Capital Supply, Financial Intermediaries, and Corporate Peer Effects

by

Matthew T. Billett[a]
Jon A. Garfinkel[b]
Yi Jiang[c]

Current draft: May 2016

ABSTRACT

We document "supply-side" channels that connect peer firms' financial policies. We find constrained firms' equity issuance decisions depend on peers' recent SEO activity, and that common financial intermediaries strengthen the transmission of peer effects. Constrained firms react positively to peer SEO announcements, and analyst coverage and institutional ownership increase following peer firms' SEOs. Constrained firms' SEO announcement returns and underwriting fees improve with "their" underwriters' recent peer-SEO experience. Peer effects are pronounced when there is more overlap with peers' financial intermediaries and major shareholders. We conclude that supply-side effects are key in the transmission of peer-to-peer financial policies.

Keywords: Financial constraints, SEOs, Hazards, Contagion, Peer effects

JEL Classification: G32

We thank Wolfang Bessler, Azi Ben-Rephael, Redouane Elkamhi, Nandini Gupta, Isaac Hacamo, Dave Mauer, Jay Ritter, Tong Yao, Yilei Zhang, and seminar participants at Bilkent University, City University of Hong Kong, Florida State University, Indiana University, Hong Kong Polytechnic University, Kent State University, Sabanci University, Santa Clara University, SKK Graduate School of Business, Tsinghua University PBCSF, University of Florida, University of Hong Kong, University of New Hampshire, University of North Carolina-Charlotte, University of Saskatchewan, as well as the 2014 FMA and 2015 MFA conferences, for many helpful comments and suggestions. This paper previously circulated under the title "The Role of Financial Intermediaries in the Transmission of Peer-to-Peer Financial Policies".

[a] Richard E. Jacobs Chair in Finance, Kelley School of Business, Indiana University, mbillett@indiana.edu

[b] Tippie College of Business, University of Iowa, jon-garfinkel@uiowa.edu

[c] Mihaylo College of Business & Economics, California State University at Fullerton, yjiang@exchange.fullerton.edu

Peer-effects in corporate financial policies are a well-documented phenomenon.[1] Yet the drivers of these links are presented from essentially one direction, the demand-side. The presumption is that firms follow their peers' actions because the peer actions are informative about the optimum for 'like-firm-types'. For example, peers' capital structure changes may inform a firm about changed investment opportunities or changes in the cost structure of their industry. Or perhaps the optimal governance structure has shifted. Even the hypothesis of sub-optimal mimicry has received support. Overall though, the peer-to-peer relationship is typically viewed through a demand lens; and in particular, it is often driven by factors that cause firms to demand more or less financial capital. However, accessing financial markets depends not only on the demand for capital but also on its supply.

This raises important questions. Who is involved in the capital raising process? Who provides the capital and under what circumstances? Whom do these questions matter for? Leary and Roberts (2014) provide the beginnings of answers. They find evidence that sensitivity to peers' financial policies is concentrated in samples of small, unrated, no payout, high Whited-Wu-index-value firms. In short, their followers have all the markings of financially constrained firms, suggesting that followers' financial constraints are likely relaxed by prior peer (leader) activity; a supply-side effect. So investors' willingness to provide capital and the price they charge, appear paramount. But the extant literature has essentially ignored such 'supply-side' considerations[2] in exploring peer effects in financial policies. We propose to fill this gap. Specifically, we ask what role, if any, do financial market participants (i.e., the supply-side) play in the transmission of peer effects.

[1] Leary and Roberts (2014) document that firms' capital structure and financial policies are influenced by peers' financing. Foucault and Fresard (2014) show that a rival's investment depends on their peers' valuation. Hoberg and Phillips (2015) find that following a negative exogenous shock to demand, firms invest in R&D and advertising to differentiate their products from those of their peers. Kaustia and Rantala (2015) find that firms are more likely to split their stock after seeing a peer firm do the same. Servaes and Tamayo (2014) find that firms respond to control threats.

[2] Aside from the sub-sampling done in Leary and Roberts (2014), which we view as our jumping-off point.

We examine the sequencing, timing, and spillover wealth effects of firms' and their peers' seasoned equity offerings (SEOs), to identify the roles that financial intermediaries and outside investors play in the transmission of common financial policies seen among peer firms. There are several important layers to our analysis. Number one, we focus on a well-known major capital raising event; SEOs. The simple magnitude of capital raised via the typical firm's SEO, is likely to increase the importance of the 'supply-side.' Second, SEOs have been shown to cluster in market-wide and industry waves, suggesting that firms may indeed be reacting to their peers (see Lucas and McDonald (1990), Choe, Masulis, and Nanda (1993), and Bayless and Chaplinsky (1996) and Rau and Stouraitis (2011)). Third, SEOs are publicly announced events, allowing the researcher to exploit the timing and sequencing among peers. This represents a crucial layer of contribution. Many prior studies on peer firm effects observe policy outcomes simultaneously, making inferences about which firms lead and which follow, more challenging to identify. Fourth, the identification of the timing and public announcement of SEOs allows us to explore information spillovers among peers in the stock market. Finally, our focus on SEOs allows us to explore equity ownership patterns and their ('supply-side') influence on firms' financial policies. This would be less feasible via exploration of debt-capital financing given the paucity of data on public debt ownership structure, at the same granular level as that observed for equity.

We begin with an examination of the factors influencing firms' SEO decisions, particularly their timing. We estimate SEO hazard rates (i.e., the probability of issuing conditional on time since last issue) and their determinants for two groups of firms: financially constrained and unconstrained firms. We choose this delineation for two reasons. Leary and Roberts (2014) show that mimicking behavior (by the firms they label as "followers") is concentrated in likely constrained firms – they are small, unrated, no payout, high Whited-Wu index firms. Second, constrained firms are typically thought to suffer from asymmetric information problems, so our focus on information-sensitive security issuance naturally encourages the split. Exploiting the timing and sequence of SEOs also helps alleviate some of the concerns due to the reflection problem (see Manski 1993). Our tests confirm Leary and Roberts' (2014) finding that constrained firms are sensitive to the prior financing activities (SEOs in our case) of peers, while unconstrained firms are not.

We next examine the role that financial intermediaries (underwriters and analysts), and investors play, in this peer-to-peer relationship. Information costs associated with constrained firms' SEOs may depend on what investors and intermediaries learn from unconstrained peers' SEOs. Analysts may cover a peer group more intensively when there is more SEO activity. Underwriters may learn more about peer prospects and investor demand through their certification efforts on prior SEOs by peers. Investors (both institutional and individual) may increase their appetite for equity as they learn more about a peer group's investment opportunities, or more simply as equity issuance ramps up. Any or all of these could reduce asymmetric information-related costs that constrained firms face when they issue equity. In other words, they may influence financing decisions through the supply-of-capital channel.

We investigate these possibilities. First, consistent with both a demand-side and supply-side argument, we show that information is indeed communicated via industry-peer equity issues.[3] Constrained firms experience positive abnormal returns at the announcement of SEOs by their unconstrained industry peers (but not vice versa). This could be driven by information that increases demand for capital, or by information that indicates greater availability or lower costs to raising capital. We observe analyst coverage and institutional ownership of constrained firms increase around the SEOs of industry peers.[4] And this apparently improves the information environment of constrained firms: their forecast dispersion and bid-ask spread decline in prior industry-peer equity issuance activity. While these represent more specific evidence of potential information conduction, they are still consistent with either a demand-side or supply-side argument.

[3] We are not the first paper to show this. Bradley and Yuan (2013) do as well, but they do not go beyond this documentation to explore the mechanism(s) behind such responses.
[4] But again, this could be driven by demand-side considerations, or may cause supply-side effects.

We next examine *overlap* in constrained and peer firms' analyst coverage and institutional ownership. If analysts and investors learn about one firm from engaging with its peers, then common analysts and common institutional investors may propel peer effects. We find that the peer effects (hazard results) are much stronger when the constrained firm has more analysts and institutional investors in common with peer firms that have recently engaged in SEOs. The position of analysts and institutional investors as financial market participants, suggests a supply-side channel to peer effects in corporate financial policies.

We pursue this thinking further with another key financial market participant – one that is crucial to capital raising activities, underwriters. We find that investment bank experience underwriting peer SEOs, is a determinant of constrained firms' SEO experience. While constrained firms' SEO hazards increase in the number of SEOs that peers have recently done, there is a strong positive incremental effect when the prior peer SEOs are facilitated by "their" underwriter. The economic effect of this common underwriter increment is substantial – roughly 50% greater sensitivity. Also, the gross spread fees charged by said underwriter decline in the same measure of experience. Finally, investors respond more positively to constrained firms' SEOs when their underwriter has more experience with recent peer issuances. Given that better investor reactions and lower spreads imply lower issuance costs, these results are more consistent with a supply-side effect in the transmission of peer-to-peer financial policies.

Finally, we turn to tests designed to further delineate between demand- and supply-side explanations for peers' influence on a firm's SEO decisions. Here we exploit a unique feature of our sampling technique. Our peer group for the above tests is quite general: all firms belonging to the same Fama/French (FF)-49 grouping. This grouping will contain a broad set of firms that likely belong to the same sector (from an investor's/supply-of-capital view) but that may or may not be direct competitors (from a product market/demand-side view). Such a broad amalgamation of firms is questioned as a technique for peer group formation by Kaustia and Rantala (2013, 2015). But we use this grouping so that we can further discriminate between "more" or "less" related firms. For example, Intel and Cisco belong to the same FF-49 group but they are not industry product market rivals. On the other hand, Intel and AMD are rivals. Thus while Intel and Cisco may face common supply-side effects (like increased investor capital delegated to the tech sector), Intel and AMD will additionally have relatively greater similarity on the demand side as well. We deem the Intel/Cisco peer pairing as "less-related", and the Intel / AMD pairing as "more-related."

We re-do our SEO sequencing and announcement return analyses, segmenting the sample based on whether the FF-49 'peers' are "more" or "less" related.[5] Remarkably, peer effects in SEO timing and information spillover are more pronounced in the samples where the peers are "less-related". This suggests that having more common demand-side among peers dampens peer effects. This seems odd given that competitive rivals will exhibit greater similarities, potentially encouraging mimicry. However, this ignores competitive dynamics. If a firm knows that certain actions will benefit its constrained rivals, then the action might be strategically avoided or timed to minimize rival benefits. This suggests that observed demand-side effects will be selectively smaller among rivals, ceteris paribus. Further bolstering supply-side effects, we find that peer effects are stronger when the firm and its less-related peers have common underwriters, analysts, and institutional owners.

Overall, our paper contributes in the following ways to the peer effects literature. We document different timing decisions on SEOs by constrained and unconstrained firms. We show that SEOs by peer 'leaders' communicate information. We find that SEO 'followers' benefit from such information communication. Most importantly, we highlight a supply-side effect to following firms' SEO decisions that is distinct from the more commonly studied demand-side effect.

[5] We define "more" related peers in three different ways: having the same 2-digit SIC, having the same 3-digit SIC, and using Hoberg and Philips' (2016) TNIC measure of product relatedness.

We also make several contributions to other literatures. There is a large literature on corporate financing waves, with SEOs a key player. Our evidence suggests that peer influences play an important role in these waves, and that unconstrained firms will tend to cluster early and constrained firms later in the waves. We also touch upon factors that may influence the cost of financial constraints. Our evidence shows that peer issuance activity may mitigate constraints or their costs, by facilitating equity issuance through reduction of asymmetric information problems. In general, our work provides additional insights into the role of financial intermediaries and information in the study of capital structure and financing decisions.

