs on economically linked partners, this paper makes contributions to the previous research that have documented the contagion effects of important firm information, such as bankruptcy filings and earnings announcements on supply chain partners, and it also contributes to studies on intra-industry information spillovers (See Lang and Stulz, 1992; Hertzel, Li, Officer, and Rogers, 2008; Pandit, Wasley, and Zach, 2011). This study also provides a more complete picture of the economic-wide impact of employee layoffs as a corporate restructuring strategy (See Chen, Mehrota, Sivakumar, and Yu, 2001; Farber and Hallock, 2009).

To investigate whether the extent of information externality is determined by the content of layoff announcement, I first classify firm layoff announcements into three categories: Restructuring and M&A, financial distress and cost, and closure (If a layoff announcement is about final closure or sale of its operation, I label it as closure). Since previous empirical findings about stock market reaction to layoff announcements are largely mixed, researchers have been trying to document whether the mixed results can be explained by the different underlying reasons provided for the layoff decision. Worrell, Davidson, and Sharma (1991) report a significant negative stock price reaction to the 192 layoff announcements examined, and they find that the market reacts much more negatively to layoff announcements attributable to financial distress as compared to those resulting from restructuring and consolidation. Palmon, Sun, and Tang (1997) find that investors consider the reasons cited by management in the layoff announcements as credible signals of firm future performance; specifically, layoffs associated with adverse market conditions such as declining demand is met with negative stock market reaction, as investors believe this layoff decision conveys information on likely worse performance in the future; however, layoffs attributed to efficiency improvements signal a better profitability going forward and lead to a positive market reaction. These findings are also supported by more recent research (Chen, Mehrotra, Sivakuumar and Yu, 2001; Jung, Kim, Lee and Yoo, 2017). To ascertain whether suppliers experience information externality differently at the time of their major customers' layoff announcements, I first study announcers' market reaction to their own announcements. Largely consistent with prior studies, the results show that restructuring and M&A layoffs are associated with positive stock market reaction, whereas distress and cost layoffs relate to negative market reaction, and that market has insignificant reaction to closure layoffs. This insignificant market reaction can be explained by the fact that, in most cases, long before a firm announces the final closure of certain parts of its operation, the firm may already have begun downsizing its employees and shrinking its operations, so the market already knows the economic situation the firm is going through. Hence, the closure layoff announcement does not bring any new information to the investors of the layoff announcing firm (Jung, Kim, Lee and Yoo, 2017).

Then I proceed to examine suppliers' stock market reaction at the time of their major customers' layoff announcements. I find that suppliers on average experience negative spillover effects after their customers announce layoff news. The analysis on both individual suppliers and supplier portfolios shows that, overall, market reacts negatively to such announcements. However, suppliers' stock reaction exhibits a different pattern from that of layoff announcing firm itself when I examine the three layoff categories separately. In particular, suppliers in the restructuring layoff category do not experience any positive information externality after their customers' layoff announcement. In addition, the negative stock price effects are not only confined to the financial distress layoffs, but also extend to suppliers affected by closure layoffs, indicating that investors of supplier firms are not fully attentive to inter-firm linkages until the customer's news on employee layoff and plant closure is made public (Cohen and Frazzini, 2008; Patatoukas, 2012), or in another word, plant closure may be long anticipated by investors of layoff announcing firms, but is still largely unexpected and thus decision-relevant for investors of supplier firms.

I also investigate whether the strength of the economic bonds between suppliers and their layoff-announcing customers affects the negative information externality suppliers experience. In many supply chain partnerships, suppliers are highly reliant on their sales to a few major customers. Major customers could encourage suppliers to invest in relationship-specific assets that enhance the operation efficiency and information sharing between firms. For example, to meet customers' demand for product quality and achieve better process integration, suppliers may purchase highly-specialized equipment that are otherwise hard to be redeployed should the supply chain partnerships terminate or customers consolidate their businesses and give up certain product lineup (Schloetzer, 2012). Pandit, Wasley and Zach (2011) also note that the magnitude of the information externality suppliers experience is determined by the level of sales dependence suppliers have on their customers. The information investors could glean from customers' operating performance should be more informative about suppliers if suppliers have greater exposure to their customers. Layoff announcements often signal uncertainty in customers' product market and the strategic movements they will adopt in the future. Therefore, the extent of suppliers' sales dependence should affect the level of impact suppliers could suffer from customers' layoff news. As predicted, I find that highly dependent suppliers do experience much more negative market reaction than their less dependent counterparts.

Next, I explore whether the supplier spillover effects are more severe when industry rivals in the announcing firm industry also experience information spillovers. An early study by Lang and Stulz (1992) finds that bankruptcy filings could lead to negative stock price reaction for filing firm's industry competitors. Although their further analysis shows that for a subset of bankruptcy filings, rather than being impaired by the bankruptcy news, remaining competitors can seize the opportunity to take up the market share of their bankrupt rival, the intra-industry contagion effects, however, largely dominate the competition effects in the case of firm bankruptcy filings. Recent studies show that layoff announcements also convey industry-wide news (Bhabra, Bhabra and Boyle, 2011; Bordeman, Kannan and Pinheiro, 2016). If layoff announcements signal a less appealing growth opportunity in the existing industry businesses, and thus cause negative spillover effects among other industry competitors, suppliers could suffer more negative information externality at the time of the announcements than in the case where the layoff announcements do not bring any negative industry-wide impact to other competitors. Since negative intra-industry contagion effects indicate that fewer opportunities exist for suppliers to switch to other customers when the entire customer industry is under heightened uncertainty (Hertzel, Li, Officer and Rodgers, 2008). I divide the sample based on the interaction of the sign of both layoff-announcing customers and their competitors' stock reaction and find that the suppliers' negative stock price effects are concentrated in the double-bad news subsample (both layoff-announcing customers and their industry competitors have negative stock price reaction at the time of layoff announcements), with little evidence of negative spillovers for suppliers in the double-good news subsample. In addition, I also find that the spillover effects for suppliers are asymmetric. Namely, customers' layoff announcements have significantly negative wealth effects on suppliers when the market perceives the layoff decision to be bad news, whereas, the wealth effects on suppliers do not turn positive even when the announcers' own stock price reaction indicates that the layoff decision is regarded by the market to be a good news. Consequently, these results suggest that as a coping strategy, firms' layoff decision can be either perceived as a proactive restructuring attempt or re active response to waning market condition, and thus leading to announcer's either positive or negative market reaction. However, for dependent suppliers, the layoff decision is more likely to involve redeployment of resources and uncertainty of future sales prospects and therefore, more likely to be associated with negative supply chain spillover effects. Furthermore, this supply chain effects could be exacerbated by horizontal effects if layoff announcements convey bad industry-wide news.

Further cross-sectional analysis on suppliers' two-day (-1,0) event period cumulative abnormal returns indicates that supplier wealth effects are correlated with economic determinants such as customer industry concentration, normal period correlations between firms' stock returns and macro-economic uncertainty for the period immediately prior to the layoff announcements. Customers' two-day abnormal returns alone do not cause significant price reaction for suppliers, but I continue to find that the information externality suppliers experience is increasing in the interaction between customers' own stock price reaction and the normal period correlation in the returns of suppliers and customers, indicating that the wealth effects from layoff announcements are strongest for those suppliers perceived by the market to be highly interdependent on their customers in normal period.

Finally, this study also provides evidence that suppliers reduce their sales dependence on layoff-announcing customers in the post announcement years, and they also decrease their investments accordingly. This finding is consistent with the notion that if one party in supply chain relations is more asymmetrically dependent on its counterpart, then the potential for hold-up increases, prompting the dependent party to decrease its reliance on the other supply chain partner (Baiman and Rajan, 2002; Schloetzer, 2012). A major customer is an important source of a supplier's current and future earnings and cash flows, the prospect of a major customer restructuring its established businesses and rearranging its personnel and resources creates uncertainty for the supplier's operation and in turn motivate the supplier to reduce its relationship-specific investments. Additionally, I also observe that a supplier is able to enhance its profitability after reducing its reliance on the layoff-announcing customer, adding fresh evidence to the debate regarding the impact of major customer relationships on supplier's operating performance (Lustgarten, 1975; Galbraith and Stiles, 1983; Kelly and Gosman, 2000; Patatoukas, 2012).

In summary, this study adds to the literature that seeks to identify and understand the underlying reasons and economic impacts of corporate layoff decisions. Prior studies have focused on examining the stock and operating performance of announcing firms themselves (e.g., Chen, Mehrotra, Sivakumar and Yu, 2001; Chalos and Chen, 2002; Farber and Hallock, 2009; Datta, Guthrie, Basuil and Pandey, 2010). Unlike prior studies, I focus on the economic bonds between the announcing firms and their supply chain partners, and the results show that the value implications of layoff decision reach far beyond the announcing firms, they reach to industry rivals and dependent suppliers as well. More generally, this study also extends prior research on inter-organizational relationships and the existence of information externality in both supply chain relations and intra-industry setting (e.g., Lang and Stulz, 1992; Amir and Lev, 1996; Fee and Thomas, 2004; Hertzel, Li, Officer and Rodgers, 2008; Pandit, Wasley and Zach, 2010), it builds on the notion that vertical supply chain spillover effects could be affected by the horizontal rival effects. The findings also add to the evolving literature on relative bargaining power in supply chain relations and its influence on firm performance (e.g.,Lustgarten, 1975; Galbraith and Stiles, 1983; Baiman and Rajan, 2002; Schloetzer, 2012). Finally, the inferences drawn could be of interest to policy makers who are considering the broad economic impacts of corporate layoffs in their efforts to formulate labor protection legislation.

The remainder of the paper is organized as follows. Section 4.2 reviews related literature and motivates the research questions. Section 4.3 describes data sample process. In Section 4.4, I provide results on suppliers' stock reaction around the major customers' layoff announcement date. Section 4.5 presents information on the effects of layoff announcements on industry rivals and the evidence on the interaction of supply chain and horizontal rival spillover effects. Section 4.6 describes the cross-sectional findings relating suppliers' price reaction to other economic determinants. Section 4.7 presents evidence on suppliers' operating performance following their major customers' layoff announcements. Section 4.8 concludes.

4.2 Background and research questions

4.2.1 Layoff decision and its impact

While my focus is on the information externality of firms' layoff announcements on their suppliers' stock returns and operating performance, a number of studies have examined the market consequences of layoff announcements for the announcing firms themselves. For example, using event-study methodology, Worrell, Davidson, and Sharma (1991) provide early evidence on the negative market reaction to 194 layoff announcements, and they find that layoff size, duration and the reason cited for the decision are all related to the magnitude of negative market reaction. Lee (1997) shows that the differences in abnormal returns of layoff announcements for U.S. and Japanese firms can be attributed to various layoff characteristics and fundamental differences in governance structures of firms in two countries. Further work by Chalos and Chen (2002) demonstrates that the heterogeneity in stock price reaction presented by former studies could result from different strategies a firm adopts to layoffs. They document that "revenue refocusing" layoffs are related to positive market reaction, whereas, "cost cutting" layoffs and "plant closing" layoffs only lead to insignificant and weak market reaction, respectively. Farber and Hallock (2009) examine how reaction of stock prices to layoff announcements changes during the 1970 to 1999 time period. They document a less negative cumulative excess returns (CER) over a 3-day event window centered on the announcement date, which they speculate could be due to the increasing fraction of "efficiency" oriented layoffs. However, they find no evidence that the stated reasons, industry makeup or other layoff characteristics have any impact on the less-negative trend in the average CER.

Given the mixed results on short-term market consequences of layoff announcements, it is not surprising that the impact of layoffs on firm's long-term operating performance is also of great interest to researchers and market alike. Cascio, Young, and Morris (1997) show that downsizing firms have no higher profitability than non-downsizing firms. However, when downsizing firms also engage in assets restructuring, their profitability and stock returns are better than their industry peers. Chen, Mehrotra, Sivakumar, and Yu (2001) find that layoff firms have better profit margins and labor productivity than their industry peers for up to 3 year subsequent to layoffs. Moreover, they show that layoff firms stay more focused by concentrating on fewer business segments, suggesting that layoff decisions are made out of firms' genuine intention to consolidate their businesses and enhance market value.

Motivated by the mixed findings on the relationship between layoff decisions and post layoff performance, researchers in Management studies begin to examine the cross-sectional determinants of performance differences. For example, Guthrie and Datta (2008) find that industry characteristics such as high R&D intensity, growth and low capital intensity could exacerbate the negative effects of corporate layoffs on operating performance. Other studies also provide evidence on the effects of corporate layoffs on firm reputation (Flanagan and O'Shaughnessy, 2005) and individual and group attitudes (De Meuse, Bergmann, Vanderheiden and Roraff, 2004; Morrison and Robinson, 1997).