The remainder of this research is as follows. In the next section, we explore both demand- and supply-oriented explanations for observed peer effects, as well as more traditional explanations for SEO issuance patterns. Data is discussed in section II. We present our results in III. Section IV offers conclusions and potential extensions via debt structure analysis.

I. Potential Drivers of Peer Effects in Corporate Behavior

In the introduction we hypothesize that both demand and supply explanations may apply to observed peer effects in corporate outcomes. This section reviews the peer effects literature, delineating the demand channel and motivating the supply channel. We also make note of alternative explanations for patterns in SEO financing decisions that we must control for in our peer effects explorations.

A. Demand Explanations for Peer Effects in Corporate Finance

Peer effects have been illustrated in the major corporate finance decision arenas: investment, financing, compensation, and others. Studying corporate investment behavior, Foucault and Fresard (2014) show the importance of peers' stock prices in conveying information that helps a firm learn about optimal investment policy. In particular, when an investing firm's peers have higher valuations, the firm invests significantly more. To overcome the alternative explanation of endogeneity (due to underlying factors influencing both peers' valuations and own firm investments), they recognize a tension between the informativeness of own-firm stock price and of peers' stock prices, for corporate investment. If a firm learns much about investment opportunities from viewing peers' stock prices, the influence of its own stock price for corporate investment should decline. Indeed it does.

For our purposes, the evidence that firms glean information from their peers, that is important for their own investment policy, is useful. It provides a demand-side perspective on peers' influence. Notably, there is no analysis related to the supply (of capital) side. Nevertheless, given that stock price informativeness is increasing in analyst coverage (Chan and Hameed (2006)), the role of (at least some) intermediaries is implicit in Foucault and Fresard's (2014) results.[6] There is therefore good reason to expect intermediaries (at least analysts) to play an important role in corporate investment decisions' sensitivity to peers.

Hoberg and Phillips (2015) also illustrate a demand-side influence of peers on corporate decisions. Examining shocks to two industries (military goods and services, and software), they show that firms respond to their product-market peers when making product offering decisions. The September 11, 2001 shock caused increases in military product similarity – firms moved their offerings 'closer to' their peers – as rivals relocated to areas of common high demand. The post-2000 bursting of the tech bubble saw divergence in product offerings, designed to differentiate and thereby capture larger shares of a shrinking market. Again, the theme of demand-side motivation for peer influence on corporate decision making is

[6] Chan and Hameed (2006) actually interpret the positive relationship between analyst coverage and stock price synchronicity in the opposite direction (they argue that it suggests coverage does not increase price informativeness). This is in line with Morck, Yeung and Yu's (2000), Wurgler's (2000), and Durnev, Morck and Yeung's (2004) view that higher synchronicity implies less firm-specific information in stock prices. The opposite argument is made by Kelly (2014) and Dasgupta, Gan and Gao (2010); that larger synchronicity implies greater firm-specific information in stock prices. Chan and Chan (2014) distinguish between these two views by studying SEO discounts and finding them to be decreasing in synchronicity, consistent with the latter views.

clear. There is little discussion though of a supply-side component, even though product adjustment can necessitate investment of financial resources.

Other peer effects in corporate decisions may be less reliant on financial resources (supply-side). Faulkender and Yang (2010) illustrate a strong peer influence on CEO compensation policy.[7] Here the demand side appears to be the motivation to pay abnormally (i.e. unexplained by size, industry, visibility and other factors) high compensation. But the financial resources to do so are unlikely to require external capital raising. Kaustia and Rantala (2015) show that firms are more likely to split their stock when peers have done so. The most supportable interpretation is that of social learning, which is consistent with a demand-side effect. Moreover, splits do not require financial resources, again illustrating the uniqueness of our perspective.

Perhaps most closely related to our work is that of Leary and Roberts (2014).[8] They note the sensitivity of firm leverage and financing decisions to peers. In particular, they show a causal effect of peers' exogenous variation in characteristics or behavior, on own-firm capital structure policies. They isolate peers' exogenous variation using an augmented market model, with industry-peer average excess returns as an additional regressor. The resulting measures of idiosyncratic equity returns among the peers (the residuals from the market model), have a significant influence on firms' leverage and financing policies.

Leary and Roberts interpret these results from a decidedly demand-side perspective. They suggest that firms learn from peers' actions and/or they respond to them. On the learning side, peers' actions influence a firm's objective function. Delving deeper to address selection concerns, they highlight common omitted factors likely to impact objective functions, such as institutional environments, production technologies and investment opportunities. Learning about these *motivates* a firm to follow.

[7] See also Bizjak, Lemmon and Nguyen (2011).

[8] Though again, we view their paper as the starting point for our analysis.

Following is characterized as response (by Leary and Roberts), which can take two forms, either to characteristics of peers or to peers' actions. But again, all of these represent demand-side arguments.

What is less clear is the mechanism behind firms' responses to peers. Put differently, why do some firms lead and others follow? Leary and Roberts start down a path to investigate their question, by focusing on two groups of firms delineated on whether they are expected to be leaders or followers. Again, their followers resemble financially constrained firms. Given financial constraints must be overcome to be able to raise finance, there is a clear suggestion of a supply-of-capital channel in their peer effects. But what makes firms financially constrained? This is where Leary and Roberts' (2014) analysis stops, and ours begins.

B. *Wherefore a Supply-side Channel for Peer Effects?*

Financial constraints are typically modeled using transactions costs and/or asymmetric information. The latter suggests that a clear potential benefit of peer influence is the resolution or mitigation of asymmetric information. What information might be communicated by peers' actions, particularly financing-related ones? The value of new investment opportunities, the willingness of investors to provide capital (for these), and/or a new lower price of that capital, are all candidate signals. The audiences for this information and their responses to it, describe the potential supply-side mechanisms for peer effects that we explore.

In terms of audiences, we begin with the firm itself. Managerial learning could be about any of the above three information pieces. The first – value of opportunities – is akin to the demand channel described earlier. The second and third characterize our supply-channel. But from whom does a firm's managers learn about the supply and cost of capital? It can be from investors or financial intermediaries. Thus our investigation of a supply channel will need to explore the participation of both categories of information producers.

What about the learning / information production of these intermediaries and investors? Here we take a wide view, with investigations of institutional and mutual fund ownership, analyst following, and investment bank underwriting activities. Each of these entities is well-known to produce information through their investment and financing behavior. We therefore explore changes in their participation as reactions to peer actions, and we look for such participation changes to alter either information statistics or measures of the cost of provided capital.

Overall, our analysis turns around the fulcrum of capital provision and its cost, both of which are influenced by information production. Constrained firms (followers in Leary and Roberts (2014), as well as in our results) benefit from this. For these firms, we show that information producers' participation changes, this affects the quantity and/or quality of information surrounding them, and this results in lower costs associated with (equity) financing.

C. Alternative Explanations for Observed Peer Effects in Equity Financing: SEOs

Our focus on the effects of asymmetric information in peer-to-peer financial policy transmission encourages us to investigate the issuance of highly information-sensitive securities: SEOs. The literature on SEOs has identified numerous factors influencing firms' issuance decisions and their pricing, which we must control for. Key to this literature is the notion that firms attempt to time the market and issue when prices (their own or the market's) are at a relative high. Asquith and Mullins (1986), Masulis and Korwar (1986), Loughran and Ritter (1995, 1997) and many others all suggest this.[9] Baker and Wurgler (2002) argue for a particular underpinning of this relationship – high investor sentiment. While our tests control

[9] Schultz (2003) suggests return patterns around IPOs (not SEOs) reflect pseudo market timing.

for pre-issuance stock price runup, we hasten to add that market timing may be construed as evidence of either a demand- or supply-side effect.

On the other hand, recent work by DeAngelo, DeAngelo and Stulz (2010) questions the importance of the market timing hypothesis in the context of SEOs. While they do show that the likelihood of an SEO is increasing in the firm's M/B ratio and prior three-year abnormal stock return, they highlight that the economic effect of market timing is less pronounced than the life-cycle effect. Moreover, both of these pale in comparison to their "cash needs" argument as a motive for the SEO. In particular, 63% of SEO firms (in their sample) would have run out of cash and 81.1% would have shown below normal cash holdings without the offer proceeds, in the year after the offer. Therefore, our tests also control for the cash needs proxy offered by DeAngelo et al. (2010). This is a decidedly demand-side effect.

Alti and Sulaeman (2012) provide a more supply-side perspective on SEO issuance, by noting another consideration when testing the market timing motivation for SEOs. They show that high stock returns trigger SEOs only when they coincide with strong market reception. They proxy for this with institutional investor demand, *Instidem*, which we also include in our tests. Given this control, our supply-side results may be viewed as truly incremental; a *peer-oriented* supply of capital influence.

Finally, Bradley and Yuan (2013) study differences between primary and secondary offerings of equity, in terms of their information spillovers. They argue that primary offerings signal favorable industry prospects while secondary offerings do not. They measure information spillovers by examining peers' reactions to SEO announcements, which we also investigate. However, they do not speak to the role of financial constraints, nor the mechanism underlying peer-to-peer effects in financial policies. In other words, *how* and to whom is information communicated? Do these peer effects represent a demand-side or supply-side phenomenon? This is the heart of our study and is likely a key component of information spillover that influences value.

II. Data and Descriptive Statistics

Our analysis centers around SEOs, with an emphasis on the transmittal of information from unconstrained firms to constrained firms. We begin with Thomson Financial's SDC Global New Issues database to identify firms that conduct SEOs during 1970–2010. Our sample satisfy the following criteria: (1) We include only common share offers listed on NYSE (the New York Stock Exchange), AMEX (the American Stock Exchange) or NASDAQ; (2) We exclude financial companies, such as banking, insurance and REITs (SIC codes between 6000–6999) and utility companies (SIC codes 4900–4999); (3) We exclude unit offers, spinoffs, carve–outs, rights, and shelf offerings[10]; (4) We include only firms with stock return data available in CRSP and with financial data available in COMPUSTAT; (4) We include only issues that are more than 50% primary offering, and (5) We exclude firms with a market cap of less than $10 million during 1970–2010 to minimize the influence of outliers in the analysis. The resulting sample consists of 7,973 SEOs. Table I Panel A reports the distribution of our sample SEO firms by year.

As shown in Table I Panel A, the number of SEO firms fluctuates over the years, suggesting that SEOs tend to occur in waves. To examine the timing of issuance within these waves by constrained and unconstrained firms, we first identify SEO waves following the moving-average method of Helwege and Liang (2004). For each decade, we calculate a three-year moving average of the number of SEOs every six months. Any four to six consecutive six-month periods with a moving average exceeding the top quartile of the six-month moving averages are labeled a "wave" period. This method results in five SEO waves with the number of SEOs in a wave ranging between 500 and 1,226.

We further examine issuance behavior within each wave in Panel B of Table I. First, we define early (late) movers as the firms issuing SEOs in the first (second) half of the SEO wave. We also group our

[10] A shelf SEO is defined as an SEO whose issue date is at least 60 days after the filing date. Following Altinkilic and Hansen (2003) and Huang and Zhang (2011), we exclude shelf registered offers.

sample firms according to whether they are classified as financially constrained. *A constrained firm* has a consistent history of zero payout (neither dividend distribution nor share repurchase) since the previous issue. *Unconstrained firms* refer to the complement sample.

Taking a look at any particular wave, we see some common patterns. Looking down a column (for either constrained or unconstrained firms), we consistently see constrained firms issuing later and unconstrained firms issuing earlier. For example, there is a much higher percentage of unconstrained early movers in wave one (out of all unconstrained issuers in that wave) – nearly 60%, than late movers – just over 40%. By contrast, there is a much larger percentage of constrained late movers in wave one (out of all constrained issuers in that wave) – over 80%, than early movers – under 20%. The results are consistent with Leary and Roberts' (2014) evidence that constrained firms respond to financing activities of unconstrained firms. We provide more formal evidence of such sequencing below and then examine mechanisms driving it.

Table II reports descriptive statistics for sample SEO firms (over 1970-2010) classified by finance constraints. We classify those firms with no share repurchases or dividends since their previous issuance as constrained.[11] For each group, we report mean, median and standard deviation of main firm and issuance characteristics, spell characteristics, as well as peer group and market conditions.[12] We test the significance of differences in means and medians across groups. Panel A reports the descriptive statistics. Panel B provides a correlation matrix of our variables. All variable name definitions are in Appendix I.

Panel A of Table 2 shows that unconstrained firms are on average larger firms with higher book-to-market and larger SEO offer size. Following DeAngelo, DeAngelo and Stulz (2010), we calculate near-term cash needs (*Cashneeds*) as a forward-looking Pro Forma Cash/TA ratio (equal to next quarter's cash minus the SEO proceeds, all divided by next quarter's assets minus the SEO proceeds). Both constrained

[11] We use a number of different measures of financial constraints and find similar results, see below.

[12] Peer groups of firms are formed on the basis of Fama and French's 49 "industries".

and unconstrained firms face a cash shortfall around the time of the SEO. However, the cash shortfall is significantly larger in constrained than in unconstrained firms at the time of the issue. Also, as noted earlier, we control for institutional investor demand following Alti and Sulaeman (2012). Their key variable (*Dinstidem*) is approximately the same (in the mean and median) across the two groups. Below, we also explore the timing and development of institutional investor appetite for issuers' shares.

Our main variable of interest, *Peer SEO,* equals the number of firms in the same FF-49 peer group that conduct an SEO in the prior six months. This measures the intensity of prior peer SEO activity. We also construct *Market SEO* to measure the intensity of market-wide SEO activity, and define it as the number of firms (outside of the peer group but in the overall market) conducting SEOs in the prior six months. On average, there are 18.47 (38.12) firms in a peer group issuing SEOs in the six months preceding a constrained (unconstrained) firm's SEO announcement. By contrast, the average number of SEOs conducted in the (rest of the) market in the prior six months is significantly higher for constrained (59.31) than for unconstrained firms (34.94). While we might expect that constrained firms would have more peer group SEOs preceding their own, these figures do not consider the time since the firm's last SEO. They may simply reflect that unconstrained firms issue throughout the wave while constrained firms cluster towards the back half of the wave, where activity has slowed down. We next use Meyer's (1990) hazard model to capture the influence of peer SEO activity conditional on the firm's time since last issuance.

The dependent variable in our hazard analysis is *Spell Length* which is defined as the number of days between IPO and first SEO or the time between consecutive SEOs. On average, unconstrained firms have longer spells than constrained firms (about 20% longer, see Panel B of Table II). This reflects the fact that unconstrained firms have ample internally generated funds and access to debt markets, resulting in a reduced reliance on external equity capital. The longer *Spell Length* for unconstrained firm's highlights the point that comparing baseline hazard rates (the probability of doing and SEO conditional on how long the spell has been) is misleading. Rather than comparing baseline hazard rates across constrained and unconstrained groups, we focus on the determinants of within group variation to identify the important determinants of the timing of the groups' SEOs. We elaborate on this below when we describe our hazard methods.

Fraction Censored refers to the percentage of left, right, and both (left and right) censored spells in the sample. There are 19% (29%) censored SEOs for constrained (unconstrained) firms. *Length Censored (uncensored)* refers to the censored (uncensored) number of days between issues. We left censor a firm whose IPO date is before 1970. For example, if a firm's SEO date is 1980, and the IPO date is 1965, then the censoring time is ten years. We right censor a firm whose SEO date is after 2010. For example, if a firm went IPO in 2004 and it never issues an SEO and the data on the firm end in 2010, the censoring time is six years. We left and right censor a firm if the IPO date is before 1970 and the SEO date is after 2010. Each SEO spell is treated as an independent event. We exclude firms with no event, that is, those with only a single censored spell. We also exclude those with one censored spell and one uncensored spell, if the censored spell is shorter than the uncensored spell.[13] This is a repeated event study.

Finally, we note that our data conform with other studies in terms of announcement returns to SEOs. The average SEO announcement is met with a significantly negative response (-1.47%). It is worse for constrained firms (-1.725%) than for unconstrained firms (-1.22%). We explore the variation in SEO announcement reactions in later tests.

III. Results

Our results are presented in the following order. We first show evidence of sequencing in SEOs that formalizes the loose inferences from Table I. We then provide several pieces of evidence on potential mechanisms for peers' documented influence on firms' SEO decisions. We offer results consistent with

[13] See Allison (1995), page 245. In estimating job durations, he excluded these events for the purpose of efficient estimates. The estimates produced by this method are robust with respect to all unobserved individual heterogeneity that is persistent over time. The drawback with this approach is that we now use only a selected sample of firms.

information communication via peers' SEOs and investigate channels involving financial intermediaries. Last, we explore peers that are unlikely to be direct competitors but are likely to be viewed by investors to be in the same sector (e.g, both technology stocks but not direct competitors), in an attempt to measure incremental peer effects emanating from the supply channel.[14]

A. Hazard Results

Table III presents estimates from hazard analysis of SEO issuance decisions by constrained and unconstrained firms.[15] One of the benefits of this approach is that hazards exploit the timing and sequencing of SEOs which helps alleviate the reflection problem inherent in regressions of firm characteristics on those of its peers (Manski (1993)). While it is still possible that endogeneity exists, by exploiting the explicit timing of SEOs relative to those of a firm's peers we can better identify who leads and who follows in calendar time.

We construct two sets of variables that are intended to capture the degree to which firms' SEO decisions depend on their own characteristics and/or peer and market characteristics. Greater dependence on peer, rather than own, characteristics suggests peer dependence. Panel A contains estimates using simple count measures of prior SEO activity which we then transform by adding one and taking the natural log (i.e, Ln(1+count)).[16] Panel B's estimates use proceeds based estimates. The count based estimates are based on the number of SEOs by a group (industry peers, or the market [excluding those in the same industry]) in the last six months. The proceeds based estimates sum proceeds across all

[14] It is important to emphasize again here, that we form our peer groups based on the FF-49 broad industry groupings. This facilitates our later segmentation of industry groups into sub-samples that are "more" or "less" related (in terms of direct competition).
[15] Again, constrained firms are those that had no payout since their last equity issue.
[16] All "count-based" results are robust to using the simple count rather than taking the log of (1+count). Results available upon request from the authors.

SEOs of the group in the last six months, measured in millions of dollars. Our inferences are the same under each proxy for prior issuance activity.

The hazard for constrained firms in the first column of Panel A indicates that sequencing, consistent with Leary and Roberts' (2014) leader-follower results, is evident in our data. The constrained firm's SEO decision is highly sensitive to prior issuance activity in the industry (*Peer SEO*); the coefficient is positive and significant. More industry-peer SEO activity recently, associates with earlier SEOs by firms in the constrained sample – i.e. the spells between issues are shorter. This is incremental to more typical results found in the literature, in particular that firms' SEO hazards increase in stock returns (firm and industry). The incremental importance of prior industry issuance activity (relative to prior returns activity) to a firm's own SEO decision is an important perspective on SEOs and highlights the role of peer actions (not just characteristics) for financing policy .

It is also noteworthy that the coefficients on prior industry vs. market issuance activity (in the constrained sample hazard) differ significantly. Prior industry issuance activity has a stronger influence on the hazard (0.099) than prior market activity does (0.031); the coefficients are statistically different at the 1% level. Industry peers' actions are even more important than market issuance effects when constrained firms make SEO decisions. Also of note is the fact that the coefficient on industry returns (*Ind_mktret*) is much larger and more significant than that on firm returns (*Firm_indret*). This suggests that, for constrained firms, the decision to issue is more sensitive to the peer stock returns than the firm's own returns. We will see this is not true for the unconstrained (leader) firms.

The second column of Panel A presents hazard estimates for our sample of unconstrained firms (those that had positive payout since their previous issue). There is little evidence of peer effects in this sample. Neither prior industry-peer issuance activity (*Peer SEO*) nor prior industry returns (*Ind_mktret*) are significantly related to unconstrained firms' SEO timing decisions. Moreover, the coefficient on prior market (not same industry) equity issuance activity is negative, consistent with unconstrained firms having superior access to equity markets and leading market activity in equity issuance.

For unconstrained firms we continue to see the typical result that firm-specific returns (net of industry average) correlate positively with SEO incidence. The positive coefficient (0.311) indicates that unconstrained firms speed up their issuance in the face of recent runup. However, the effect is much stronger than we saw among constrained firms (note the significant difference in coefficients documented in column 3), indicating greater SEO timing sensitivity to own-firm returns among unconstrained firms. Overall, there are real differences between constrained and unconstrained firms in their sensitivity of issuance decision to peers.

Panel B of Table III presents similar results using proceeds based measures of prior SEO activity.[17] Constrained firms' SEO hazards are significantly increasing in prior *Peer SEO* issuance activity and more so than unconstrained firms' sensitivity (which is now also significant). The industry issuance sensitivity is also significantly larger than market issuance sensitivity for constrained firms. All of these results are incremental to prior stock returns (firm, industry and market level).

Table IV offers robustness checks of our basic SEO hazard results. In particular, we consider various alternative definitions for constrained firms, and re-estimate the tests. Given the debate over measurement of financial constraints,[18] our approach is to illustrate the sensitivity of results to the choice of proxy. In short, our results are robust. Whether we proxy for constraint with firm Age (above or below sample median), firm Size (top and bottom quartile and middle 50%), KZ index, Whited-Wu Index, or the existence of a long term credit rating, our inferences do not change. Constrained firms show a stronger and significant influence of prior industry peer SEO activity on their own SEO hazard.

---

[17] Again, prior Peer SEO activity equals the average (across all industry-peer SEOs in the last six months) of the peer's SEO proceeds divided by the peer's market value of equity.

[18] See Fazzari, Hubbard and Petersen (1988), Kaplan and Zingales (1997), Whited and Wu (2006), Hadlock and Pierce (2010) and Farre-Mensa and Ljungqvist (2016) in particular (though their results bias us away from documenting ours). There is also the cash savings perspective in Almeida, Campello and Weisbach (2004) and McLean (2011).

Overall, our hazard results highlight the importance of industry peers' actions to constrained firms' financing decisions (SEO timing decisions). This is consistent with the extant peer effects in corporate finance literature, but it also highlights the need to understand the mechanism. The remainder of our paper studies this, with a particular eye on supply-side effects and the roles of financial intermediaries and investors in it.

B. Summary Information Communicated by Peers' SEOs

Given the link between peer activity and firms' own SEO timing decisions, we begin our search for a mechanism with a simple event study. On the basis of constrained firms suffering (at least partly) from asymmetric information problems/costs, information communication through peers' SEOs could be influential for constrained firms. We therefore examine announcement returns to constrained firms when their unconstrained peers conduct an SEO. We report the results in Table V. We find that, on average, when unconstrained firms announce an SEO, constrained firms experience a significantly positive 3-day abnormal return (35 bps). We see a muted effect in the opposite case. When constrained firms announce an SEO, unconstrained firms experience an insignificant 7 bps. Confirmation of the difference between these two results is found in the last column.