Overall, layoff efforts are made to consolidate firms' unprofitable businesses and redeploy firms' resources to cater to the shift in product market condition. However, this strategy could also result in lower organizational commitment among employees and higher perceived uncertainty among investors. Considering these hidden costs, it is far from clear whether layoff-announcing firms could maintain their competitive advantages derived from the layoff efforts and whether their major trading partner-dependent suppliers would suffer from this restructuring attempt. For example, as one Bloomberg analyst comments on automakers' recent strategic shift to electrical vehicle, "….this will take away some of the core intellectual property areas that automakers and traditional auto suppliers have built up over a long time on internal combustion engine…..". Thus, although prior literature has documented extensively on the impacts of layoff announcements on market consequences and operating performance of the announcing firms themselves, it provides no evidence of supply chain effects for firms' layoff decision. With corporate growth and profitability increasingly coming from interfirm processes and routines (Dyer and Sinh, 1998), it is time to fill the gap and develop an expanded view of "beyond firm" impacts of corporate layoffs.

4.2.2 Mandatory disclosure requirement on firm's exit and disposable activities

In an effort to increase the informativeness of corporate disclosure and improve the price formation in the capital market, effective on August 2004, SEC has required firms to disclose certain material events previously not reported in Form 10-K now in Form 8-K filings on a more efficient basis. Among these new added material events, corporate exit and disposal activities (Item 2.05) are the focus of this study. Under the new regulation, firm needs to report costs associated with exit or disposal activities within four business days after the activities take place. Manual reading suggests that form 8-K filed under the Item 2.05 coupled with the attached press releases contains detailed layoff information, such as layoff announcement date, layoff size, and the reasons for layoff. This initial sample collection tactic follows Jung, Kim, Lee, and Yoo (2017) and is arguably more suitable for the purpose of this study than the conventional media article search widely adopted in prior layoff literature. For one, prior studies relying on media article search can only track those firms actively covered by news media, with most of these studies focusing on S&P 500 firms or other important capital market index. Since these firms are usually large and dominant players in their respective industry, their higher bargaining power over their suppliers is likely to inflate any impact layoff announcements could have on these suppliers, thus, potentially limiting the generalizability of the findings. By collecting layoff announcements of all public firms from Form 8-K filings, this study is less vulnerable to such "large firm" bias. The other superiority of this tactic is that it recognizes the original intention of SEC to push every public firm, media attracting or not, to provide a better information environment and a "level playing field" for all stakeholders. As is argued in Beyer, Cohen, Lys, and Walther (2010), the existence of financial externalities and real externalities are two major rationales for imposing mandatory disclosure regulation. In line with their argument, firm's disclosure of its layoff decision should be informative not only about its own financial position, but also about that of its major trading partners or even more broadly, about the overall industry dynamics, and hence, the disclosed layoff information is expected to affect stakeholders' real decisions. Viewed from this perspective, this study also adds evidence to the debate on the impacts of mandated increase in mandatory disclosure (Leuz and Wysocki, 2016; McMullin, Miller and Twedt, 2018).

4.2.3 Information externality and supply chain relations

Ever since interfirm relations were first recognized as a key factor explaining future "industrial company success" (Forrester, 1958), firm's ability to integrate resources and achieve knowledge-sharing beyond its boundary has been regarded as a major competitive advantage (Dyer and Singh, 1998). With industry competition being more efficiency- and quality-focused, firms have increasingly looked to coordinate a closer relationship with their suppliers. The economic links between supply chain partners result in significant operational and financial interdependence (e.g., Metzer, DeWitt, Keebler, Min, Nix, Smith and Zacharia, 2001; Banerjee, Dasgupta and Kim, 2008; Cremers, Nair and Peyer, 2008) and also generate information externality across these firms. For example, early work in this area by Olsen and Dietrich (1985) finds evidence of significant changes in suppliers' stock prices at the time of retailers' monthly sales announcements, and the stock price reaction becomes more pronounced for those suppliers with higher sales dependence on the retailer.

Further, suppliers would consider major customers' earnings prospect in their investment decisions on relationship-specific assets. Thus, to influence suppliers' perceived revenues from the relationship and to seek higher relationship-specific investments from the supplier, customers are motivated to undertake earnings management (Raman and Shahrur, 2008). However, if a major customer is experiencing financial distress, the prospect of the supplier not getting payment for existing orders or even losing a major source of revenue in the future could result in significant negative market reaction, bringing economic loss to the suppliers and even contagion effects to their respective industries (Hertzel, Li, Officer and Rodgers, 2008). Pandit, Wasley and Zach (2011) show that, due to the economic bonds between suppliers and their customers, the information contained in customers' earnings announcements could convey useful information about the suppliers' future cash flow, and hence, allowing investors to reassess their expectations about the suppliers' future performance, causing suppliers to experience significant information externality at the time of their major customers' earnings announcements. Additionally, since market often underreacts to the news of economically-related firms, a trading strategy that exploits the return predictability deriving from supply chain spillover effects could yield abnormal returns for investors (Cohen and Frazzini, 2008; Patatoukas, 2012).

Moreover, investors can also elicit private information from their existing relations with supply chain partners. For instance, Gong and Luo (2018) document that the established relationship with borrower's major customer gives lenders access to more accurate and timely information about the borrower, gaining information advantage, lenders are willing to lower the level of accounting conservatism they demand from the borrower. Finally, the financial interdependence in supply chain relations also makes it viable to infer one party's financial position from its trading partner's equity issuance events. A latest research by Johnson, Kang, Masulis, and Yi (2018) shows that suppliers' announcements of seasoned equity offerings (SEO) lead to negative stock returns for major customers, who, in the post-SEO period, also experience significant declines in sales, operating performance and credit ratings, a finding consistent with their prediction that suppliers' SEO signals information about the deteriorating financial condition of their major customers.

4.2.4 Motivation

Prior research suggests that information externality is pervasive in supply chain relations. Because of the integrated operational and financial processes between customers and suppliers, it is feasible to infer private information on suppliers' future performance from customers' disclosure event. For example, customers' bankruptcy announcements send signal to investors that the suppliers may underperform in the future if they can't switch their focus and sell product to other non-bankrupt customers (Hertzel, Li, Officer and Rodgers, 2008). Similarly, an upbeat financial result in customers' earnings announcements can lower the uncertainty associated with suppliers' future earnings and cash flows and leads to positive market reaction for suppliers (Pandit, Wasley and Zach, 2010). As such, since customers' layoff decision represents a major restructuring attempt, reflecting not only the firms' past operating performance, but also the shift in their future strategic emphasis (Chalos and Chen, 2002; Datta, Guthrie, Basuil and Pandey, 2010), as trading partners with businesses closely intertwined with the customers, suppliers are expected to experience information externality from their major customers' layoff announcements. However, distinguished from prior studies, in which bankruptcy, earnings announcements, or seasoned equity offerings have unambiguous negative or positive valuation impacts, in the case of layoff announcements, the average market reaction is not easily determined as either positive or negative, making it even harder to predict how suppliers will react to such information externality and how their performance will hold up in the future.

Further, it is also likely that measures of information externality based solely on suppliers' stock price reaction at the time of customers' layoff announcement date could underestimate the overall supply chain spillover effects and may even lead to insignificant findings. Because suppliers may well in advance know about how the business is going for the customers and whether the customers plan to restructure the business from their daily interaction with the customers. Supply chain management literature shows that seamless process and information integration enhances financial performance (Chen and Paulraj, 2004). Hence, customers wanting to achieve better performance are more likely to engage in efficient information transferring, so that their suppliers can adjust the production accordingly. For example, Daimler, a pioneering automaker warned in its recent annual report about the impacts of the company's strategic shift to electrified vehicles on its suppliers' profitability. Its annual report said: "Due to the planned electrification of new model series…..could result in over- or under-utilization of production capacities for certain suppliers…..". In this case, the proactive information sharing takes place even before the company undertakes any material restructuring activities, indicating that suppliers may have already digested part of the information externalities by the time the company makes its formal announcement.

However, prior research also finds that in order to avoid supplier hold-up problem, customers will go to great length to undertake earnings management in order to motivate suppliers to increase their relationship-specific investments (Raman and Shahrur, 2008). The fact that some customers are willing to manipulate suppliers' perception of their future prospects suggests that suppliers may not know all the private information about the customers' operation, and thus, could also be caught off guard by customers' layoff announcements. For example, in the month leading to Target Corporation's announcement to close its stores in Canada in January 2015, the company did not inform its suppliers about its liquidation plan, rather, it significantly increased its inventory orders from its suppliers, clearly in an effort to mislead its suppliers about the company's strategy and performance. Although not all customers will deliberately hold back key information from their suppliers like Target did, it is reasonable to assume that there is always private information about customers' future cash flows that is going to generate spillover effects for suppliers once this piece of information is made public.

Taken together, these factors make it unclear whether customers' layoff news will necessarily lead to significant information externality for suppliers at the time of the announcements, and how suppliers will perform in the post announcement period. Stated formally, the research question is as follows.

RQ: How does major customer's layoff announcement affect the valuation and operating performance of its dependent suppliers?

4.3 Data and sample procedure

4.3.1 Layoff firms and announcements

Effective on August 2004, SEC has required firms to disclose major corporate events in Form 8-K filings on timely basis. Under the new regulation, firm needs to report costs associated with exit or disposal activities within four business days after the activities take place. More specifically, if a firm plans to engage in exit or disposal activities, or disposes of long-lived asset or terminates employees, it is required to disclose: the date of the commitment to the course of action, a description of the action, and each major type of cost associated with the course of action. In this study, I focus on 8-K filing associated only with employee termination. Examples of Item 2.05 are illustrated in Appendix 1. As is previously argued, this sample collection tactic is better suited to the purpose of this study than the conventional media article search tactic. By collecting layoff announcements of all public firms from Form 8-K filings, this study is less prone to “large firm” bias, which is usually the case in prior studies.

First, I extract all 8-K filings containing Item 2.05 from August 2004 to December 2017 from SEC Edgar. This initial procedure collects 6,148 observations of 8-K filings relating to corporate exit or disposal activities of 2,532 unique firms. Then I restrict the sample to U.S. firms only and further exclude observations from financial and utility industries (SIC 4900-4999, 6000-6999) due to their highly regulated nature. To make sure each filing firm has stock return data, I merge the sample with CRSP database and eliminate observations if they lack stock price information. After these procedures, the initial sample consists of 4,244 8-K filings of 1,609 unique firms.

In terms of supply chain relations, this information is available in the COMPUSTAT database. Based on SEC’s requirements, public firms must disclose the amount of revenue derived from each customer that accounts for at least 10% of total revenue. The disclosures of the type and name of a major customer along with their dollar amount of annual sales generated from each major customer are available from COMPUSTAT Segment Files. However, the customers’ names are often abbreviated or sometimes too vague to be clearly matched to a unique firm (e.g., 3 customers, distributors). To form the sample of filing firm suppliers, I identify all COMPUSTAT firms that list the firm in the above sample of 1,609 filing firms as a major customer by manually matching each of the abbreviated customers’ names to one of the 1,609 filing firms. Following this conservative manual matching process, 1,826 observations are retained, representing 568 unique filing firms of which I can gain supplier information from COMPUSTAT Segment Files.

By reading each of the 1,826 Form 8-K filings and the attached press releases retained after the above preliminary screening process, I then eliminate observations not associated with employee termination and those without detailed layoff information, including the date of the layoff announcement, number or percentage of employees impacted, or the reason for employee layoff. Following prior studies (e.g., Chalos and Chen, 2002; Jung, Kim, Lee and Yoo, 2017), I classify reasons for firm layoff into three categories: Restructuring and M&A, financial distress and cost, and closure. If a layoff is due to restructuring or consolidation of operations or M&A activities, it is labeled as Restructuring and M&A. If a layoff is due to weak economy, financial distress, or declining revenue and higher cost, I label it as financial distress and cost. A layoff due to closure, sale or discontinuance of operation is labeled as closure. I also include additional restrictions to isolate the impacts of layoff announcement from other confounding events. First, I eliminate any layoff that is part of a broader layoff plan disclosed in previous announcement, as this layoff news does not bring any new information to the market. Second, in order to avoid any concurrent announcements impacting stock returns, I eliminate any layoff announcement that occurs within a [-5, +5] window around the firm's earnings or dividend announcements. Third, I eliminate firms that delist within 180 days from the announcement. Since exchanges are required to disclose firm's delisting decision 180 days prior to the event, I exclude these cases to prevent the layoff effect being confounded by firm's delisting decision. After imposing these additional restrictions, I get a sample of 632 layoff announcements from 350 distinct firms.