These effects are driven by the responses of constrained firms that had not yet issued an SEO recently. When we split our constrained firm samples into those that had done an SEO within the last six months and those that had not, the significantly positive abnormal returns apply only to the non-issuers (see the later results in Panel A).[19] This suggests that the information communicated by peers' issuance activity is "valuable" only for constrained firms that may face information barriers/costs to issuance; those barriers have apparently been overcome already by the constrained firms that issued earlier.

[19] This highlights one of the benefits of a hazard framework. There is an important difference in the effects of peer issuance activity between constrained firms that had or had not done an SEO recently. Static models do not account for time since last event whereas hazard models do.

The above noted corollary is also noteworthy: stock price reactions among unconstrained firms (who had not recently done an SEO) are close to zero, when there is an SEO by a constrained firm. There is little evidence of valuable information communication from constrained firms' SEOs to industry peers that are financially unconstrained. Put simply, we find information spillover occurs from unconstrained to constrained firms, but not the reverse. This is consistent with constrained firms suffering from significant asymmetric information costs that unconstrained firms do not face.

Our univariate tests may suffer from clustering concerns.[20] The samples actually contain many repeats of the test firms, just on different days. If we are observing constrained firm reactions to unconstrained firm SEO announcements, then we examine *each* same-industry constrained firm's reaction on the day of the unconstrained firm's SEO. Given N constrained firms and M unconstrained firm SEOs, we analyze MxN observations.

To control for firm clustering and also for prior own-firm issuance activity, we run regressions in Panel B of Table V, and we cluster at the unconstrained SEO event level. The regressions offer four different specifications that recognize whether the test firm did a prior SEO within the last several months. In the first four columns we study constrained firm responses to unconstrained firm SEOs. Column 1 does not control for prior constrained firm issuance activity. Columns 2, 3 and 4 include (respectively) dummies equal to one if the constrained firm had an SEO within the last 6, 9 or 12 months.

Each of the regressions in the first four columns indicates significant positive abnormal returns to constrained firms when unconstrained firms announce an SEO (about 35-36 bps). Also, we confirm the evidence from panel A that recent prior equity issuance by the constrained firm mutes the value added by (information contained in) the unconstrained peer's SEO. The coefficients on the indicators for prior issue within 6 or 9 or 12 months are all significantly negative, with economic magnitudes between -0.25 and -0.27.

[20] Indeed, we recognize this briefly in panel A with cluster-adjusted t-statistics.

The last four columns of Table V study unconstrained firm responses to announcements of SEOs by constrained firms. The evidence (mirroring that in Panel A) indicates no significant response. Overall, our evidence highlights the existence of value-implying information in prior industry-peer issuance activity, for constrained firms. We now delve deeper into investigation of possible forms and producers of this information.

C. Changes in Information Environment

Our results thus far suggest valuable information is communicated through prior industry issuance activity. Constrained firms issue sooner when there is more industry issuance activity recently, suggesting that peer activity mitigates some form of issuance costs; asymmetric information related costs are a known candidate. Too, constrained firms experience positive abnormal returns to the announcement of SEOs by industry peers, particularly if they have not issued recently.[21] The latter emphasizes possible substitution between value-relevant information communicated through own-firm equity issuance and peer-firm issuance.

Here we investigate steps in the process of information communication through peers' SEOs, and in particular those that are common to known information producers or intermediaries. We begin with recognition that in the context of our study, the information producers must learn from the SEOs of the industry peers. Different intermediaries learn in different ways. For example, analysts learn by covering a stock, institutions invest in information gathering as part of their investment process, investment banks learn through their underwriting process. So our first tests investigate changes in analyst coverage and institutional ownership of constrained firms (that have not recently issued equity), around the dates of

[21] In untabulated results, we also find that constrained firms' SEO ARs are less negative when conducted during hot industry issuance periods, consistent with positive value being communicated through prior peer issuance.

industry-peer SEOs.[22] We then examine analyst forecast dispersion and bid-ask spread changes for constrained firms around the same events.

Table VI shows results from studying changes in constrained firms' analyst coverage and institutional holdings, from before to after SEO issuance by unconstrained firms. The constrained firms must not have done an SEO within the last six months. *Change in analyst coverage* equals the number of analysts covering the constrained firm in the month after an unconstrained firm SEO, minus analyst coverage of the constrained firm in the month before the unconstrained firm's SEO. The corollary is built for institutional holdings (as a percentage of shares outstanding). These changes are regressed on the usual controls and our two measures of SEO activity – peer and market SEO counts in the prior six months. Since each unconstrained firm SEO event is accompanied by analysis of several constrained firms' dependent variables, we cluster our standard errors at the unconstrained SEO event level.

The results indicate strong influences of prior industry-peer SEO activity on both analyst coverage and institutional holdings of constrained firms. The coefficients on the *Peer SEO* count are positive and statistically significant. When unconstrained industry peers do an SEO, the constrained firms experience an increase in both analyst coverage and institutional ownership. In all likelihood, information production rises for constrained firms after their unconstrained industry peers conduct an SEO. Moreover, given the need for sufficient institutional demand to conduct an SEO, these results are consistent with the notion that a firm's institutional demand increases around the time of its peers' SEOs.

We next confirm the presumed information production increase noted above. Given that analysts and institutions are both information producers,[23] their increased presence/activity in constrained firms in response to industry-peer actions is likely to reduce asymmetric information concerns. In turn, this represents a potential explanation for peer effects in corporate financing.

[22] The indications of underwriter activity are captured by the count variable in our hazard tests earlier. We study a variant of this, related to underwriter identity, in later tests.
[23] See respectively Lys and Sohn (1990) and Chemmanur, He and Hu (2009).

More specifically, we now look for precise indicators of reduced asymmetric information (tied to analysts or institutional investors) for constrained firms, around the SEOs of industry-peers. We examine analyst forecast dispersion changes and bid-ask spread changes for constrained firms, around the SEOs of their unconstrained peer firms' SEOs. *Forecast dispersion* is the standard deviation of analysts' forecasts, divided by stock price two days prior.[24] *Bid-ask spread* is the average over a month of daily values of percentage bid-ask spread, in which the divisor is daily closing price.[25]

Table VII presents the results of these tests, structured the same way as those above (from Table VI). The coefficient on *Peer SEO* in the regression explaining change in forecast dispersion is -0.122, significant at the 10% level. More prior *Peer SEO* activity recently, associates with larger drops in forecast dispersion around SEOs by unconstrained industry peers. This suggests a reduction in asymmetric information in response to prior industry issuance activity. We show another side of this asymmetric information cost reduction in the bid-ask spread change regression. The coefficient on *Peer SEO* is -0.125, significant at the 5% level. Given spreads are partially driven by asymmetric information concerns, their larger reduction in the presence of more industry peer SEO activity suggests reduced asymmetric information due to the actions of peers. Overall, the results in this section support the idea of reduced asymmetric information via analysts and institutions, in response to peer SEOs. Given information costs are one possible barrier to equity financing by constrained firms, the reductions represent possible mechanisms for documented peer influences on corporate financial policies.

D. Financial Intermediaries' and Investors' Learning and Information Transmission

Our next set of tests connects the dots implied in the above. Given increases in financial market participants' activity around constrained firms (in response to the unconstrained peers' SEOs), does the

[24] Countless papers proxy AI with forecast dispersion. See Healy and Palepu (2001) for a nice review.
[25] Glosten and Harris (1988) estimate components of bid-ask spread, one of which is AI-related.

associated reduction in asymmetric information facilitate SEOs by the constrained? Here we also include underwriters as potential conduits of information associated with peer effects in corporate financial policies.[26]

There are two levels to the expected underwriter effect. First, the bank must learn from repeated underwriting of industry peers' SEOs. There is precedent for this. James (1992) shows that underwriters develop relationship-specific assets through their activities. In short they acquire valuable information, and this learning may be (at least partially) about industry prospects that drove the SEO decisions which they underwrote. Assuming less than perfectly correlated information across industry-peer SEOs they underwrite, more SEOs handled implies more information learned by the bank. Second, given their learning, underwriters may use it to more efficiently price and sell industry-peers' SEOs. They may reduce asymmetric information related costs by addressing concerns raised by end-buyers of equity securities during the underwriting process. These effects should be most important and pronounced among constrained firms, for whom asymmetric information related costs are significant.

Our test of the above thinking returns to the hazard framework presented in Table III, but with the inclusion of a new variable that is designed to pick up learning by the underwriter. The new variable, *Ln(Common Underwriter)*, is the natural log of one plus the number of SEOs by industry peers, underwritten by the same investment bank (that the constrained firm uses) over the last six months.

Table VIII Panel A indicates the results from the hazards including the common underwriter count variable. For constrained firms, we continue to see the importance of the *Peer SEO* count variable (significant). Now we also see incremental importance of the common underwriter count variable, significant at the 1% level. When the constrained firm's underwriter has led more industry-peer SEOs to market recently, this increases the hazard for the constrained firm. In the spirit of Whited (2006), a factor

[26] There is general precedent for this in the IPO literature. Benveniste, Ljungqvist, Wilhelm and Yu (2003) find that a firm's decision to execute an IPO depends on the experience of its primary market contemporaries.

that raises the hazard essentially aids in/speeds up the process of overcoming barriers to the event. The logical candidate is asymmetric information, since underwriters acquire information and communicate it, thus reducing associated costs. Notably, there is no such influence on unconstrained firms.

In Panel B we offer an alternative perspective on information communication, tied to the documented increased analyst coverage result in Table VI. We build a second "common" information intermediary variable based on analyst coverage. Each constrained firm is (potentially) covered by several analysts. For each analyst that follows a constrained firm, we determine whether that analyst follows any of the firm's industry peers that have conducted SEOs in the last six months. We then divide the number (of analysts) that did so, by the total number of analysts that follow the firm, to create *Common Analyst*. We also construct the corollary for each unconstrained firm.[27] The results indicate that higher values of *Common Analyst* associate with steeper hazards, for constrained firms. This is consistent with the value of reducing asymmetric information, since coverage of industry peers likely produces more industry-specific information, and reduced asymmetric information (costs) is also likely to speed up equity issuance by constrained firms. Notably, the coefficient on *Common Analyst* is insignificant in the hazard for the sample of unconstrained firms.

Common investors may also be involved in the transmission of peer effects. If investors in one firm of the industry observe its financing activities, they may better understand whether the action is suitable for other firms they invest in. To see if this is the case we explore whether peer effects are more pronounced when the firm has institutional owners (and separately, active mutual fund owners) that also own shares of peer firms that have conducted recent SEOs, using measures similar to those from Cohen and Frazzini (2008). We construct a measure of common ownership (*Common institutional holdings*) from 13F filings (using Thomson-Reuters institutional holdings data). We compute this as the number of

[27] In other words, *Common Analyst* is the *percentage* of all analysts covering a firm, that also covered an industry peer. This measure is adopted from Cohen and Frazzini (2008).

institutional investors reporting holdings of an SEO firm as well as of any of the industry Peers that issued an SEO in the prior 6 months, divided by the number of institutional investors holding the SEO firms.[28] We also use Thomson-Reuters mutual fund holdings data to construct *Common mutual fund holdings;* defined as the number of actively-managed equity mutual funds reporting holdings in the SEO firm and in any of its industry Peers that issued an SEO in the prior 6 months, divided by the number of actively-managed equity mutual funds holding the SEO firms.

We report the results from hazards including these common ownership variables, in Panel C of Table VIII. We find that both common ownership variables have positive and significant coefficients for constrained firms and insignificant coefficients for unconstrained firms. These results emphasize the role of investors in propelling peer effects. They are consistent with institutional investors learning from industry peers' financing activities, which gives them greater ability to assess the SEO prospects of follower firms. They also suggest an intimated willingness of these investors to take up a portion of the SEO, given what they learned from prior peer SEOs.

Our final tests of this sub-section delve more specifically into indicators of reduced asymmetric information costs associated with more common underwriter relationships. We examine announcement returns to, and gross spreads charged on, SEOs by constrained firms. If underwriters learn about the potential SEO (i.e. constrained) firms from the prior SEOs of its peers, then we would expect asymmetric information related costs to decline in our common underwriter variable.

Table IX presents regression results for these tests. Constrained firms' SEO announcement abnormal returns are increasing (less negative / more positive) in our common underwriter variable. More underwriting of industry-peers' SEOs recently, likely improves the bank's information set and this knowledge can be used to reduce asymmetric information related costs at the constrained firm's SEO. Similarly, the gross spread fees charged on constrained firms' SEOs are decreasing in our common

[28] In other words, the construction approach mirrors that for the *Common Analyst* variable.

underwriter count variable. Again, this is consistent with a reduction in asymmetric information related costs, through underwriter experience with industry-peer SEOs.

E. More versus less related peers and the demand and supply channel

Finally, we attempt to further distinguish between the demand and supply channels that may be driving peer effects in financial policies. Our analysis is predicated on how similar the peer firms are from a product market perspective. Peer effects may be driven by both demand- and supply-channels. To attempt isolation of one of these, we parse the sample into those peers that are more likely to have a common demand channel, "more" related peers, and those that will be "less" related from the demand side but still share similar capital supply effects. Specifically, we partition our FF-49 peers into two subsamples. Those peers with the same FF-49 and that share the same 2-digit SIC code versus those with the same FF-49 but with different 2-digit SIC codes. For robustness, we also segment by same 3-digit SIC code and (separately) by "nearest peers" based on Hoberg and Phillips' (2016) TNIC measure, to parse peers.

The TNIC measure deserves discussion. We begin by obtaining data from the Hoberg-Phillips Data Library.[29] TNIC score is calculated as the cosine similarity of product descriptions provided by firms *k* and *j* in year *t*, where in our case TNIC is measured between the peer firm and the SEO issuing firm, in the event year. This variable ranges between zero and one, with larger values indicating greater similarity between the product descriptions of the two firms. We then use TNIC to rank all of the peers for a given SEO issuing firm (i.e., all firms in the same FF-49). We define peer firms as more/less related to the SEO issuing firm, when their TNIC sore is above/below the median of TNIC score of all the SEO firm's peers.

We predict that the sample of "less" related peers will concentrate the influence of supply-side peer effects. The "more" related peers will have both supply and (potentially heightened) demand-side

[29] We are grateful that they make their data available at http://cwis.usc.edu/projects/industrydata/

effects. The latter could either increase or dampen peer effects as follows. On the one hand, the greater commonality of more related peers should increase peer-effects. On the other hand, demand-side effects will be strategically considered when unconstrained firms choose to take actions. In a strategic setting, a leader firm may purposely avoid actions that benefit its constrained rivals, suggesting that the SEOs by unconstrained firms may be intentionally timed to occur when rival spillover benefits are minimal.

We explore the peer effects of more and less related peers in Table X. Again we estimate our usual hazard models, but we break out the peer SEOs variable into *Peer SEO_more* and *Peer SEO_less*. Panel A shows that regardless of which method we use to delineate peers (2-digit, 3-digit, or TNIC) the coefficients on both variables are positive and significant for the constrained firm sample. This is consistent with generally a peer effect on financial policies. Notably, the coefficient on *Peer SEO_less* is roughly four times larger than the coefficient on *Peer SEO_more*. Thus even though the demand effect (embodied in the coefficient on *Peer SEO_more*) is significant, the supply effect appears to be incrementally larger. Also notably, for the sample of unconstrained firms the coefficients on *Peer SEO_more* and *Peer SEO_less* are generally insignificant.[30]

We continue with our exploration of more and less related peers, by revisiting the common underwriter channel. Again in Panel A of Table X, we split the common underwriter variable into *Common Undwrt_more* and *Common Undwrt_less*, which are the counts of prior SEOs conducted by more and less related peers, that were also underwritten by the firm's underwriter over the past six months. We see that the coefficient on *Common Undwrt_more* is insignificant for both the constrained and unconstrained samples. By contrast, the coefficient on *Common Undwrt_less* is positive and highly significant for the constrained firm sample and insignificant for the unconstrained firm sample. These results suggest that supply-side peer effects are quite pronounced, in general, and are further propagated through common

[30] Tests of differences across the two samples indicate that the sensitivity to *Peer SEO_less* is significantly larger for constrained firms, while the sensitivities to *Peer SEO_more* are insignificantly different.

financial intermediaries. They also suggest an element of strategic behavior by more related peers, eschewing actions that may alleviate asymmetric information costs for constrained product market competitors (more related peers).[31]

In Panels B, C, and D of Table X we revisit the effects of common analysts, common institutional ownership, and common mutual fund ownership on constrained (and unconstrained) firms' SEO hazards. Again we stratify the overlaps based on more and less related peers. In general we see the same pattern as found in the common underwriter results. Namely, the common analyst, institutional ownership, and mutual fund ownership channels are more pronounced when they connect less related peers. We interpret these results as consistent with strong supply-side peer effects.

For our final set of tests, we revisit information spillover from peers' SEO announcements, to more versus less related peers. Earlier we showed that constrained firms react positively to unconstrained firms' SEO announcements, particularly when the constrained firm had not recently conducted an SEO. In Table XI we offer results from similar regressions (dependent variable is the firm's three-day CAR around peer firm SEOs), but we now include a dummy variable *Less related Peer* that equals one if the peer SEO is less related (defined by 2-digit SIC code, 3-digit SIC code, and TNIC). We also include a *Prior 6 month issue* dummy variable that indicates whether the firm has a recent SEO, along with an interaction of this variable and *Less related Peer*.

In the first three columns (constrained firms' reactions to unconstrained firms' SEO announcements), we see that the coefficient on *Less related Peer* is positive and significant. This suggests that the positive information spillover is more pronounced when the peer that conducted an SEO is less related. When we reverse the experiment and look at information spillover from constrained firm SEO announcements to unconstrained firms, we find no such effect. These results, taken together with the

[31] A viable alternative interpretation is that the strategic behavior is on the part of the underwriter. They may be unwilling to underwrite product market competitors' SEOs in close time proximity. Feedback during seminars, from faculty that often interact with investment bankers, suggest this may be the case.

aforementioned hazard results in this section, suggest there are strong peer effects that emanate from the supply-side.

F. Strategic Behavior by Unconstrained Firms

In several places above, we intimate that strategic considerations influence more related peers' willingness to execute an SEO, if it would release financial constraints of product market competitors. This is a difficult notion to test, but here we provide first evidence consistent with such strategic thinking.

We explore time-series patterns of average cash ratios for constrained firms, around SEOs by unconstrained firms. The formation of the average cash ratio is done on a quarterly basis, and in event time relative to the unconstrained peer firm's SEO. Thus for each unconstrained firm SEO, we calculate the average cash ratio across all of the unconstrained firm's (constrained) peers, in each quarter of [-4, 4] (where 0 is the quarter containing the unconstrained firm's SEO). Given one average cash ratio of constrained firms for each unconstrained SEO event, we then average across all unconstrained SEO events.

We present Figure II, showing the time-series of quarterly average cash ratios of constrained firms, around the SEOs of unconstrained firms. There are three lines: blue (solid), red (dashed) and green (small dashed) for the sample of constrained firms whose cash ratios are averaged around the SEO events of all, more related, and less related unconstrained peer firms. We first focus on the full sample results illustrated with the blue line.

The data show an interesting trend in built-up slack by constrained firms in event time. One year prior to the unconstrained firm's SEO, cash ratios average about 17% of assets. This does not change meaningfully for six months. Then cash build-up begins and steadily climbs, and reaches (a local) peak in the quarter after the unconstrained firm's SEO. Afterwards, it appears to flatten again.

The build-up is the key. One interpretation is that unconstrained firms wait until their constrained peers had built up enough slack, such that it reduces the benefits these constrained firms would get from released financial constraints (driven by the unconstrained firm's SEO). In other words, the constrained firms were nearing the point of ability to compete effectively with the unconstrained firms, due to sufficient slack, even though they might have difficulty conducting an SEO (or it would be expensive). Therefore, the unconstrained firm does not experience the strategic cost of releasing its peers' financial constraints, because they have effectively been released through the build-up of slack.

The lean towards strategic considerations though, also suggests that the pattern should be more pronounced among *more* related peers. This was the sub-group that showed weaker supply-side effects, which we hypothesized could be due to such strategic considerations. Figure II indeed shows this to be the case. The slope of the red line is steeper than the slope(s) of (both) the green (and blue) line(s).[32] In other words, the build-up in slack preceding unconstrained firms' SEOs is more pronounced among the more related peers. This is consistent with strategic behavior, because the opportunity cost of reducing asymmetric information costs for constrained firms is smaller, when these constrained firms have acquired sufficient slack to compete with the more related peer in the product market.

IV. Conclusions

Peer effects are known to be influential in corporate finance policy. Investment, capital structure, executive compensation, all show some form of sensitivity to industry cohort characteristics. We examine the role of capital supply, information and particularly intermediaries in the transmittal of these effects.

We study SEO timing decisions, the industry factors that influence them, and their costs' sensitivity to industry information. Constrained firms' SEO hazards are increasing in the number of

[32] Parenthetical results are obvious since the blue should be the average of red and green results.

industry-peer SEOs recently. Information is communicated from prior industry equity issuance that encourages constrained firms to speed up their own equity issuance.

We confirm information communication with significant responses by constrained firms to their industry-peers' SEO announcements. We show several possible conduits for the information flow: analyst coverage and institutional ownership increase in recent *Peer SEO* counts; forecast dispersion and bid-ask spread decline in the same.

Underwriters play a particular role in the information communication. When a constrained firm's SEO underwriter has had more experience marketing SEOs of industry peers recently, the constrained firm speeds up its SEO, it experiences a better announcement return to it, and it pays a lower gross spread fee on it. We also find that peers that are less related from the demand side but still relate from the supply side, demonstrate strong peer effects, and suggest a large supply-side channel in peer effects.

Overall, our research highlights the critical role of intermediaries in the transmittal of peer-to-peer financial policies. Yet our focus has been on equity and therefore sidesteps the potential for peer effect transmittal through debt issues. Given that bank loans are important sources of funding for smaller firms with greater information problems, future research in this direction may be fruitful.

References

Allison P., 1995. Survival Analysis Using the SAS System: A Practical Guide. SAS Institute Inc., North Carolina.

Almeida, H., Campello, M., Weisbach, M., 2004. The Cash Flow Sensitivity of Cash. *Journal of Finance* 59, 1777–1804.

Altinkilic, O., Hansen, R., 2003. Discounting and underpricing in seasoned equity offers. *Journal of Financial Economics* 69, 285–324.

Alti, A., Sulaeman, J., 2012. When do high stock returns trigger equity issues? *Journal of Financial Economics* 103, 61–87.