4.3.2 Layoff firm's suppliers

In previous procedure, I take manual name matching step to make sure each layoff firm in the sample has at least being disclosed once as a major customer by its suppliers, but it is possible that the once disclosed supply chain relationship has already terminated by the time the layoff news is made public, so I follow prior studies (e.g., Hertzel, Li, Officer, and Rodgers, 2008) and restrict the supplier-customer (layoff firm) matches to the three years prior to (and including) the layoff announcing year. If the matching process generates multiple matches between supplier-customer (layoff firm) pairs over the three-year preannouncement period, I choose the match-year closest to the announcement year. This procedure further reduces the sample size down to 271 layoff announcements from 172 unique layoff firms, of which I manage to identify 772 supplier matches.

Next, I add following filters to the supplier matches to isolate layoff effect for supplier firms. First, I eliminate supplier firms not listed in one of the three main exchanges (NYSE, AMEX, and NASDAQ). Second, I eliminate supplier firms with earnings or dividend announcement occurring within a [-5, +5] event window around their customers' layoff announcements since these concurrent announcements may affect suppliers' stock returns. Third, I restrict the sample to supplier firms with enough stock return data in CRSP. After the above data screenings, the final baseline sample consists of 173 layoff announcements for 121 distinct layoff-announcing firms and a sample of 420 suppliers, representing 696 supplier-announcement observations during the sample period from August 2004 to December 2017.

4.3.3 Layoff firm's rivals

To calculate the value implications of layoff news on an announcing firm's rivals, I follow prior studies (Lang and Stulz, 1992; Hertzel, Li, Officer and Rodgers, 2008) and form a value-weighted portfolio of all firms with the same four-digit standard industrial classification (SIC) code as the 121 layoff announcing firms. To be included in the analysis, first, the sample rival must be U.S. firm listed in one of the three main stock exchanges (NYSE, AMEX, NASDAQ); second, the rival must have sufficient returns on the CRSP file around the layoff announcement date; finally, they must not simultaneously be layoff announcing firm's suppliers.[33]The average number of rivals per announcing firm is 28.

In summary, after the above data screening process imposed on layoff firms, their suppliers and rivals, the final sample for Event study analysis consists of 173 layoff announcements, 696 supplier-announcement observations and 4,818 rival-announcement observations which then form 173 value-weighted rival portfolios.

4.3.4 Sample distribution

Panel A of Table 1 shows the annual distribution of layoff announcements of all sample firms. The sample contains 121 unique layoff announcing firms that have at least one supplier, 420 unique suppliers and 1,429 unique rivals. The sample layoff announcements are concentrated in the time period of 2007-2009, the period around 2008 Financial Crisis. Panel B provides the industry composition of the sample customers, suppliers, and rivals using the 48 industry classifications of Fama and French 1997. The

[33] A close inspection of customers' potential rivals suggests that, in some cases, the rivals may also be the layoff-announcing firms' suppliers. To analyze how the horizontal effects interact with vertical supply chain effect of customers' layoff announcements, it is necessary to eliminate all the supplier firms from the rival portfolios.

results show that almost half of the sample of the layoff firms is concentrated in pharmaceutical products, wholesale, computer, and business services, and the same holds true for the rival firms. Supplier firms are mostly concentrated in pharmaceutical products, computers, real estate and personal services. The largest two industries in the layoff firm sample are pharmaceutical products (21.49 percent) and wholesale (12.4 percent), with no other industry accounting for more than 12 percent of the layoff firm sample. In the supplier sample, pharmaceutical products (19.52 percent) and computers (17.86 percent) are the largest represented, with no other industry accounting for more than 11 percent of the supplier sample. The industry breakdown indicates that industries having the largest sample presence are usually those with higher amount of payment for labor cost.

4.3.5 Select financial characteristics for the subsample of firms in multivariate analysis

Out of the 696 supplier-announcement observations in Event study part, 108 observations are eliminated because the datadate for these observations' segment sales figure is later than the customer's layoff announcement date, which means supplier's sales volume to its major customer could have already been affected by its customer's layoff decision. To calculate the proportion of supplier's annual sales to its customer, I require the datadate for supplier's sales figure to be no later than its customer's layoff announcement date. This sample is further reduced by 28 due to a lack of annual total sales data for suppliers in COMPUSTAT. The final sample for multivariate analysis consists of 355 distinct suppliers and 105 distinct layoff-announcing firms, representing 560 supplier-event observations.

Table 2 reports descriptive statistics for select financial characteristics of layoff-announcing customers and their suppliers. Since a customer firm could make several layoff announcements during the sample period from August 2004-December 2017, the supplier-customer pairs could appear repeatedly in the sample, although each layoff announcing event is unique. As such, the values reported in the table use data for the most recent year a firm appears in the sample. As is shown in Panel A and B, customers are much bigger than suppliers with mean (median) total assets of $5,9847.54 ($27,789) million compared to $2,976.37($505.85). Suppliers also have much lower sales volume and market capitalization than customers, with suppliers' mean (median) sales of $2,240.36 ($316.14) compared to customers' mean (median) sales of $53,292.28 ($36,622), and suppliers' market capitalization only a tenth of customers' market capitalization. Suppliers and customers exhibit similar profitability as evidenced by equal median return on assets (ROA) of 2.8 percent (customers exhibit a slightly higher mean value, 0.29 versus 0.28 for suppliers). In terms of growth opportunities, customers have higher growth potential than suppliers, with a mean book-to-market ratio of 0.71 compared to 0.68. In terms of debt capacity, in line with their larger size, customers exhibit much higher leverage ratio (total liabilities divided by the market value of assets) at both the mean and median than suppliers, with customers' leverage ratio almost 50 percent higher than their suppliers'. Turning to suppliers' sales dependence on their customers, they sell an average of 16 percent (median=13 percent) of their total annual sales to their major customers, suggesting that suppliers and customers have close economic linkages and suppliers are highly reliant on their customers' business. Overall, compared to prior studies (e.g., Pandit, Wasley, and Zach, 2010), the sample customers and suppliers in this study are slightly larger in size and more profitable, and it is probably due to the fact that prior studies focus on general customers, whereas in this study, the sample consists only of firms which announce mass employee layoffs. Firms larger in size usually recruit more employees than smaller firms, and plus, they are more likely to engage in labor adjustment activities, both of which result in the sample of customers and their dependent suppliers slightly larger and more profitable compared with prior studies.

In Panel C, the average level of Chicago Board Option Exchange (CBOE) daily volatility index, VIX, which is used to measure macroeconomic uncertainty, exhibits a mean (median) value of 23.17 (15.58) over the 22-day period immediately prior to the customer's layoff announcement. The VIX presented in this study is still within a normal range by Whaley (2009)'s standard based on their long-run analysis over the sample period from 1986 to 2008, but is slightly higher than that in Pandit, Wasley, and Zach (2010), which could be due to the fact that a large proportion of layoff announcements examined in this study are made during or immediately following the 2008 financial crisis, a period of time featuring stock market turmoil and extreme economic uncertainty.

4.4 Wealth effects associated with customer firm layoff announcement

In this section I estimate separately the wealth effects for the layoff-announcing firms and their dependent suppliers around the announcement date. I construct cumulative abnormal returns (CARs) around this date using the market model abnormal returns and the value-weighted market return from CRSP estimated over the 200 days period ending 101 days before the layoff announcement.

4.4.1 Wealth effects for customer firms around their layoff announcement date

Prior research has shown quite mixed results of the overall value implications of layoff announcements (e.g., See review in Chalos and Chen, 2002; Farber and Hallock, 2009). Several layoff characteristics, such the reason cited in the layoff announcements and the layoff size (Worrell, Davidson and Sharma, 1991; Palmon, Sun, and Tang, 1997; Chen, Mehrotra, Sivakuumar and Yu, 2001; Jung, Kim, Lee and Yoo, 2017) could all explain the heterogeneity in investors' short-term market reaction around the customer firms' layoff announcement date. To set a broad context for the results associated with the announcements' value implications on suppliers and industry rivals, I first examine CARs for layoff-announcing customer firm itself. These results are presented in Table 3 Panel A.

The results are reported for the full sample as well as those for the subsamples divided based on different types of layoff reasons. I will focus on the narrowest two-day window (-1, 0), but also report results for three other longer window for robustness. The mean layoff announcement returns are 0.36 % (significant at the 10% level) for the full sample. The small magnitude of average abnormal returns for layoff-announcing firms is consistent with prior findings in literature. Since prior research shows that the reasons cited in layoff announcements send credible signals to investors about the real financial condition and future prospect of the layoff firms, and hence, accounts for the heterogeneity in short-term market reactions (Palmon, Sun and Tang, 1997; Chalos and Chen, 2002; Chen, Mehrotra, Sivakuumar and Yu, 2001; Jung, Kim, Lee and Yoo, 2017), I also estimate announcement returns for the three subsamples of layoff firms separately. I find that layoff announcements related to Restructuring and M&A result in overall significantly positive returns of around 0.76% within event window of (-1, 0), while those related to financial distress and costs have the lowest announcement returns with a negative value of 0.12%, and this negative abnormal return becomes larger in magnitude when the event window is extended from (-1, 0) to (-5, 3), for which the abnormal return reaches to -3.04% in value, suggesting that firm's layoff decision attributed to distress and lower profitability is partially known before the announcement date and thus already priced in by the market. When using the average market value of the layoff-announcing firms in the month prior to the layoff announcements, the 3.04% drop translates into a 594 million dollar loss, while the 0.76% return increase for restructuring and M&A subsample translates into a 128 million dollar gain, showing that the wealth effects of layoff announcements accounted for by these two types of reasons are not only statistically significant but more importantly, economically significant. Additionally, these figures also confirm prior findings that investors perceive layoff decision associated with restructuring or M&A as a value-enhancing strategy aimed at lifting the firm out of the current unsatisfactory market condition through refocusing firm's resources, while announcements related to financial distress and cost are interpreted by investors as a signal that the firm is currently struggling in an adverse economic environment and is unlikely to maintain its profitability unless it slashes labor costs by laying off employees. Turning to the closure subsample, I note that firms that attribute layoff decision to the discontinuance of operation or sale of business unit don't experience any significant market reaction (no significant abnormal return across different event windows), a result consistent with what has been documented in Chalos and Chen (2002). This finding is largely expected, since in most cases, long before a firm announces the final closure of certain parts of its operation, the firm may have already begun downsizing its employees and shrinking its operations, indicating that investors are already informed of the economic condition the firm is going through. Hence, the layoff announcement associated with closure of business unit does not bring any new information to the investors of the layoff-announcing firms.

4.4.2 Wealth effects for supplier firms around their customers' layoff announcement date

As is shown in the Table 3 Panel A, layoff announcements can have significant value implications for the announcing firm itself. In the current economy defined by intertwined business relations and integrated operating process, one examining the economic impact of firms' layoff decision ought to take a broader view, so what are the value consequences of layoff decision for supplier firms that are highly reliant on the layoff-announcing customers? On the one hand, as supply chain partners engage in seamless process integration and efficient information sharing, suppliers may well know in advance customers' market performance and their future strategic movement, and may even start to adapt their production plan accordingly, hence, information externalities may have already been partially absorbed prior to customers' layoff announcements, resulting in insignificant value implications for suppliers at the time when announcement is made public. If, however, the layoff decision is considered as a confidential strategic movement that, once leaked to suppliers prematurely, would cause disruptions to customer firms' supply chain management, and hence hasn't been shared with suppliers before the announcement date, then it could result in significant market response from investors of supplier firms. Therefore, the effect of customers' layoff announcements on suppliers is an empirical question.

The CARs for the supplier firms around the customers' layoff announcements are reported in Table 3 Panel B. I find that individual suppliers, on average, exhibit a negative stock price reaction to the layoff announcements of their major customers. The results are marginally significant for the (-1, 0) window, but not for the other windows. Thus, the general impacts of the layoff announcements on individual supplier firms are negative, but not so strongly. This could result from the variation in the levels of supplier firms' sales dependence on customers. Suppliers that are highly reliant on their customers are more likely to invest in relationship-specific assets that are hard to redeploy if their major customers terminate the supply chain relations or restructure the existing product lineup, and hence these highly dependent suppliers could suffer more negative price impacts from customers' layoff announcements. Whereas, for suppliers less reliant on their customers' business, a layoff announcement would not necessarily cause great value consequences as their sales are more dispersed and it is much easier for them to rearrange their production and find substitute customer should their business relations with the layoff-announcing customer come to an end. As expected, after parsing the sample based on the level of sales dependence, I find that the reaction is much stronger for highly dependent suppliers than their less dependent counterparts. The abnormal return for highly dependent suppliers over the (-1, 0) window is -0.77%, which is significant at the 5% level. If gauged by dollar value, the 0.77% drop translates into a 23 million economic loss for the suppliers. This evidence indicates that suppliers suffer more when they have stronger economic bonds with the customers and hence, are more exposed to the customers' uncertain future.