Asquith, P., Mullins, D., 1986. Equity Issues and Offering Dilution. *Journal of Financial Economics* 15, 61–89.

Baker, M., Wurgler, J., 2002. Market Timing and Capital Structure. The *Journal of Finance* 57, 1–32.

Bizjak, J., M. Lemmon and T. Nguyen, 2011. Are all CEOs above average? An empirical analysis of compensation peer groups and pay design. *Journal of Financial Economics* 100, 538-555.

Bayless, M., and S. Chaplinsky, 1996, Is there a window of opportunity for seasoned equity issuance? *Journal of Finance* 51, 253-278.

Bradley, D., Yuan, X., 2013. Information Spillovers Around Seasoned Equity Offerings. *Journal of Corporate Finance* 21, 106–118.

Chan , K. and Y. Chan, 2014. Price Informativeness and Stock Return Synchronicity: Evidence from the Pricing of Seasoned Equity Offerings. *Journal of Financial Economics* 114, 36-53.

Chan, K. and A. Hameed, 2006. Stock Price Synchronicity and Analyst Coverage in Emerging Markets. *Journal of Financial Economics* 80, 115-147.

Chemmanur, T., S. He and G. Hu, 2009. The Role of Institutional Investors in Seasoned Equity Offerings. *Journal of Financial Economics* 94, 384-411.

Choe, H.; R. W. Masulis; and V. Nanda, 1993, Common stock offerings across the business cycle: Theory and evidence. *Journal of Empirical Finance* 1, 3-31.

Cohen, L. and Frazzini, A. (2008) Economic links and predictable returns, *Journal of Finance* 63, 1977-2011.

Dasgupta, S., J. Gan and N. Gao, 2010. Transparency, Price Informativeness and Stock Return Synchronicity: Theory and Evidence. *Journal of Financial and Quantitative Analysis* 45, 1189-1220.

DeAngelo, H., DeAngelo, L., Stulz, R., 2010, Seasoned equity offerings, market timing, and the corporate life–cycle. *Journal of Financial Economics* 95, 275–295.

Durnev, A., R. Morck and B. Yeung, 2004. Value-Enhancing Capital Budgeting and Firm-Specific Stock Return Variation. *Journal of Finance* 59, 65-105.

Fama, E., French, K., 1997. Industry costs of equity. *Journal of Financial Economics* 43, 153–193.

Farre-Mensa, Joan, and Alexander Ljungqvist, 2016, "Do measures of financial constraints measure financial constraints?", Review of Financial Studies 29, 271-308.

Faulkender, M., Yang, J., 2010. Inside the black box: the role and composition of compensation peer groups. *Journal of Financial Economics* 96, 257-270.

Fazzari, S. M., Hubbard, R. G., Petersen B. C., 1988. Financing Constraints and Corporate Investment. Brookings Papers on Economic Activity 1, 141–195.

Foucault, T., Fresard, L., 2014. Learning from Peers' Stock Prices and Corporate Investment. *Journal of Financial Economics* 111, 554-577.

Gao, X., Ritter, J., 2010, The Marketing of Seasoned Equity Offerings. Journal of Financial Economics 97, 33-52.

Glosten, L. and L. Harris, 1988. Estimating the Components of the Bid/Ask Spread. *Journal of Financial Economics* 21, 123-142.

Hadlock, C., Pierce, J., 2010. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Review of Financial Studies* 23, 1909–1940.

Healy, P. and K. Palepu, 2001. Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature. *Journal of Accounting and Economics* 31, 405-440.

Helwege, J., Liang, N., 2004. Initial public offerings in hot and cold markets. *Journal of Financial and Quantitative Analysis* 39, 541–569.

Hennessy, C. and T. Whited, 2007. How costly is external financing? Evidence from a structural estimation, *Journal of Finance* 62, 1705-1745.

Hoberg, G. and G. Phillips, 2016. Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy*, forthcoming.

Huang, R., Zhang, D., 2011. Managing underwriters and the marketing of seasoned equity offerings. *Journal of Financial and Quantitative Analysis* 46, 141–170.

James, C., 1992. Relationship-Specific Assets and the Pricing of Underwriter Services. *Journal of Finance* 47, 1865-1885.

Kaplan, S., Zingales, L., 1997. Do financing constraints explain why investment is correlated with cash flow? *Quarterly Journal of Economics* 112, 169–216.

Kaustia, M. and V. Rantala, 2013, Common Analyst-Based Method for Defining Peer Firms. Working paper.

Kaustia, M. and V. Rantala, 2015. Social learning and corporate peer effects, *Journal of Financial Economics*, 117, 653-669.

Kelly, P., 2014. Information Efficiency and Firm-Specific Return Variation. *Quarterly Journal of Finance* 4 (4), 1450018.

Lamont, O., C. Polk, and J. Saa-Requejo, 2001. Financial constraints and stock returns, *Review of Financial Studies* 14, 529–554.

Leary, M. and Roberts, M., 2014. Do peer firms affect corporate financial policy? *Journal of Finance* 69, 139-178.

Loughran, T. and Ritter, J., 1995. The New Issues Puzzle. The *Journal of Finance* 50, 23–51.

Loughran, T. and Ritter, J., 1997. The Operating Performance of Firms Conducting Seasoned Equity Offerings. The *Journal of Finance* 52, 1823–1850.

Lys, T. and S. Sohn, 1990. The Association Between Revisions of Financial Analysts' Earnings Forecasts and Security-Price Changes. *Journal of Accounting and Economics* 13, 341-363.

Manski, C., 1993, Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60, 531-542.

Masulis, R., Korwar, A., 1986. Seasoned Equity Offerings: An Empirical Investigation. *Journal of Financial Economics* 15, 91–118.

Mclean, R., 2011. Share Issuance and cash savings. *Journal of Financial Economics* 99, 693–715.

Meyer, B.D., 1990. Unemployment insurance and unemployment spells. *Econometrica* 58, 757–782.

Morck, R., B. Yeung and W. Yu, 2000. The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements? *Journal of Financial Economics* 58, 215-260.

Rau, P.R., Stouraitis, A., 2011, Patterns in the timing of corporate event waves, *The Journal of Financial and Quantitative Analysis* 46, pp. 209-246.

Schultz, P., 2003. Pseudo market timing and the long-run underperformance of IPOs. *Journal of Finance* 58, 483–517.

Servaes, H., Tamayo, A., 2014, How do industry peers respond to control threats? *Management Science* 60, 380-399.

Whited, T.M., 2006. External finance constraints and the intertemporal pattern of intermittent investment. *Journal of Financial Economics*, 467-502.

Whited, T.M., Wu, G., 2006. Financial constraints risk. *Review of Financial Studies* 19, 531–559.

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

Appendix I: Variable Definitions

3-day CAR: the SEO 3-day announcement period abnormal returns calculated using standard market model over the event days –1, 0, and +1, where day 0 is the filing date.

Age*:* the number of years since founding.

Book-to-market: the ratio of book equity (CEQ) of fiscal year ending in year t-1 to market equity (from CRSP) at the end of year t-1.

Cashneeds: the Pro Forma Cash/TA ratio = (Cash $_{t+1}$- SEO proceeds from primary shares)/(Total Assets $_{t+1}$ - SEO proceeds from primary shares), which follows DeAngelo, DeAngelo and Stulz (2010).

Change in analyst coverage*:* the number of analysts covering the constrained firm in the month after an unconstrained firm SEO, minus analyst coverage of the constrained firm in the month before.

Change in analyst forecast dispersion: the difference in the forecast dispersion after and before the SEO announcement. Forecast dispersion is defined as the cross-sectional standard deviation of analyst forecasts on earnings per share, divided by the stock price and the end of the month. The data are from IBES.

Change in bid-ask spread: the change between two monthly values of average bid-ask spread. We calculate ([ask minus bid]/closing price) on each day of the month, and then average across the days in the month.

Change in institutional holdings: the percentage of shares outstanding held by institutional investors of constrained firms after an unconstrained SEO, minus the percentage of shares outstanding held by institutional investors of constrained firms in the month before.

Common analyst: the number of analysts providing EPS forecasts for an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of analysts covering the SEO firms. The data are from the IBES Detailed History File. This closely follows the definition from Cohen and Frazzini (2008).

Common Analyst_More/ Less: the number of analysts reporting coverage on an SEO firm as well as on any of the "same-industry" more/less Peers that issued an SEO in the prior 6 months, divided by the number of analysts covering the SEO firms. More/less related Peers are those peers that have the same/different 2-digit SIC code/3-digit SIC code as the issuing firm, or more/less related TNIC score to the issuing firm. Peer firms are more/less related to the SEO issuing firms when their TNIC sore is above/below the median of the TNIC score of all peers that are deemed related to the issuing firm using this TNIC data.

Common institutional holdings: the number of institutional investors reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of institutional investors holding the SEO firms. The data are from Thomson-Reuters institutional holdings (i.e., 13F). This closely follows the definition from Cohen and Frazzini (2008).

Common Insti_More/Less: the number of institutional investors reporting holdings on an SEO firm as well as on any of the "same-industry" more/less related Peers that issued an SEO in the prior 6 months, divided by the number of institutional investors holding the SEO firms. More/less related Peers are those peers that have the same/different 2-digit SIC code/3-digit SIC code as the issuing firm, or more/less related TNIC score to the issuing firm. Peer firms are more/less related to the SEO issuing firms when their TNIC sore is above/below the median of the TNIC score of all peers that are deemed related to the issuing firm using this TNIC data.

Common mutual fund holdings: the number of actively-managed equity mutual funds reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of actively-managed equity mutual funds holding the SEO firms. The data are from Thomson-Reuters mutual fund holdings. This closely follows the definition from Cohen and Frazzini (2008).

Common MF_More/Less: the number of actively-managed equity mutual funds reporting holdings on an SEO firm as well as on any of the "same-industry" more/less related Peers that issued an SEO in the prior 6 months, divided by the number of actively-managed equity mutual funds holding the SEO firms. More/less related Peers are those peers that have the same/different 2-digit SIC code/3-digit SIC code as the issuing firm, or more/less related TNIC score to the issuing firm. Peer firms are more/less related to the SEO issuing firms when their TNIC sore is above/below the median of the TNIC score of all peers that are deemed related to the issuing firm using this TNIC data.

Common Underwriter is defined as the number of “same industry” firms that used the same lead underwriter as the issuing firm in the prior 6 months.

Common Undwrt_More/Less is the number of "same-industry" more/less related peer firms that used the same lead underwriter as the issuing firm in the prior 6 months. More/less related Peers are those peers that have the same/different 2-digit SIC code/3-digit SIC code as the issuing firm, or more/less related TNIC score to the issuing firm. Peer firms are more/less related to the SEO issuing firms when their TNIC sore is above/below the median of the TNIC score of all peers that are deemed related to the issuing firm using this TNIC data.

Constrained dummy: a dummy variable that equals to one if the firm is constrained.

Constrained firms**:** firms that have a consistent history of zero distribution & share repurchase since their previous issue.

Dinstidem: a dummy variable that takes the value of one if the institutional demand variable (new holdings) is in its highest quintile, which follows Alti and Sulaeman (2012).

Firm_indret: the firm’s cumulative return in the prior 3 months, minus industry cumulative return in the prior three months before the SEO.

Firm size**:** the natural logarithm of the book value of assets (Compustat item at).

Forecast dispersion: the cross-sectional standard deviation of analyst forecasts on earnings per share, divided by the stock price and the end of the month.

Fraction Censored: the percentage of left, right, and both left and right censored spells in the sample.

KZ Index**:** it is constructed following Lamont, Polk, and Saa-Requejo (2001) as –1.001909[(ib + dp)/lagged ppent] + 0.2826389[(at + prcc_f×csho - ceq - txdb)/at] + 3.139193[(dltt + dlc)/(dltt + dlc + seq)] – 39.3678[(dvc + dvp)/lagged ppent]–1.314759[che/lagged ppent], where all variables in italics are Compustat data items.

Length Censored (uncensored)**:** the censored (uncensored) number of days between issues (spells).

Less-related Peer**:** a dummy variable that equals to one if constrained (unconstrained) firms have different 2-digit SIC code/different 3-digit SIC code/less-related TNIC as SEO issuing unconstrained (constrained firms) in the same industry.

Less-related Peer* Prior 6 month issue: the interaction term of *Less-related Peer* and *Prior 6 month issue*.

Ln(Common Underwriter) is the natural logarithm of (1+Common Underwriter).

Ln(Common Undwrt_More/Less*)* is the natural logarithm of (1+ **Common Undwrt_More/Less**).

Ln(Market SEO): the natural logarithm of (1+Market SEO).

Ln(Peer SEO)**:** the natural logarithm of (1+Peer SEO).

Ln(Peer SEO_More): the natural logarithm of one plus the number of firms conducting SEOs in the industry in the prior 6 months that has the same 2-digit SIC code / same 3-digit SIC code / more related TNIC score to the issuing firm.

Ln(Peer SEO_Less): the natural logarithm of one plus the number of firms conducting SEOs in the industry in the prior 6 months that has different 2-digit SIC code/different 3-digit SIC code/less related TNIC score to the issuing firm.

Ind_mktret: the industry cumulative return in the prior 3 months, minus NYSE/Amex value weighted cumulative return in the prior three months before the SEO.

Lnmv: the Natural logarithm of market capitalization, computed as share price times shares outstanding (both from CRSP) as of the end of June of year t.

Market SEO: the number of firms conducting SEOs in the market in the prior 6 months, minus the number of firms conducting SEOs in the industry in the prior 6 months.

Mktret: the NYSE/Amex value weighted cumulative return in the prior three months before the SEO.

Non-rated firms: firms that do not have a credit rating from S&P, using data obtained from Compustat (variable splticrm).

Offer size: the total proceeds raised by the firm in the SEO offering.

Peer SEO: the number of firms conducting SEOs in the I same FF-49 industry in the prior 6 months.

Prior 6 month issue**:** a dummy variable that equals to one if a constrained firm issue SEO in prior 6 months in Panel D.

Spell Length: the number of days between IPOs and first SEOs and the time between consecutive SEOs.

The percentage of constrained SEOs in the wave: the number of constrained SEOs in the corresponding 6-month window period of the wave, divided by the total number of constrained SEOs in the wave.

The percentage of unconstrained SEOs in the wave: the number of unconstrained SEOs in the corresponding 6-month window period of the wave, divided by the total number of unconstrained SEOs in the wave.

Unconstrained firms**:** Unconstrained firms refer to the complement sample.

WW Index**:** it is constructed following Whited and Wu (2006) and Hennessy and Whited (2007) as –0.091 [(ib + dp)/at] – 0.062[indicator set to one if dvc + dvp is positive, and zero otherwise] + 0.021[dltt/at] – 0.044[log(at)] + 0.102[average industry sales growth, estimated separately for each three-digit SIC industry and each year, with sales growth defined as above] – 0.035[sales growth], where all variables in italics are Compustat data items.

Table I, Panel A. Number of SEOs by year

The table reports 7,973 uncensored SEOs from January 1970 to December 2010 in the U.S. The sample excludes financials, utilities, and shelf registrations and those that are comprised of less than 50% primary shares.

Year	Number of SEOs
1971	24
1972	59
1973	77
1974	72
1975	126
1976	112
1977	82
1978	109
1979	93
1980	173
1981	165
1982	309
1983	275
1984	129
1985	251
1986	249
1987	154
1988	64
1989	122
1990	85
1991	305
1992	249
1993	360
1994	265
1995	357
1996	449
1997	420
1998	233
1999	285
2000	305
2001	189
2002	182
2003	215
2004	261
2005	215
2006	207
2007	215
2008	99
2009	213
2010	219

Table I, Panel B. Summary of SEO Waves

7,973 uncensored SEOs from January 1970 to December 2010 in U.S. market are used to identify SEO waves for each decade. SEO waves are identified following the moving-average method of Helwege and Liang (2004). Panel A reports start and end time and total number of SEOs of each SEO wave. There are five SEO waves from January 1970 to December 2010. Panel B reports the number and percentage of constrained /unconstrained firms of each SEO wave. *Constrained firms* are firms that have a consistent history of zero dividend distribution & share repurchase since their previous issue. *Unconstrained firms* refer to the complement sample. The *percentage of constrained SEOs* in the wave is number of constrained SEOs in the corresponding 6-month window period of the wave, divided by the total number of constrained SEOs in the wave. The *percentage of unconstrained SEOs in the wave* is number of unconstrained SEOs in the corresponding 6-month window period of the wave, divided by the total number of unconstrained SEOs in the wave.

Panel A: SEO Waves from 1970 to 2010

Waves	Period	Total Number of SEOs
Wave 1	1982-1983	584
Wave 2	1985-1986	500
Wave 3	1991-1993	914
Wave 4	1995-1997	1226
Wave 5	1999-2000	590

Panel B: Constrained and unconstrained SEOs during waves

Waves	Period	# of SEOs constrained	# of SEOs unconstrained	% of constrained SEOs in the wave	% of unconstrained SEOs in the wave
Wave 1	Jan.1982-June 1982	7	138	8.64%	27.44%
	July 1982-Dec.1982	7	157	8.64%	31.21%
	Jan.1983-June 1983	38	111	46.91%	22.07%
	July 1983-Dec.1983	29	97	35.80%	19.28%
Wave 2	Jan.1985-June 1985	41	75	20.40%	25.08%
	July 1985-Dec.1985	32	103	15.92%	34.45%
	Jan.1986-June 1986	76	61	37.81%	20.40%
	July 1986-Dec.1986	52	60	25.87%	20.07%
Wave 3	Jan.1991-June 1991	79	75	14.31%	20.72%
	July 1991-Dec.1991	80	71	14.49%	19.61%
	Jan.1992-June 1992	87	72	15.76%	19.89%
	July 1992-Dec.1992	53	37	9.60%	10.22%
	Jan.1993-June 1993	117	54	21.20%	14.92%
	July 1993-Dec.1993	136	53	24.64%	14.64%
Wave 4	Jan.1995-June 1995	99	69	11.88%	17.56%
	July 1995-Dec.1995	113	76	13.57%	19.34%
	Jan.1996-June 1996	187	70	22.45%	17.81%
	July 1996-Dec.1996	123	69	14.77%	17.56%
	Jan.1997-June 1997	162	58	19.45%	14.76%
	July 1997-Dec.1997	149	51	17.89%	12.98%
Wave 5	Jan.1999-June 1999	68	74	18.48%	33.33%
	July 1999-Dec.1999	84	59	22.83%	26.58%
	Jan.2000-June 2000	128	54	34.78%	24.32%
	July 2000-Dec.2000	88	35	23.91%	15.77%

Table II. Descriptive Statistics

The table reports descriptive statistics for sample SEO firms classified by finance constraints over 1970-2010. Firms are classified into 49 industries following Fama and French (1997). *Constrained firms* refer to a sample of firms that have a consistent history of zero dividend distribution & share repurchase since their previous issue. *Unconstrained firms* refer to the complement sample. *Peer SEO* is the number of firms conducting SEOs in the industry in the prior 6 months. *Market SEO* is defined as the number of firms conducting SEOs in the market in the prior 6 months, minus the number of firms conducting SEOs in the industry in the prior 6 months. *Book-to-market* is the ratio of book equity (CEQ) of fiscal year ending in year *t-1* to market equity (from CRSP) at the end of year *t-1. Firm_indret* is firm's cumulative return in the prior 3 months, minus industry cumulative return in the prior three months before the SEO. *Ind_mktret* is industry cumulative return in the prior 3 months, minus NYSE/Amex value weighted cumulative return in the prior three months before the SEO. *Mktre*t is NYSE/Amex value weighted cumulative return in the prior three months before the SEO. *Cashneeds* is the Pro Forma Cash/TA ratio = (Cash $_{t+1}$- SEO proceeds from primary shares)/(Total Assets $_{t+1}$ - SEO proceeds from primary shares), which follows DeAngelo, DeAngelo and Stulz (2010). *Dinstidem* is a dummy variable that takes the value of one if the institutional demand variable (new holdings) is in its highest quintile, which follows Alti and Sulaeman (2012). *Ln(MV)* is the Natural logarithm of market capitalization, computed as share price times shares outstanding (both from CRSP) as of the end of June of year *t. Proceeds* is measured as the total proceeds raised by the firm in the SEO offering. *Forecast dispersion* is defined as the cross-sectional standard deviation of analyst forecasts on earnings per share, divided by the stock price and the end of the month. *Spell Length* is the number of days between IPOs and first SEOs and the time between consecutive SEOs. *Fraction Censored* refers to the percentage of left, right, and both left and right censored spells in the sample. *Length Censored (uncensored)* refers to the censored (uncensored) number of days between issues (spells). See Appendix II for details about censoring. Panel A reports the firm and deal characteristics for constrained and unconstrained SEOs separately. Panel B reports the spell characteristics. Panel C is the correlation matrix. Asterisks indicate significant difference across subsamples. The difference in means *t-test* assumes unequal variances across groups when a test of equal variances is rejected at the 10% level. The significance level of the difference in medians is based on a Wilcoxon sum-rank test. A ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	Constrained SEOs			Unconstrained SEOs		
	Mean	Median	Std.	Mean	Median	Std.
Panel A. Firm and Deal Characteristics						
Peer SEO	18.47	11.00	22.98	38.12***	27.00***	35.05
Market SEO	59.31	64.00	26.58	34.94***	32.00***	35.84
Book-to-market	0.49	0.46	0.26	0.74***	0.78***	0.30
Firm_indret (%)	6.67	1.31	30.02	1.68***	-0.03***	19.13
Ind_mktret (%)	5.08	2.91	14.09	1.78***	1.39***	15.16
Mktret (%)	4.88	5.17	6.37	5.67***	4.95	12.12
Cashneeds	-0.15	-0.07	0.36	-0.07***	-0.02***	0.19
Dinstidem	0.20	0.00	0.40	0.20	0.00	0.40
Ln(MV)	5.79	5.79	1.34	6.12***	6.12***	1.48
Proceeds	90.79	51.85	150.22	101.83**	46.80***	267.07
Forecast dispersion	0.010	0.005	0.021	0.005***	0.002***	0.015
Number of obs.	3964			4009		
Panel B. Spell Characteristics						
Spell Length (days)	1920.64	902.00	2401.81	2510.5***	1205.50***	2962.41
Fraction Censored	0.19			0.29		
Length Censored (days)	4432.48	4040.00	3143.94	4908.0***	4484.00*	3590.12
Length Uncensored (days)	1326.26	680.50	1717.65	1513.6***	693.00	1919.30