In addition to examining individual suppliers' market reaction, I also form supplier portfolios to correct potential correlation in stock returns across multiple individual suppliers of the same customer firm. I find that the mean CARs for equally-weighted supplier portfolio are not only negative in value but larger in magnitude than those of individual suppliers, corroborating the findings that customers' layoff decision brings negative price impacts to their suppliers. The mean CAR for supplier portfolio over the event window (-1, 0) is negative at 1.03%, which is statistically significant at the 1% level. When using average supplier portfolio's market capitalization in the month prior to the layoff announcement to calculate the economic impact, the negative stock return at -1.03% can amount to a loss of 146.24 million dollars.

4.4.3 Layoff reason and supplier firms' stock price reaction

Next, I examine whether different types of layoff reasons and the nature of announcer's reaction affect the size of the wealth effects suppliers receive. As documented previously, investors consider layoff reasons as containing additional information about the firm's current performance and future cash flows, and thus, investors' different reactions are associated with the reasons cited in layoff announcements. However, it is not obvious how layoff reasons can relate to suppliers' market reaction. Although financial distress and cost related layoffs and closure related layoffs could supposedly be associated with overall negative impact for suppliers, restructuring related layoffs do not send such a clear signal to suppliers. Because no matter if restructuring attempt will help customer firms regain competitiveness and therefore receive positive reaction among investors, for suppliers who make large relationship-specific investments, any restructuring efforts made by their major customers could indicate assets redeployment, changes in production plan and other market uncertainties on their part. Hence, it is worth examining whether supplier firms exhibit a similar pattern of market reaction to that of layoff-announcing customers in terms of the relations between layoff reasons and varied market responses.

The wealth effects associated with this subsample analysis are presented in Table 3 Panel B. The results show that suppliers have statistically negative and significant CARs on customers' layoff announcement dates when such layoff is attributed to financial distress and cost control. However, this negative value implications are not only confined to this subsample of suppliers, but also extend to suppliers affected by closure layoffs, suggesting that plant closure may be long anticipated by investors of layoff-announcing firms, and hence does not generate any significant price impacts for these firm, but for investors of supplier firms, who are not fully attentive to inter-firm linkages (Cohen and Frazzini, 2008; Patatoukas, 2012), customer's closure related layoff decision is still largely unexpected and thus bring negative value consequences for them. More importantly, I also find that suppliers in the restructuring layoff category do not experience any positive information externality subsequent to their customers' layoff announcements, with the CARs not being statistically significant across all four event windows. The findings that restructuring and M&A layoffs are associated with positive price reaction for layoff firm itself but is not necessarily perceived as value-enhancing by investors of suppliers indicate that frictions do arise along supply chain relations (Fee, Hadlock and Thomas, 2006), and customer's restructuring attempt could fill uncertainties into suppliers' future operations.

To further explore the variation in suppliers' market reaction, I also divide sample supplier firms according to the announcer's stock reaction: good news and bad news announcements.[34] The result in Panel C shows that supplier firms experience asymmetric spillover effects. In particular, when layoff announcement turns out to be bad news for the customer firm, it also rubs off in a negative way on its dependent suppliers, however, that market synchronization does not occur in good news situation, where customers have positive price reaction at the time of their layoff announcements but the suppliers do not receive any significantly positive value impacts from the news.

Thus, the results in Table 3 suggest that although firm's layoff decision can be regarded as either a proactive restructuring attempt or an essential reaction towards pessimistic economic outlook, and hence is associated with either positive or negative market reaction for the firm itself, for dependent suppliers, it is largely associated with negative value consequences. However, the above analysis focuses solely on the vertical supply chain spillover effects while ignoring the possibility that the horizontal effects could interact with vertical effects and result in different findings, and that is what I am about to explore in the next section.

4.5 Wealth implications and the interaction of horizontal and vertical spillover effects

Prior studies have shown that the contagion effects of corporate bankruptcy along supply chain are intertwined with intra-industry rival effects (Lang and Stulz, 1992; Hertzel, Li, Officer and Rodgers, 2008). More specifically, if bankruptcies relate to broader-based industry problem and thus, cause negative intra-industry contagion effects, then supplier contagion effects could turn much more negative compared to the situation where there are no intra-industry contagion effects. Researchers attribute such interactions of vertical and

[34] A layoff announcement is classified as good (bad) news for the announcer if the firm has positive (negative) cumulative abnormal return over the event window of (-1, 0).

horizontal contagion effects to the diminished possibilities for suppliers to replace their existing bankrupt customers with other financially healthy industry rivals once the whole customer industry is on the brink of financial distress. To test this notion of the interaction of vertical and horizontal information spillover effects in the current setting of layoff announcements, I first investigate what are the value implications of layoff announcements for industry rivals, and then I proceed to examine how supply chain information externality is influenced by intra-industry rival effects.

4.5.1 Wealth effects for portfolio of industry rivals around their peer's layoff announcement date

Recent studies show that layoff announcements also convey industry-wide news (Bhabra, Bhabra and Boyle, 2011; Bordeman, Kannan and Pinheiro, 2016). However, by focusing on layoff announcements that are only covered by major media outlets, these studies could suffer from "large firm bias", making it more likely to find intra-industry spillover effects. In contrast, the nature of sample construction process in this study can relatively mitigate the concern over this problem. To more accurately identify industry rivals, I specify that if a firm shares exactly the same four-digit SIC code with layoff-announcing firms, then it is considered an industry rival. There are a total of 4,818 rival observations representing 1,429 distinct rival firms. Table 4 Panel A presents the results.

I find that industry rivals suffer large, negative contagion effects from their peer's layoff announcement when such announcement is perceived as bad news by the market. The portfolio cumulative abnormal returns are statistically significant across all event windows. However, for the subsample of good news layoff announcement, industry rivals are largely not affected; except for window (-3, 0), the CARs for the industry rivals are insignificant for all the other windows. This evidence of more pronounced contagion effects for bad news layoff announcement compared to good news layoff announcement indicates that when layoff announcement generates positive market reaction for the announcer, its impact is often perceived by the market to be firm-specific, with no ripple effect on other industry rivals; whereas, when layoff announcement is associated with negative market reaction, investors often become more vigilant and consider it as containing adverse industry-wide information. This conservative behavior is in line with the fundamental risk aversion hypothesis about investors.

I further divide the sample according to the level of industry competitiveness. As is documented in prior studies (Lang and Stulz, 1992; Hertzel, Li, Officer and Rodgers), industry competitiveness influences the extent of intra-industry contagion effects of bankruptcy announcements. Firms in highly competitive industries usually share similar cash flow characteristics with the bankrupt firm and thus, are more likely to suffer from negative contagion effects subsequent to other firm's bankruptcy announcement, as the market can reasonably assume those non-bankrupt firms probably have similar problems to their bankrupt peers; however, if firms operate in highly concentrated industries, the possibility of taking up market shares of the bankrupt firms and redistributing wealth within the industry makes the firms less prone to the negative contagion effects, but instead more subject to competitive effects. During the entire corporate life cycle, layoff decision is obviously a less extreme issue compared to bankruptcy, and so its impact on the firm itself and its rivals should be less pronounced compared to bankruptcy announcement. Therefore, it is less clear whether the level of competition plays a role in the way industry rivals are affected by their peer's layoff announcement.

Panel A shows the results broken down by layoff firm industry concentration. Following Hertzel, Li, Officer and Rodgers (2008), industry concentration is measured based on Herfindahl-Hirschman Index (HHI), which is calculated as the sum of squared industry market shares using sales data for all firms in the same four-digit SIC code from COMPUSTAT. I find that industry rivals in highly competitive (above median HHI) industries do suffer more severe negative contagion effects from peer's layoff announcement, with the CAR (-1, 0) at a value of -0.72%, significantly negative at the 0.1% level. However, for the subsample of firms in more concentrated industries, the contagion effects are still predominant over competitive effects, albeit the -0.73% decline in industry rivals' market value is only weakly significant at 10% level. This finding is similar to those in Lang and Stulz (1992) and Hertzel, Li, Officer and Rodger (2008), in which the contagion effects of bankruptcy still dominate competitive effects in highly concentrated industries. For the subsamples under good news cases, no matter if the layoff firm industry is highly competitive or not, industry rivals do not react significantly to their peer's layoff announcement, supporting my earlier finding that the market perceives the layoff decision to be a more firm-specific value-enhancing strategy when the announcer has positive abnormal return.

4.5.2 Interaction of supply chain information externality and intra-industry rival effects

I next turn to examine the interaction of the vertical and horizontal information spillovers. To test for such effects, I divide sample supplier firms into four subsamples based on the interaction of the sign of both announcing firm and its rivals' stock reaction for (-1, 0) window. The results from the analysis are presented in Panel B of Table 4. I find that the suppliers' negative stock price effects are concentrated in the double-bad news subsample, while for supplier firms in double-good news subsample, there is little evidence of negative supply chain spillovers. In fact, the returns around the (-1, 0) window for supplier firms in double bad news subsample is -1.14%, which is significant at the 5% level and results in 135.56 million economic losses for the portfolio of suppliers, while the (-1, 0) window for double good news subsample firms is -0.57%, which is not statistically significant. For supplier firms in subsample of two good-bad news combinations, the results are mixed, except for window (-1, 0), for which the CARs are significantly negative, the CARs of all the other windows are insignificant. In summary, the results provide additional support to the previous finding that the customers' layoff announcements are largely associated with negative value implications for dependent suppliers, and furthermore, these results show that the negative information externality brings more serious value consequences to the dependent suppliers when the entire customer industry is impaired under the layoff announcements.

4.6 Multivariate analysis and economic determinants of information externalities on suppliers

So far, the analysis has focused on univariate tests, to further explore the determinants of the information externality of customers' layoff announcements on dependent suppliers, in this section, I examine a multivariate setting. I include several economic factors that previous research suggests might explain the magnitude of the information externality suppliers experience at the time of the customers' corporate disclosure. In particular, these factors include basic layoff characteristics, the underlying correlation in economic activities between customers and their dependent suppliers, customer firm industry concentration, macroeconomic uncertainty and supplier's firm-specific risk.

First, to the extent that the number of employees to be laid off declared in the announcement reasonably measures the size of the impact a customer's layoff decision is on the normal operational activities of its own and its suppliers, I expect larger layoff size introduces higher level of operational uncertainty to the dependent suppliers and therefore, could result in more negative price reaction from suppliers. I also expect that suppliers that are more reliant on their major customers, and those that have closely synced return movement with their customers during normal trading period are more likely to suffer from larger contagion effects from the customers' layoff announcement. To test this prediction, I include in the model the level of suppliers' sales dependence and the interaction term of customer firms' abnormal stock return multiplied by the normal period correlation in the market-adjusted returns between suppliers and their major customers (Corr).

Suppliers' sales dependence is constructed as the ratio of sales derived from a major customer divided by the suppliers' total annual sales, while the Corr is constructed in a similar way as in Pandit, Wasley, and Zach (2011) and is measured as the Pearson correlation between supplier and its customer's market-adjusted returns over the year prior to the customer's layoff announcement. I also expect that suppliers of layoff-announcing firms in more concentrated industries are more likely to be positively influenced by the horizontal competitive effects as opposed to contagion effects among the announcing firms' industry rivals, and thus are more likely to have less negative price reaction at the time of customers' layoff announcements.

I also predict that market uncertainty prevailing at the time of customers' layoff announcements could reinforce the co-movement of stock returns between supplier and customer firms, and therefore contributes to more pronounced contagion effects. Following prior studies (Roger, Skinner and Van Biskirk, 2009; Williams, 2015; Whaley, 2009; Pandit, Wasley and Zach, 2011), I use the Chicago Board of Option Exchange Volatility Index (VIX) as a measure of macroeconomic uncertainty. VIX is calculated as the average level of the CBOE daily volatility index over the 22 trading days immediately prior to a customer's layoff announcement.

Further, another factor that could impact the size of the stock market reaction for supplier's stock at customer's layoff announcements is supplier's firm-specific risk. If the supplier is associated with higher idiosyncratic risk characterised by highly volatile price movement, then the market is expected to rely on more external information to gauge the value of supplier's stock, which in the current setting, could result in more pronounced contagion effects of customer's layoff announcement. Toward that end, I include a proxy for firm-specific risk defined as the standard deviation of the residuals of a market model regression of the supplier's daily stock return on the market return over the 200 trading days immediately prior to its customer's layoff announcement. See the Appendix 3 for variable definitions.

Table 5 presents the coefficient estimates from the OLS regression of the two-day (day 0, the day of the customer's layoff announcement and day -1, the day prior to the announcement) cumulative abnormal returns for supplier firms (Supp_car) on the two-day cumulative abnormal stock returns of customers (Cust_car) and other economic determinants mentioned above. I include industry fixed effects into the regression model, and the standard errors are clustered by industry accordingly. Model 1 includes layoff characteristics and measures for the underlying correlation in economic activities between a customer and its dependent suppliers. Consistent with the prediction, the wealth impacts of customers' layoff announcements are significantly more negative for announcements with larger layoff size. Model 2 includes the Herfindahl-Hirschman Index (HHI) to quantify the industry competition for customer firm industry. In order to control the scale effects of the raw data of this variable, I take the natural log of this index to normalize its distribution. This variable is labeled as In(HHI).

The coefficient of In(HHI) is positive and significant at the 1% significance level, which suggests that supplier firms with major customers in more concentrated industry experience less negative wealth effects from the customers' layoff announcements. Since as is indicated from the univariate results in Section 5, in the case of highly concentrated industries, the negative contagion effects which the industry rivals experience are more likely to be offset by competitive effects, resulting in potential benefits for suppliers, because it suggests that they can switch to other customer firms should their business with the original layoff-announcing customers gets impaired. However, I also note that both the main effect of non-event period return correlations and the coefficient of the interaction term Cust_car*Corr are insignificant. The result is probably due to the complexities of the relations between suppliers and their major customers and the customers' industry rivals.

Model 3 and 4, I split the sample based on customer firm industry concentration score[35]. Model 3 shows that the coefficient estimate for the interaction term Cust_car*Corr

[35] Following the guide from U.S. Department of Justice & FTC, I split the sample by the cut-off HHI score of 2500 and 1500. A HHI higher than 2500 points is considered to be highly concentrated, and below 1500

is significantly positive at the 5% level in highly competitive customer industry, suggesting that intra-industry contagion effects of layoff announcements can reinforce the supply chain contagion effects, while the results for highly concentrated customer industry still show insignificant relation between suppliers and customers' stock price reaction.

To examine how the macroeconomic uncertainty and firm-specific risk affect the wealth impacts suppliers experience, I include VIX and the standard deviation of the residuals of suppliers' market-adjusted returns into the models. As can be seen from model 5, the main effect of VIX is positive, indicating that suppliers' stock price reaction is less negative if layoff announcements are made during uncertain economic conditions, and hence is interpreted as involving less firm-specific issues. However, different from the results found in prior study (Pandit, Wasley and Zach, 2011), the coefficient of the interaction term VIX*Cust_car is insignificant, which could be attributed to the limited time period of my sample, and thus less variation in variable VIX.

As stated above, firm-specific risk could influence investors' decision on how much weight they want to place on external information to assess the value of suppliers' stock, in order to examine the influence of this factor, I partition the sample into two subsamples of highly-uncertain suppliers and less-uncertain suppliers. As is shown in Model 6 and 7, the coefficient of interaction term Cust_car*Corr in both models is positive, but is weakly significant in subsample of highly-uncertain suppliers, which suggests that investors do attach more importance to the information contained in customers' layoff announcements when they update their beliefs about the suppliers' future cash flows, resulting in larger

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is highly competitive. Model 3 applies to observations in highly competitive customer industry and model 4 for highly concentrated customer industry.

magnitude of information externality suppliers experience. Additionally, the coefficient on suppliers' sales dependence is negative in all model specifications, which indicates that higher level of business reliance on the part of suppliers' side is associated with more negative price reaction at the time of their customers' layoff announcements. But unexpectedly, the coefficient is not significant, which could result from the lack of variation in sales dependence for the remaining observations in this multivariate analysis. Panel B presents the results of using CARs (-3, 0) to replace the two-day window for the purpose of robustness, and the tenor of the results remain unchanged.

Overall, the results reported in Table 5 provide partial evidence indicating that customers' layoff announcements generate information externality for suppliers, and that the magnitude of this information externality is affected by economic determinants such as layoff size, customer industry concentration, firm-specific risk, macro level uncertainty and etc. I attribute the lack of or weak statistical significance of certain variables (e.g., sales dependence, VIX) in the tests to small sample sizes, lack of variation in observations, noisy measures for some of the factors included in the model, and more importantly, as similarly argued in Hertzel, Li, Officer, and Rodgers (2008), the complicated nature of supply chain relations and the added complexities from the layoff announcements' intra-industry effects in the current setting.

4.7 Effect of customers' layoff announcements on the operating performance of dependent suppliers

Thus far, the univariate tests and the multivariate regression performed in this study mainly focus on examining the short-window information externality experienced by suppliers right after their major customers' layoff announcements. While important, these findings do not provide insights into how the information externality suppliers experience changes their future business and financial policies or affects their post-announcement operating performance. Hence, to provide further evidence on these questions, I investigate whether the information externality suppliers experience induce significant changes in their sales dependence, peer-adjusted operating performance and financial policies in the post-announcement period.

As argued previously, for suppliers who make large relationship-specific investments, customers' layoff decision, whether it is deemed as a proactive restructuring attempt or a temporary distress copying strategy, sends signals to suppliers that they probably have to change their production plan, or redeploy their assets, or in the worst case scenario, terminate their established relations with the customer. The overall uncertainties involved raise the likelihood that suppliers can incur economic loss for their relationship-specific investments in the future. Thus, in order to lower this possibility, suppliers are expected to more evenly distribute their sales and reduce their sales dependence on the layoff-announcing customers.

I report average changes in suppliers' sales dependence on the layoff-announcing customers from the year prior to layoff announcements to each of the two years following the announcements, as well as the changes in median sales dependence. The results are presented in Table 6. Significance levels in Panel A are calculated using T test, while in Panel B they are calculated using a Wilcoxon signed-rank test. Overall, I find evidence of significant decline in suppliers' sales dependence on their major customers in the two years after the customers' layoff announcements, with the average sales dependence (percentage of annual sales made by the supplier to the layoff-announcing customer) declining by 0.92%

from Year -1 to Year +1 and by 1.86% from Year -1 to Year +2. This result is consistent with the prediction that suppliers will try to reduce their reliance on their layoff-announcing customers in the future, since layoff decision largely results in negative value implications and higher uncertainty for the suppliers' operation.

This finding is further supported by the results in subsample analysis. Specifically, for the subsample of suppliers whose major customers' layoff decision is perceived as bad news by the market at the time of the announcement (Bad news for the announcer), the decrease in post-announcement sales dependence is more pronounced than for suppliers whose major customers' layoff announcements receive relatively positive market reaction from the market (Good news for the announcer). For example, the average decrease in sales dependence from Year -1 to Year +1 for suppliers affected by negatively-perceived layoff announcements is -1.56%, which is statistically significant at the 1% level, while for suppliers affected by positively-perceived layoff announcements, the figure is -0.42%, and is insignificant. To the extent that layoff announcements that receive negative market reaction from investors are more likely to signal either a relatively pessimistic industry-wide outlook or layoff firm's less competitiveness compared to its rivals, suppliers affected by these layoff announcements should be more concerned about the value consequences associated with this customer's layoff decision and in turn are more likely to reduce their reliance on sales to this customer.

To put these results into perspective, when multiplying the changes in sales dependence ratio by the suppliers' pre-announcement annual sales, I note that the 0.92% decrease from Year -1 to Year 1 is translated into a 20.549 million dollar cut in sales revenue from the layoff-announcing customer, and for period from Year -1 to Year +2, the reduction in sales revenue is even more significant, the 1.86% decline could amount to 41.628 million dollar loss of revenue that has to be made up for from other customers.

Next, I proceed to examine suppliers' post-announcement operating performance. I am primarily interested in how suppliers' investments, financing activities and profitability change as a result of their major customers' layoff decision. Specifically, the variables of interest are defined as follows: relationship-specific investments is defined as the R&D expenses (COMPUSTAT item 46) divided by total assets (item 6); total investments is defined as the sum of R&D expenses (item 46) and capital expenditures (item 128) divided by total assets (item 6); operating return on assets is defined as the operating income before depreciation (item 13) divided by total assets (item 6); debt is defined as long term debt (item 9) divided by total assets (item 6); profit margin is defined as the operating income before depreciation (item 13) divided by sales (item 12).

To analyse suppliers' operating performance, I use difference-in-differences approach. For each supplier firm, I first select a matching firm that is from the same industry and is of similar size. Prior research shows that matching firms based solely on industry classification and size is likely to result in mis-specified test statistics, to avoid the difference in pre-event performance between the sample firm and its matching firm contaminating the test results, it is essential to control for pre-event operating performance (Barber and Lyon, 1996; Lie, 2001), so on top of imposing industry and size criteria, I select the matching firm that has the narrowest discrepancy in pre-event asset profitability with the sample firm. Specifically, I first match on four-digit SICs, and loosen up in turn to three-digit, two-digit and one-digit SICs if there are not enough matches meeting the size requirement. Size is measured as the sales in the year prior to customer's layoff announcement. I require that the size of each matching firm is within 50-150% of the size of the sample supplier firm. Once the industry and size requirment are satisfied, I choose from the pool of matching firm candidates the one of which the operating return on assets (ROA) is closest to that of the sample firm.

The results are presented in Table 7. I compare the pre-post performance difference of the sample firms to that of their matched group in the 3 years following the layoff announcements. When observations have missing data in any of the variables of interest and have be to dropped, I will choose the next closest matching firm. There are two columns specifying the number of observations in this analysis, the left column shows the number of observations for the analysis on relationship-specific investments, total investments, return on assets, and debt, while the column on the right side is for analysis on profit margin. I find that supplier firms significantly reduce their relationship-specific investments and total investments, and that this effect is significant for suppliers that are affected by positively-perceived layoff decision as well, consistent with my earlier finding that even customer's restructuring attempt that is regarded as value-enhancing by its investors could bring uncertainties to the suppliers and lead to hold-up problems.

Meanwhile, since specific investments are hard to redeploy and thus worth less in other uses (Fee, Hadlock and Thomas, 2006; Costello, 2013), as suppliers reduce their investments on specific assets and their reliance on the layoff-announcing customers, they are able to make higher ROA and profit margin in the 3 years following the customers' layoff announcements, a finding that adds fresh evidence to the debate regarding the impact of major customer relationships on supplier firm performance (Lustgarten, 1975; Galbraith and Stiles, 1983; Kelly and Gosman, 2000; Patatoukas, 2012). I do not detect any differences regarding debt levels.

4.8 Conclusions

In the current economy marked by rapidly-changing market demand and intense industry competition, almost every firm, large or not, has to engage in layoff strategy at some point in the firm's life cycle. As corporate layoffs have become a new normal in practice, our understanding of the impacts of this decision should not be limited to the layoff-announcing firm itself, rather, with interfirm relations, especially supply chain relations becoming an key channel for firms to integrate resources and derive efficiency and competitiveness, understanding how a firm's layoff decision has value implications for its suppliers has become ever more important. In this study, I take a broadened perspective about the impacts of firm's layoff announcements. I examine the financial and operational performance consequences for dependent suppliers when their major customers make layoff announcements. While layoff announcement could indicate that the customer firm will restructure its business and refocus the resources to more profitable uses, and thus, potentially benefit its dependent suppliers, it also could have negative information spillover effects on suppliers due to the fact that suppliers may have to change production plans, redeploy their assets, and face increased operational uncertainties in the future.

I find that customers' layoff announcements largely bring negative value consequences for suppliers. Classifying sample supplier firms based on the reasons cited in the customers' layoff announcements, and on the sign of customer firms' own stock price reaction, I note that the negative effect is not restricted to suppliers affected by customers' financial distress and cost layoffs and closure layoffs, but extend to those affected by restructuring and M&A layoffs. Moreover, the results also show that the spillover effects for suppliers are asymmetric. Bad news layoff announcements lead to significantly negative wealth effects for suppliers, whereas good news layoff announcements do not generate a positive price reaction for suppliers. Meanwhile, suppliers tend to go through more negative value consequences when they have higher level of sales dependence on the layoff-announcing customers.

In addition to examining vertical effects alone, I also show that vertical effects could interact with horizontal contagion effects and result in more negative value consequences for suppliers. Further tests show that suppliers' negative stock price effects are concentrated in the double-bad news subsample, which indicates that if layoff announcements signal a less appealing growth opportunity in the existing industry businesses, and thus cause negative horizontal contagion effects among industry rivals, suppliers could suffer more negative information externality at the time of the announcements. Furthermore, several economic determinants such as layoff size, customer firm industry concentration, macroeconomic uncertainty and suppliers' firm-specific risk are all found to affect the magnitude of information externality suppliers experience.

I also examine several dimensions of investment and operational performance for suppliers in the three-year period following the layoff announcement. Suppliers tend to reduce their investments and their sales dependence on layoff-announcing customers, and they tend to experience a higher profit margins and investment profitability in the years after the layoff announcements. This finding is consistent with the notion that downstream uncertainties will create hold-up problems for upstream trading partners. To avoid being impaired by the customers' future operation subsequent to their layoff decision, suppliers will adjust their relationship-specific investments and reduce their reliance on layoff-announcing customers.

Overall, this paper provides evidence that, while firms' layoff decision can be regarded as a proactive restructuring attempt or a temporary measure to cope with firms' waning economic condition, and thus leading to either positive or negative market reaction for the layoff-announcing firms, for dependent suppliers, layoff announcements can lead to reduction of shareholder wealth and subsequently, their investment levels, which may not be desirable for the layoff-announcing customers in the first place.

4.9 References, tables and appendices

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Table 1

This table provides sample distribution by year (Panel A), and sample distribution by industry (Panel B). The sample consists of 173 layoff announcements by U.S. public companies during the August 2004 to December 2017 period, 696 supplier-announcement pairs and 4,818 rival-announcement pairs. I obtain information on layoff announcements by extracting information from SEC EDGAR and manually reading firm's 8-K Form filed under Item 2.05. I remove announcements made within five trading days before or after firm's earnings or dividend announcements. I also exclude announcements that are part of previously announced broader layoff plans, those by firms with missing stock return data in CRSP or financial data in COMPUSTAT, those that are delisted within 180 days from the announcements, and those by firms in regulated industries. (SIC codes between 4900 and 4999 and between 6000 and 6999). Suppliers of layoff firms are identified through pre-announcement FAS 14 disclosures obtained from COMPUSTAT Segment File, any firm listing the layoff announcing firm as a customer in the three years prior to the layoff announcement is labeled a supplier. I require that the supplier firms have enough stock return data in CRSP and be listed in one of the three main stock exchanges. I also exclude supplier-announcement pairs that are concurrent with supplier's earnings or dividend announcement within five trading days before or after the layoff announcement. The industry rivals of layoff announcing firms consist of U.S. firms of the same four-digit SIC code as layoff announcing firm (excluding any firm that has been identified as a supplier), are listed in one of the three main stock exchanges, and have enough stock return data in CRSP. There are 696 supplier-announcement pairs representing 420 unique supplier firms, and 4,818 rival-announcement pairs representing 1,429 unique rivals.

Panel A Sample distribution by year

Year	Number of layoff announcements	Number of firms issuing layoff announcements	Number of supplier-announcement match	Number of suppliers	Average number of suppliers in the portfolio	Number of rival-announcement match	Number of rivals	Average number of rivals in the portfolio
2004	8	8	102	100	12.8	198	198	24.8
2005	14	13	74	70	5.3	281	223	20.1
2006	11	11	40	38	3.6	126	122	11.5
2007	14	14	44	44	3.1	383	255	27.4
2008	27	26	107	101	4.0	577	405	21.4
2009	36	34	110	101	3.1	1054	411	29.3
2010	5	5	17	17	3.4	214	149	42.8
2011	10	10	27	27	2.7	175	127	17.5
2012	6	5	22	20	3.7	121	104	20.2
2013	7	7	45	45	6.4	188	188	26.9
2014	9	9	36	35	4.0	324	313	36.0
2015	17	17	58	58	3.4	587	580	34.5

2016	4	4	8	8	2.0	404	403	101.0
2017	5	5	6	6	1.2	186	99	37.2
Total	173	168	696	670	4.0	4818	3577	27.8
Number of Unique firms		121		420			1429	

Panel B Sample distribution by industry

	Industry	Layoff firms(%)	Suppliers(%)	Competitors(%)
1	Agriculture	0.83	0.24	0.35
2	Food Products	2.48	1.19	0.56
3	Candy & Soda	0.00	0.00	0.00
4	Alcoholic Beverages	0.83	0.24	0.07
5	Tobacco Products	0.00	0.00	0.00
6	Recreation	0.00	1.19	0.00
7	Entertainment	0.83	0.00	1.47
8	Printing and Publishing	0.83	0.24	0.21
9	Consumer Goods	3.31	0.71	0.98
10	Apparel	0.83	2.62	0.77
11	Healthcare	0.00	0.00	0.00
12	Medical Equipment	2.48	1.43	4.69
13	Pharmaceutical Products	21.49	19.52	29.04
14	Chemicals	1.65	1.19	0.77
15	Rubber and Plastic Products	0.00	0.48	0.00
16	Textiles	0.00	0.71	0.00
17	Construction Materials	0.83	0.48	0.21
18	Construction	0.00	0.24	0.00
19	Steel Works, etc.	0.83	0.71	0.42
20	Fabricated Products	0.00	0.48	0.00

21	Machinery	3.31	2.62	1.96
22	Electrical Equipment	0.00	0.48	0.00
23	Miscellaneous	3.31	4.76	1.96
24	Automobiles and Trucks	1.65	0.00	0.77
25	Aircraft	0.00	0.24	0.00
26	Shipbuilding, Railroad Equipment	0.00	0.24	0.00
27	Defense	0.00	0.00	0.00
28	Precious Metals	0.00	0.00	0.00
29	Nonmetallic Mining	0.83	0.00	0.28
30	Coal	4.96	1.90	9.59
31	Petroleum and Natural Gas	0.00	0.48	0.00
32	Utilities	2.48	1.43	1.82
33	Telecommunications	0.83	0.24	0.21
34	Personal Services	5.79	10.71	17.70
35	Business Services	8.26	7.14	5.95
36	Computers	10.74	17.86	10.08
37	Electronic Equipment	3.31	3.10	3.29
38	Measuring and Control Equipment	1.65	1.19	0.77
39	Business Supplies	0.00	0.48	0.00
40	Shipping Containers	0.00	2.14	0.00
41	Transportation	3.31	2.38	1.47
42	Wholesale	12.40	0.00	4.62
43	Retail	0.00	0.00	0.00
44	Restaurant, Hotel, Motel	0.00	0.00	0.00
45	Banking	0.00	0.24	0.00
46	Insurance	0.00	0.00	0.00
47	Real Estate	0.00	9.76	0.00
48	Trading	0.00	0.95	0.00

Note: Panel B reports the percentage of customers (layoff-announcing firmS), suppliers, and rivals by industry based on 48 industry classification from Fama and French 1997.

Table 2

Select financial characteristics of subsample of suppliers and customers

This table presents summary statistics for select financial characteristics of sample suppliers (Panel A) and customers (Panel B) that have enough financial data available in COMPUSTAT for multivariate analysis. The subsample of firms available for Section 6 multivariate analysis consists of 560 supplier-announcement pairs (observations) and 145 customer-announcement pairs that represent 355 unique suppliers and 105 unique customers respectively. Panel C reports the level of market uncertainty (Chicago Board of Option Exchange Volatility Index, VIX) prevailing at the time of customers' layoff announcements. Supply chain relations are identified through FAS 14 disclosure accessed from COMPUSTAT Segment File for the 2001-2017 time period. As some sample suppliers and customers are associated with several layoff announcements at different points in time in the sample period from August 2004 to December 2017, the summary statistics for suppliers and customers are calculated using data for the last year the firm appears in the subsample for multivariate analysis. See the Appendix for variable definitions.

Panel A: Suppliers (number of unique suppliers in multivariate analysis N=355)	Mean	Median	Std. dev
Total assets (in millions of dollars)	2,976.37	505.85	9,467.80
Sales (in millions of dollars)	2,240.36	316.14	5,959.33
Market capitalization (in millions of dollars)	3,910.40	454.22	14,622.24
Return on assets (ROA)	0.28	0.28	0.31
Book-to-market	0.68	0.67	0.33
Leverage	0.30	0.27	0.21
Sales dependence	0.16	0.13	0.13
Firm specific risk	0.03	0.03	0.02
Panel B: Customers (number of unique customers in multivariate analysis N=105)	Mean	Median	Std. dev
Total assets (in millions of dollars)	59,847.54	27,789.00	78,136.78
Sales (in millions of dollars)	53,292.28	36,622.00	49,883.24
Market capitalization (in millions of dollars)	36,696.97	24,824.58	47,659.32
Return on assets (ROA)	0.29	0.28	0.20
Book-to-market	0.71	0.69	0.23
Leverage	0.46	0.41	0.22
Panel C: Market uncertainty (For N=560 observations in cross sectional analysis)			
VIX(Chicago Board of Option Exchange Volatility Index)	23.17	15.58	13.07

Table 3

This table reports cumulative abnormal returns (CARs) for layoff firms (Panel A) and their dependent suppliers (Panel B) and supplier portfolios (Panel C) around layoff announcement dates. In Panel A, the sample consists of 173 layoff announcements by U.S. listed firms during August 2004 to December 2017 time period. The daily abnormal stock return is calculated using the market model. The market model parameters are estimated using 200 trading days of return day ending 101 days before the announcement. Abnormal returns are cumulated for the indicated windows relative to the layoff announcement date, with the CRSP value-weighted return used as a proxy for the market return. The information on layoff reason is obtained through manually reading each 8-K form and related press release filed with SEC. I classify the reason cited in layoff announcements into three categories: Restructuring and M&A, financial distress and cost, and closure. Specifically, if a layoff is due to restructuring or consolidation of operations or M&A activities, it is labeled as Restructuring and M&A. If a layoff is due to weak economy, financial distress, or declining revenue and rising cost, I label it as financial distress and cost. A layoff due to closure, sale or discontinuance of operation is labeled as closure. In Panel B, the sample consists of 696 supplier-announcement observations that representing 420 unique supplier firms and 173 equally-weighted supplier portfolios of these individual suppliers. Equally-weighted supplier portfolios are formed from the individual suppliers for each layoff announcement. Out of the 696 supplier-announcement observations, only 560 observations have data available from COMPUSTAT Segment File to calculate sales dependence ratio. Sales dependence is defined as the percentage of a supplier's annual sales to its customer in the fiscal year preceding the latter's layoff announcement. Firms are divided into high and low sales dependent firms according to the sample median sales dependence. In Panel C, the sample consists of 173 equally-weighted supplier portfolios. The sample supplier portfolios are divided based on layoff reason cited in customer's layoff announcement and the sign of the CARs for layoff firms. Layoff announcement is considered as Good news for announcer when the announcer's CARs for window (-1, 0) is positive, and is considered as Bad news for announcer when the announcer's CARs for window (-1, 0) is negative. Standard errors are computed as described in Patell (1976). ***, **, or * indicates that the average is significantly different from zero (using a two-sided t-test) at the 1%, 5%, or 10% level (respectively).

Panel A: Wealth effects for layoff-announcing firms (%)

		Subsample divided on layoff reason		
Variable	Full sample (N=173)	Restructuring and M&A (N=117)	Distress and cost (N=27)	Closure (N=29)
CAR(-1,0)	0.36*	0.76***	-0.12	-0.80
CAR(-3,0)	1.39*	2.04***	-1.63*	1.57
CAR(-3,3)	0.98	1.42	-2.30**	2.25
CAR(-5,3)	0.49	0.31	-3.04***	4.48

Panel B: Wealth effects for dependent suppliers (%)

	Individual suppliers			Portfolio of suppliers	
Variable	Full sample (N=696)	Above median sales dependence (N=280)	Below median sales dependence (N=280)	Variable (equally-weighted)	Supplier portfolios (N=173)
Individual CAR(-1,0)	-0.46 *	-0.77**	0.01	Portfolio CAR(-1,0)	-1.03***
Individual CAR(-3,0)	-0.43	-0.76*	-0.06	Portfolio CAR(-3,0)	-0.62
Individual CAR(-3,3)	-0.56	-1.00	-0.45	Portfolio CAR(-3,3)	-0.86
Individual CAR(-5,3)	-0.63	-1.13*	-0.30	Portfolio CAR(-5,3)	-1.20*

Panel C: Wealth effects for dependent suppliers (%)-Layoff reasons and announcer's reaction

	Portfolio of suppliers (divided on layoff reason)			Portfolio of suppliers (divided on announcer's reaction)	
Variable (equally-weighted)	Restructuring and M&A (N=117)	Distress and cost (N=27)	Closure (N=29)	Good news for announcer (N=93)	Bad news for announcer (N=80)
Portfolio CAR(-1,0)	-1.02	-1.09**	-1.05**	-0.76	-1.35***
Portfolio CAR(-3,0)	-0.63	-1.14*	-0.10	-0.56	-0.69*
Portfolio CAR(-3,3)	-0.82	-0.27	-1.54*	-1.02	-0.67
Portfolio CAR(-5,3)	-1.16	-0.07	-2.43**	-1.41	-0.95*

Table 4

This table reports cumulative abnormal returns (CARs) for the portfolio of industry rivals (Panel A) and the portfolio of suppliers (Panel B) of layoff firms. Panel A contains cumulative abnormal returns (CARs) for the value-weighted portfolio of industry rivals of layoff firms and subsamples based on the sign of CARs to layoff firms at (-1, 0) window and below- and above-median layoff firm industry Herfindahl indices. Industry rivals are identified as all firms with the same four-digit SIC code as the layoff firm (excluding any firm that has been identified as a supplier), I also require industry rivals to be listed in one of the three main stock exchanges and have enough stock return data in CRSP. Layoff firm industry Herfindahl indices are also based on four-digit SIC code. Abnormal returns are cumulated for the indicated windows relative to the layoff announcement date, with the CRSP value-weighted return used as a proxy for the market return. The average cumulative abnormal return to rivals is the equally weighted average of value-weighted portfolios of rival returns formed for each layoff announcement. Panel B reports the CARs for subsample of portfolios of suppliers. The full sample of 173 portfolios of suppliers is divided into four subsamples based on whether the CARs to layoff firm at window (-1, 0) are positive (Good news for announcer) or negative (Bad news for announcer), and whether the CARs for layoff firm's industry rivals at window (-1, 0) are greater than (Good news for rivals) or less than zero (Bad news for rivals). Standard errors are computed as described in Patell (1976). ***, **, or * indicates that the average is significantly different from zero (using a two-sided t-test) at the 1%, 5%, or 10% level (respectively).

Panel A: Wealth effects for portfolio of industry rivals (%)

	Full sample (N=173)	Portfolio of industry rivals (Bad news for announcer)			Portfolio of industry rivals (Good news for announcer)		
Variable(value-weighted)		Bad news for announcer (N=80)	Highly competitive (N=44)	Less competitive (N=36)	Good news for announcer (N=93)	Highly competitive (N=43)	Less Competitive (N=50)
CAR(-1,0)	-0.21	-0.72****	-0.72 ****	-0.73*	0.23	0.26	0.21
CAR(-3,0)	-0.18	-0.98****	-0.81 ****	-1.18**	0.50**	0.91*	0.14
CAR(-3,3)	-0.63	-0.89**	-0.07	-1.90**	-0.40	0.23	-0.95
CAR(-5,3)	-0.58	-0.88**	-0.50	-1.34**	-0.32	0.44	-0.98

Panel B: Interaction of supply chain information externality and intra-industry effects

	Portfolio of suppliers (Bad news for announcer N=80)		Portfolio of suppliers (Good news for announcer N=93)	
Variable (equally-weighted)	Bad news for rivals (N=54)	Good news for rivals (N=26)	Good news for rivals (N=50)	Bad news for rivals (N=43)
Portfolio CAR(-1,0)	-1.14**	-1.78**	-0.57	-0.99*
Portfolio CAR(-3,0)	-0.77 *	-0.51	-0.55	-0.57
Portfolio CAR(-3,3)	-0.43	-1.15	-0.42	-1.72
Portfolio CAR(-5,3)	-1.06	-0.71	-1.29	-1.56

Table 5

This table reports the results of cross-sectional regressions of suppliers' two-day CARs (-1, 0) on a few economic determinants hypothesized to affect the magnitude of the information externality suppliers experience at the time of their customers' layoff announcements. The sample consists of 560 supplier-announcement observations of US listed firms that announce layoffs during August 2004 to December 2017 time period. The sample selection process is described in Table 1 and Table 3. These economic determinants include basic layoff characteristics, the underlying correlation in economic activities between customers and their dependent suppliers, customer firm industry concentration, macroeconomic uncertainty and individual stock return volatility. In Model 1, *Cust_car* is customer firm's cumulative abnormal returns for window (-1, 0) around its own layoff announcement. *Corr* is the Pearson correlation between supplier and its customer's market-adjusted returns over the year prior to the customer's layoff announcement, a variable capturing the normal correlation in the daily market adjusted returns between suppliers and their major customer. *Layoff size* is the number of employees affected by the layoff divided by the total number of employees for the fiscal year ended prior to the layoff announcement. If the announcement only specifies the range of the number of employees affected, the middle point of the range is used as the number of employee laid off. *Sales dependence* is the percentage of a supplier's annual sales to its customer in the fiscal year preceding the latter's layoff announcement. In Model 2, *In(HHI)* is the natural logarithm of Herfindahl-Hirschman Index (HHI) calculated as the sum of squared industry market shares using sales data for all firms in the same four-digit SIC code from COMPUSTAT. In Model 3 and 4, suppliers firms are divided into those with major customer firm operating in highly competitive (HHI<1500) industries and highly concentrated (HHI>2500) industries respectively to examine how the level of customer firm industry competition affects the magnitude of the contagion effects for suppliers . In Model 5, *VIX* is defined as the average level of the Chicago Board of Option Exchange Volatility Index (CBOE) over the 22 trading days immediately prior to a customer's layoff announcement. *Firm specific risk* measures the idiosyncratic risk of supplier's stock and is defined as the standard deviation of the residuals of a market model regression of the supplier's daily stock return on the market return over the 200 trading days immediately prior to a given customer's layoff announcement. In Model 6 and 7, supplier firms are divided based on above- and below-median firm specific risk to examine how firm-specific risk influences the level of value impact from customer's layoff announcement on suppliers. For the purpose of robustness, Panel B reports the results of cross-sectional regressions of suppliers' four-day CARs (-3, 0) on *Cust_win1*(customer firm's four-day CARs (-3, 0)) and the rest of the economic determinants are defined in Panel A. See the Appendix for the details of variable definitions. Two-tailed P-values based on robust industry-clustered standard errors are reported in parentheses. ***, **, or * indicates significant level at the 1%, 5%, or 10% level (respectively).

Panel A Regression of suppliers' CAR (-1, 0) on various economic determinants.

VARIABLES	(1) supp_car	(2) supp_car	(3) supp_car	(4) supp_car	(5) supp_car	(6) supp_car	(7) supp_car
Cust_car	-0.0197	-0.0239	0.0182	-0.1130*	0.1230	0.1560	0.1400
	[0.563]	(0.432)	(0.815)	(0.068)	(0.378)	(0.292)	(0.548)
Corr	0.0068	0.0081	0.0275	0.0106	0.0051	0.0047	0.0072
	[0.643]	(0.542)	(0.536)	(0.578)	(0.660)	(0.796)	(0.661)
Cust_car * Corr	0.5480	0.5520	1.6910**	-0.2190	0.5900	1.0040*	0.1940
	[0.237]	(0.206)	(0.038)	(0.551)	(0.177)	(0.099)	(0.633)
Layoff_size	-0.0635**	-0.0497*	-0.0181	-0.0198	-0.0444**	-0.0216	-0.1090
	[0.016]	(0.064)	(0.736)	(0.783)	(0.045)	(0.208)	(0.152)
Sales_dep	-0.0059	-0.0068	0.0003	-0.0096	-0.0071	0.0078	-0.0415
	[0.743]	(0.706)	(0.994)	(0.221)	(0.704)	(0.755)	(0.131)
VIX					0.0003*	0.0006**	-2.83e-05
					(0.066)	(0.017)	(0.892)
VIX * Cust_car					-0.0044	-0.0046	-0.0057
					(0.242)	(0.293)	(0.439)
Firm specific risk					-0.1330*		
					(0.079)		
In (HHI)		0.0113***			0.0117***	0.0111***	0.0107*
		(0.000)			(0.000)	(0.002)	(0.070)
Constant	0.0008	-0.0905***	-0.0070	0.0020	-0.0973***	-0.1110***	-0.0735
	[0.775]	(0.000)	(0.513)	(0.619)	(0.000)	(0.000)	(0.119)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	560	560	78	377	560	280	280
Adjusted_R^2	0.022	0.027	0.113	0.012	0.033	0.043	0.046

Note: pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Panel B: Robustness Test-Suppliers' CAR (-3, 0)

VARIABLES	(1) Supp_win1	(2) supp_win1	(3) supp_win1	(4) supp_win1	(5) supp_win1	(6) supp_win1	(7) supp_win1
Cust_win1	0.0611	0.0551	0.0828	0.0369	0.0718	-0.0885	0.2690***
	(0.224)	(0.268)	(0.251)	(0.643)	(0.531)	(0.513)	(0.004)
Corr	0.0169	0.0182	0.0729	0.0175	0.0142	0.0420	0.0053
	(0.202)	(0.141)	(0.375)	(0.365)	(0.186)	(0.125)	(0.748)
Cust_win1 * Corr	0.8710	0.8850	1.3470*	0.5900	0.8800	1.3360***	0.0176
	(0.149)	(0.127)	(0.067)	(0.288)	(0.122)	(0.003)	(0.963)
Layoff_size	0.0119	0.0271	0.0973	0.0398	0.0340*	0.0566**	-0.0627
	(0.570)	(0.196)	(0.581)	(0.535)	(0.069)	(0.018)	(0.383)
Sales_dep	-0.0097	-0.0108	0.0128	-0.0155	-0.0105	0.0025	-0.0360
	(0.667)	(0.634)	(0.859)	(0.193)	(0.650)	(0.934)	(0.158)
VIX					0.0002*	0.0002	0.0001
					(0.086)	(0.324)	(0.665)
VIX * Cust_win1					-0.0005	0.0059	-0.0112**
					(0.905)	(0.139)	(0.037)
Firm specific risk					-0.1700*		
					(0.065)		
In(HHI)		0.0124***			0.0121***	0.0112**	0.0097
		(0.002)			(0.002)	(0.031)	(0.195)
Constant	-0.0050	-0.1050***	-0.0194	-0.0033	-0.1030***	-0.1090***	-0.0737
	(0.198)	(0.001)	(0.525)	(0.424)	(0.001)	(0.009)	(0.191)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	560	560	78	377	560	280	280
Adjusted R^2	0.026	0.035	0.103	-0.004	0.035	0.076	0.030

Note: pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6

This table reports the results of changes in suppliers' average (Panel A) and median (Panel B) sales dependence on layoff-announcing customers from one year before to each of the two years after customer firms' layoff announcements. The sample consists of 294 supplier observations with available data for the change analysis from Year -1 to Year 1 and 230 supplier observations for the change analysis from year-1 to year +2. The full sample is further divided into two subsamples in each panel based on whether the CARs to layoff firm at window (-1, 0) are positive (Good news for announcer) or negative (Bad news for announcer). ****, ***, **, or * indicates that the average (median) is significantly different from zero based on two-sided t-tests (Wilcoxon signed rank tests) at the 0.1%, 1%, 5%, or 10% level (respectively).

	#Observations	Year -1 to Year +1	#Observations	Year -1 to Year +2
Panel A: Changes in mean sales dependence for supplier firms from prior to post layoff announcement period				
All	294	-0.92%**	230	-1.86%***
Bad news for announcer	129	-1.56%***	95	-1.97%**
Good news for announcer	165	-0.42%	135	-1.78%**
Panel B: Changes in median sales dependence for supplier firms from prior to post layoff announcement period				
All	294	-1.46%****	230	-1.20%****
(Positive, Negative)		(116,178)		(87,143)
Bad news for announcer	129	-1.00%***	95	-2.00%***
(Positive, Negative)		(48,81)		(33,62)
Good news for announcer	165	-1.61%**	135	-0.73%**
(Positive, Negative)		(68,97)		(54,81)

Table 7

This table presents the matching firm-adjusted measures of operating performance for dependent suppliers with available data in the 280 instances from August 2004 to December 2017. I calculate the (Post-Pre) difference of each measure as the difference between the post-layoff announcement and pre-layoff announcement value of the measure. I matching firm-adjust the (Post-Pre) difference by subtracting the (Post-Pre) value of the corresponding matching firms. Matching firms are in the same industry, of similar size (50-150% of sales), and has the closest past performance (measured as the operating ROA in the year prior to layoff announcement) to that of sample suppliers. Year 0 is the year of layoff announcement. Mean and median denote the mean and median of this matching firm-adjusted difference. Cust_car is defined as the customer firm's cumulative abnormal returns for window (-1, 0) around its own layoff announcement. The left #Obs column shows the number of observations for analysis on relationship-specific investments, total investments, return on assets, and debt, while the #Obs column on the right side shows the number of observations for analysis on profit margin. See Appendix for the details on variable definitions. ****, ***, **, or * indicates that the average (median) is significantly different from zero based on two-sided t-tests (Wilcoxon signed rank tests) at the 0.1%, 1%, 5%, or 10% level (respectively).

		Relationship specific investments		Total investments		Operating return on assets		Debt		#Obs	Profit margin	
	#Obs	Mean	Median	Mean	Median	Mean	Median	Mean	Median		Mean	Median
Panel A: Year +1												
Full Sample	280	-0.0169*	-0.0002	-0.0202**	-0.0035*	0.0410**	-0.0024	-0.0196	0.0000	167	0.0304**	-0.0011
		(0.07)	(0.31)	(0.05)	(0.08)	(0.02)	(0.62)	(0.11)	(0.14)		(0.02)	(0.62)
Cust_car<0	132	-0.0193**	-0.0014	-0.0252**	-0.0061	0.0343*	-0.0026	-0.0322*	-0.0009	81	0.0617***	0.0011
		(0.04)	(0.24)	(0.02)	(0.11)	(0.06)	(0.60)	(0.07)	(0.16)		(0.01)	(0.41)
Cust_car>0	148	-0.0148	0.0000	-0.0157	-0.0023	0.0470	-0.0024	-0.0084	0.0040	86	0.0009	-0.0014
		(0.23)	(0.53)	(0.22)	(0.23)	(0.08)*	(0.60)	(0.35)	(0.99)		(0.47)	(0.77)
Panel B: Year +2												
Full Sample	218	-0.0257	0.0000	-0.0253	-0.0060	0.0971**	-0.0052	-0.0149	0.0000	135	0.0289**	-0.0006
		(0.25)	(0.42)	(0.26)	(0.11)	(0.07)	(0.68)	(0.24)	(0.53)		(0.02)	(0.57)
Cust_car<0	112	-0.0145	-0.0021	-0.0154	-0.0068	0.0194	-0.0052	-0.0111	0.0000	71	0.0438**	0.0123
		(0.12)	(0.28)	(0.13)	(0.35)	(0.15)	(0.61)	(0.29)	(0.38)		(0.04)	(0.50)
Cust_car>0	106	-0.0376	0.0001	-0.0357	-0.0055*	0.1793*	-0.0040	-0.0188	0.0000	64	0.0125	-0.0008
		(0.32)	(0.65)	(0.33)	(0.10)	(0.09)	(0.69)	(0.31)	(0.69)		(0.13)	(0.65)

		Relationship specific investments		Total investments		Operating return on assets		Debt		#Obs	Profit margin	
Panel C: Year +3												
Full Sample	170	-0.0931**	-0.0010	-0.0963**	-0.0065*	0.0696	0.0021	-0.0014	0.0000	103	0.0618***	0.0105
		(0.04)	(0.24)	(0.04)	(0.08)	(0.15)	(0.41)	(0.48)	(0.35)		(0.01)	(0.28)
Cust_car<0	83	0.0237	0.0000	0.0224	-0.0016	-0.0411	-0.0062	0.0373	0.0000	53	0.1017**	0.0153
		(0.79)	(0.46)	(0.77)	(0.46)	(0.19)	(0.67)	(0.88)	(0.71)		(0.03)	(0.29)
Cust_car>0	87	-0.2045**	-0.0029	-0.2095**	-0.0110**	0.1752*	0.0042	-0.0384	-0.0002	50	0.0194*	0.0069
		(0.02)	(0.23)	(0.02)	(0.04)	(0.07)	(0.26)	(0.16)	(0.16)		(0.06)	(0.44)

Appendix 1

Examples of Item 2.05. in Form 8-K

Example 1 Twitter's 2015 layoff announcement

Item 2.05 Costs Associated with Exit or Disposal Activities.

On October 12, 2015, the Board of Directors of the Company approved a restructuring and reduction in force plan of up to 336 employees, constituting approximately 8% of the Company's global workforce. The restructuring is part of an overall plan to organize around the Company's top product priorities and drive efficiencies throughout the Company. The Company intends to reinvest savings in its most important priorities to drive growth. The Company estimates it will incur approximately $10 million to $20 million of cash expenditures, substantially all of which will be severance costs. Total restructuring expenses are estimated at $5M to $15M, which is lower than cash restructuring costs due to a credit related to non-cash stock-based compensation expense reversals for unvested stock awards. The Company expects to recognize most of these pre-tax restructuring charges in the quarter ended December 31, 2015.

Example 2 Texas Instruments Incorporation's layoff announcement (Concurrent with earnings announcement)

ITEM 2.02. Results of Operations and Financial Condition

The Registrant's news release dated January 26, 2009, regarding its fourth quarter and 2008 results of operations and financial condition is attached hereto as Exhibit 99 and is incorporated by reference herein.

ITEM 2.05. Costs Associated with Exit or Disposal Activities

The Registrant today announced a plan of termination and other cost reductions to align the Registrant's spending with demand that has weakened in the slowing economy. The plan will reduce employment by about 3,400, or 12 percent. The reductions begin immediately and are expected to be complete in the third quarter of 2009. Restructuring charges for these actions are estimated to be about $300 million, all of which will be associated with severance and related benefits. Based on FASB Statement of Financial Accounting Standards No 112, *Employers' Accounting for Postemployment Benefits*, the Registrant accrued restructuring charges of $121 million for these actions in the fourth quarter of 2008.

Excerpt from its Exhibit 99---Press release for 4Q08

"DALLAS (Jan. 26, 2009) – Texas Instruments Incorporated (TI) (NYSE: TXN) today announced fourth-quarter revenue of $2.49 billion, net income of $107 million and earnings per share (EPS) of $0.08.

These financial results include restructuring charges of $0.13 per share. Without the charges, EPS would have been $0.21, considerably better than the company's mid-quarter expectations. (See reconciliation table below.)

TI also announced it is making reductions in employment because demand has continued to weaken with the slowing economy. Employment will be reduced 12 percent through 1800 layoffs and 1600 voluntary retirements and departures. Charges for these employment reductions will be about $300 million. Annualized savings from these reductions, plus those announced in October for the restructuring of the company's Wireless business, will be about $700 million after all reductions are complete in the third quarter of 2009…….."

Appendix 2

Sample Construction

Panel A Layoff firm and announcement

Data Attribution Process	No. of firms	No.of filing
Number of Item 2.05 reported on Form 8-K for the period 2004-2017	2,532	6,148
Exclude:		
Non US firms and firms in regulated industries	(630)	(1,187)
Firms without daily stock return data available on CRSP file	(293)	(717)
Firms whose name cannot be manually matched to a company in the Compustat Segment File	(1,041)	(2,418)
Events that are not associated with employee termination; without detailed layoff information (e.g., announcement date, layoff size, reason);part of a broader layoff plan from previously announced	(180)	(1,026)
Layoffs within 5 days of other announcements or within 180 days of exchanges' delisting decisions	(38)	(168)
Number of layoff announcing firms with potential supplier information available	350	632

Panel B Suppliers

Data Attribution Process	No. of Supplier firms	No. of observations	No. of Customer (layoff)firms	No. of layoff announcement
Number of layoff announcing firms with potential supplier information available	-	-	350	632
Exclude:				
Customer-supplier match formed beyond 3 years prior to the layoff announcing year	-	-	(178)	(361)
Number of supplier firms	772		172	271
Exclude:				
Supplier firms not listed in one of the three main stock exchanges (NYSE, AMEX, Nasqaq)	(203)			
Number of public supplier firms	569	1,096	152	238
Exclude:				
Layoffs within 5 days of other supplier's announcements	(25)	(139)	(7)	(19)
Suppliers without daily stock return data available on CRSP file	(124)	(261)	(24)	(46)
Final sample of supplier-customer (layoff) matches	420	696	121	173

Panel C Rivals

Data Attribution Process	No. of rivals	No.of observations
Number of US listed firms with the same four-digit SIC code with layoff announcing customer	2,155	8,322
Exclude:		
Rival firms that are simultaneously layoff announcing firm's suppliers	(205)	(1,247)
Rival firms without daily stock return data available on CRSP file	(521)	(2,257)
Final sample of rival firms	1,429	4,818

Appendix 3

Variable definitions

Variable	Definition
Book-to-market	layoff firm's or its supplier's ratio of book value of common equity to market value of common equity measured in the year prior to a given layoff announcement.
Corr	Pearson correlation between supplier and its customer's market-adjusted returns over the year prior to the customer's layoff announcement.
Cust_car	Customer firm's cumulative abnormal returns for window (-1, 0) around its own layoff announcement.
Cust_win1	Customer firm's cumulative abnormal returns for window (-3, 0) around its own layoff announcement.
Debt	Supplier firm's or its matching firm's long term debt divided by its total assets.
Firm specific risk	Supplier's firm-specific risk defined as the standard deviation of the residuals of a market model regression of the supplier's daily stock return on the market return over the 200 trading days immediately prior to a given customer's layoff announcement.
In(HHI)	Natural logarithm of Herfindahl-Hirschman Index (HHI) calculated as the sum of squared industry market shares using sales data for all firms in the same four-digit SIC code as layoff firm from COMPUSTAT.
Layoff size	The number of employees affected by the layoff divided by the total number of employees for the fiscal year end prior the layoff announcement (If the announcement only specifies the range of the number of employees affected, the middle point of the range is used as the number of employee laid off).
Leverage	Layoff firm's or its supplier's total liability divided by the market value of assets (book value of assets minus book value of equity plus market value of equity).
Market capitalization	Layoff firm's or its supplier's market value of common stock measured as the number of shares outstanding multiplied by the common stock price as of the beginning of the year to which a given layoff announcement applies.
Operating return on assets	Supplier firm's or its matching firm's the operating income before depreciation divided by its total assets.
Profit margin	Supplier firm's or its matching firm's operating income before depreciation divided by its total sales.
Relationship specific investments	Supplier firm's or its matching firm's R&D expenses divided by its total assets.
Return on assets (ROA)	Layoff firm's or its supplier's ratio of net income to total assets for the year prior to which a given layoff announcement applies.
Sales dependence	The percentage of supplier's annual sales to its layoff-announcing customer in the fiscal year prior to which a given layoff announcement applies.
Sales	Layoff firm's or its supplier's sales for the year prior to which a given layoff announcement applies.
Total assets	Layoff firm's or its supplier's total assets as of the beginning of the year to which a given layoff announcement applies.
Total investments	Supplier firm's or its matching firm's sum of R&D expenses and capital expenditure divided by its total assets.
VIX	The average level of the CBOE daily volatility index over the 22 trading days immediately prior to a given customer's layoff announcement.

Chapter 5: Conclusions

Information disclosure generates significant externalities. The recent trade disputes between major economies and the subsequent implications on individual firms' operation and the spillover effect on industry competition and supply chain disruptions illustrate that no firm can survive in isolation. Firms are subject to the externalities of the disclosure of other economically related parties. Such externalities could influence firms' investment decisions, stock price reactions, operating performance, and other relevant aspects in firms' operation. Managers also take advantage of the externalities of their firms' disclosure to achieve strategic benefits. This dissertation is composed of three essays that contribute to the discussion on this crucial issue of corporate disclosure and information externalities.

Findings of the first two studies in this dissertation show that intra-industry information externalities are prevalent in the initial public offerings. For industry peers, they can strategically exploit the externalities of their positive disclosure during the quiet period to affect the IPO process and preempt the IPO competitive effects; for IPO firms, they can select peers with better information environment and take advantage of the externalities of peers' high-quality information environment to address the information uncertainty associated with their forthcoming public issue. The first two studies contribute to the strategic disclosure literature. They provide evidence that when examining the information externalities of corporate disclosure, one needs to question if it is still feasible to take a firm's disclosure event as exogenous and if it is possible for some firms to take advantage of the spillover effects of their disclosure to influence other related peers. Turning to information externalities along supply chain relations, the results presented in the third essay show that the value implications of layoff decisions reach far beyond the announcing firms, they reach to industry rivals and dependent suppliers as well. Moreover, it builds upon prior literature by showing that vertical supply chain spillover effects could be affected by intra-industry effects.

Studies contained in this dissertation also have practical implications. For starters, although IPO quiet period regulation has attracted a lot of attention from academics and professionals, very few studies examine the unintended consequences of this quiet period rules on industry rivals' strategic disclosure and the IPO success. By showing that identified rivals take advantage of the information externalities of their disclosure to preempt IPO competitive effects, the first essay adds fresh evidence to the debate on the relevance and implications of this regulation. And then, the findings from the second essay point out a feasible approach that IPO firms can act on to address the information asymmetry issues related to their public offering, namely, by identifying peers with better information environment in the registration statement IPO firms can tap into a richer information environment to facilitate IPO valuation. Finally, the third essay about the supply chain implications of customer firms' layoff announcement suggests that it is important to look at the whole picture of the effects of adopting this strategy. Customer firms' layoff decision can be regarded as a proactive restructuring attempt or a temporary measure to cope with firms' less satisfactory economic condition, and thus leading to either positive or negative market reaction for themselves, for dependent suppliers, however, their major customers' layoff decision is more likely to cause redeployment of resources and uncertainty of future sales prospects. Therefore, the market reaction suppliers experience is overall negative. Suppliers also reduce their sales dependence and investment levels, which may not be desirable for layoff-announcing customers in the first place.

The studies included in this dissertation are subject to some limitations. First, I restrict the sample to US-listed firms. Further research is needed to confirm the generalizability of my findings in other major economies. Second, I apply entropy balancing matching in my first essay in order to match my treatment firms of identified rivals and control firms of unidentified industry peers. This matching procedure is critically important to single out other industry or economy-wide factors. Future research can validate my findings by applying other matching estimators. Third, while my dissertation finds that identified rivals strategically adjust the tone of their voluntary disclosure during the IPO quiet period and then normalize their disclosure behavior in the post-quiet period, future research can extend the window of that post-quiet period and investigate whether identified rivals keep their disclosure behavior unchanged in the long run. Fourthly, while my dissertation documents that peer information environment plays an important role in IPO firms' peer selection, it is possible that other governance factors, such as board connection or common ownership, also influence IPO firms' decisions about which firms they intend to identify in their registration statement.