Panel C. Correlation Matrix

	Peer SEO	Mkt. SEO	Book-to-mkt	Firm_indret	Ind_mktret	Mktret	Cashneeds	Dinstidem	Ln(MV)	Proceeds	Forecast dispersion
Peer SEO	1.000										
	-										
Mkt. SEO	-0.798	1.000									
	(0.000)	-									
Book-to-mkt	0.301	-0.383	1.000								
	(0.000)	(0.000)	-								
Firm_indret	-0.067	0.063	-0.141	1.000							
	(0.000)	(0.000)	(0.000)	-							
Ind_mktret	-0.127	0.161	-0.145	0.028	1.000						
	(0.000)	(0.000)	(0.000)	(0.014)	-						
Mktret	0.059	-0.105	0.052	0.015	-0.290	1.000					
	(0.000)	(0.000)	(0.000)	(0.168)	(0.000)	-					
Cashneeds	0.097	-0.152	0.188	-0.050	-0.088	0.014	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.228)	-				
Dinstidem	-0.148	0.093	-0.055	0.001	0.050	-0.009	0.047	1.000			
	(0.000)	(0.000)	(0.000)	(0.942)	(0.000)	0.398	(0.000)	-			
Ln(MV)	-0.131	0.101	-0.130	0.070	0.049	0.017	0.149	0.501	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)	(0.000)	(0.000)	-		
Proceeds	-0.150	0.117	-0.039	0.044	0.063	-0.028	-0.010	0.331	0.478	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.379)	(0.000)	(0.000)	-	
Forecast dispersion	-0.024	0.021	-0.030	0.008	0.000	-0.009	-0.003	-0.012	-0.006	0.001	1.000
	(0.032)	(0.067)	(0.008)	(0.500)	(0.986)	(0.430)	(0.781)	(0.267)	(0.591)	(0.943)	-

Table III. Semiparametric Hazard Model Estimates

The table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1970-2010. Cox regression model with time-dependent covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$.The dependent variable is the number of days between IPOs and first SEOs and between consecutive SEOs. *Ln(Peer SEO)* is the natural logarithm of (1+*Peer SEO*). *Ln(Market SEO)* is the natural logarithm of (1+Market SEO). All other variables are defined as in Table 2, including industry and year effects. All other variables are defined as in Table 2, including industry and year effects. Panel A reports the hazard model estimation of the time between offerings. Panel B reports the robustness tests by using the dollarized value of *Peer SEO* and *Market SEO*. *Peer SEO ($)* is the dollar volume of SEOs in the industry in the prior 6 months. *Market SEO ($)* is defined as the dollar volume of SEOs in the market in the prior 6 months, minus the dollar volume of SEOs in the industry in the prior 6 months. Standard errors are in parentheses. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Duration Analysis of the Time between Offerings

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.099***	0.007	0.092**
	(0.022)	(0.029)	[2.512]
Ln(Market SEO)	0.031***	-0.068***	0.099***
	(0.009)	(0.010)	[7.501]
Book-to-market	-0.983***	-0.079	-0.903***
	(0.069)	(0.064)	[-9.598]
Firm_indret	0.119**	0.311***	-0.193**
	(0.042)	(0.087)	[-1.999]
Ind_mktret	0.636***	-0.115	0.751***
	(0.104)	(0.142)	[4.261]
Mktret	-0.331	-0.157	-0.174
	(0.292)	(0.185)	[-0.504]
Cashneeds	-0.075***	-0.042**	-0.033
	(0.022)	(0.018)	[-1.127]
Dinstidem	0.407***	0.155***	0.251***
	(0.048)	(0.048)	[3.710]
Ln(MV)	-0.002	-0.079***	0.079***
	(0.015)	(0.012)	[4.161]
Proceeds	0.007	0.011**	-0.004
	(0.010)	(0.004)	[-0.360]
Log Likelihood	-30695.267	-32005.302	
Likelihood Ratio test	490.938***	316.649***	
Diff test: Peer SEO	0.068***	0.075***	
−Market SEO	(0.005)	(0.001)	

Panel B. Robustness Check: Duration Analysis of the Time between Offerings

	Constrained Firms	Unconstrained firms	Difference
Peer SEO ($)	0.032***	0.015***	0.017***
	(0.003)	(0.002)	[5.187]
Market SEO ($)	0.017***	0.007***	0.010***
	(0.001)	(0.001)	[7.273]
Book-to-market	-0.988***	0.149**	-1.138***
	(0.068)	(0.062)	[-12.365]
Firm_indret	0.122**	0.288***	-0.166*
	(0.044)	(0.086)	[-1.722]
Ind_mktret	0.584***	-0.304**	0.888***
	(0.107)	(0.141)	[5.02]
Mktret	-0.140	0.064	-0.204
	(0.283)	(0.183)	[-0.605]
Cashneeds	-0.087***	-0.037*	-0.050
	(0.024)	(0.020)	[-1.607]
Dinstidem	0.430***	0.161***	0.269***
	(0.048)	(0.047)	[3.974]
Ln(MV)	0.048***	-0.078***	0.126***
	(0.016)	(0.012)	[6.431]
Proceeds	-0.008	0.005	0.000
	(0.011)	(0.005)	[-1.138]
Log Likelihood	-30298.796	-31904.730	
Likelihood Ratio test	792.943***	201.134***	
Diff test: Peer SEO ($)–Market SEO ($)	0.015***	0.008***	
	(0.001)	(0.001)	

Table IV. Robustness Checks (Alt Proxies for Financial Constraints) Semiparametric Hazard Model Estimates

The table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1970-2010. Cox regression model with time-dependent covariates is specified as hi(t)=h0(t)eX(t)β.The dependent variable is the number of days between IPOs and first SEOs and between consecutive SEOs. *Ln(Peer SEO)* is the natural logarithm of (1+*Peer SEO*). *Ln(Market SEO)* is the natural logarithm of (1+Market SEO). All other variables are defined as in Table 2, including industry and year effects. In Panel A, ***Age*** is years since founding. Constrained (Unconstrained) firms are firms whose age is below (above) the median age group in the sample. In Panel B, ***Firm size*** is defined as the natural logarithm of the book value of assets (Compustat item *at*). Constrained (Unconstrained) firms are firms whose size is ranked in the bottom 25% (top 25%) in the sample. In Panel C, ***KZ Index*** is constructed following Lamont, Polk, and Saa-Requejo (2001) as –1.001909[(*ib + dp*)/lagged *ppent*] + 0.2826389[(*at + prcc_f*×*csho - ceq - txdb*)/*at*] + 3.139193[(*dltt + dlc*)/(*dltt + dlc + seq*)] – 39.3678[(*dvc + dvp*)/lagged *ppent*]–1.314759[*che*/lagged *ppent*], where all variables in italics are Compustat data items. Following convention, firms are sorted into terciles based on their index values in the previous year. Firms in the top tercile are coded as constrained and those in bottom tercile are coded as unconstrained. In Panel D, ***WW Index*** is constructed following Whited and Wu (2006) and Hennessy and Whited (2007) as –0.091 [(*ib + dp*)/*at*] – 0.062[indicator set to one if *dvc + dvp* is positive, and zero otherwise] + 0.021[*dltt/at*] – 0.044[log(*at*)] + 0.102[average industry sales growth, estimated separately for each three-digit SIC industry and each year, with sales growth defined as above] – 0.035[sales growth], where all variables in italics are Compustat data items. Following convention, firms are sorted into terciles based on their index values in the previous year. Firms in the top tercile are coded as constrained and those in bottom tercile are coded as unconstrained. In Panel E, ***Non-rated*** firms are those that do not have a credit rating from S&P, using data obtained from Compustat (variable *splticrm*). Non-rated firms are coded as constrained and rated firms are coded as unconstrained. Standard errors are in parentheses. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Duration Analysis of the Time between Offerings (Use Age)

	Below median age	Above median age	Difference
Ln(Peer SEO)	0.088***	0.042	0.046*
	(0.028)	(0.038)	[1.777]
Ln(Market SEO)	0.018*	-0.020	0.038**
	(0.011)	(0.014)	[2.206]
Book-to-market	-0.563***	-1.182***	0.620***
	(0.083)	(0.092)	[5.003]
Firm_indret	0.183***	0.208***	-0.025
	(0.011)	(0.069)	[-0.306]
Ind_mktret	0.705***	0.755***	-0.050
	(0.129)	(0.132)	[-0.273]
Mktret	-1.044*	0.038	-1.082*
	(0.406)	(0.417)	[-1.859]
Cashneeds	-0.586***	0.247***	-0.833***
	(0.029)	(0.063)	[-12.067]
Dinstidem	0.164***	0.363***	-0.199**
	(0.059)	(0.066)	[-2.245]
Ln(MV)	0.080***	-0.194***	0.275***
	(0.019)	(0.021)	[9.812]
Proceeds	0.005***	0.003***	0.002
	(0.001)	(0.001)	[0.928]
Log Likelihood	-18094.732	-14816.627	
Likelihood Ratio test	538.376***	288.582***	

Panel B. Duration Analysis of the Time between Offerings (Use Firm size)

	(1) Bottom 25%	(2) Middle Group	(3) Top 25%	(1)-(2)	(1)-(3)	(2-3)
Ln(Peer SEO)	0.222***	0.160***	0.096	0.061	0.126***	0.065*
	(0.034)	(0.022)	(0.032)	[1.526]	[2.697]	[1.661]
Ln(Market SEO)	0.030**	0.013	-0.016	0.017	0.046**	0.028**
	(0.014)	(0.008)	(0.012)	[1.042]	[2.486]	[1.998]
Book-to-market	-0.431***	-0.434***	-0.546***	0.003	0.115	0.112
	(0.099)	(0.062)	(0.084)	[0.027]	[0.890]	[1.075]
Firm_indret	0.309***	0.291***	0.007	0.018	0.302***	0.284***
	(0.067)	(0.066)	(0.081)	[0.192]	[2.873]	[2.718]
Ind_mktret	0.601***	0.145	0.189	0.456**	0.412*	-0.044
	(0.159)	(0.117)	(0.191)	[2.315]	[1.662]	[-0.196]
Mktret	-0.506	0.331*	-1.466***	-0.838**	0.959*	1.797***
	(0.328)	(0.196)	(0.370)	[-2.192]	[1.940]	[4.287]
Cashneeds	-1.079***	-0.364***	0.038	-0.715***	-1.117***	-0.402***
	(0.084)	(0.057)	(0.032)	[-7.022]	[-12.436]	[-6.150]
Dinstidem	0.329***	0.429***	0.874***	-0.100	-0.546**	-0.446**
	(0.051)	(0.045)	(0.217)	[-1.471]	[-2.448]	[-2.009]
Ln(MV)	-0.391***	0.097***	0.221***	-0.488***	-0.612***	-0.124***
	(0.033)	(0.032)	(0.036)	[-10.645]	[-12.474]	[-2.569]
Proceeds	0.003***	0.000	0.040***	0.003	-0.037***	-0.040***
	(0.000)	(0.003)	(0.001)	[0.934]	[-3.707]	[-3.962]
Log Likelihood	-13016.094	-32622.56	-14439.687			
Likelihood Ratio test	579.647***	353.320***	194.283***			

Panel C. Duration Analysis of the Time between Offerings (Use KZ index)

	Constrained	Unconstrained	Difference
Ln(Peer SEO)	0.152***	0.073	0.079*
	(0.028)	(0.033)	[1.812]
Ln(Market SEO)	0.036***	-0.033***	0.069***
	(0.011)	(0.011)	[4.506]
Book-to-market	-0.047	-0.803***	0.756***
	(0.066)	(0.085)	[6.991]
Firm_indret	0.333***	0.015	0.318***
	(0.059)	(0.061)	[3.739]
Ind_mktret	0.223*	0.390***	-0.167
	(0.142)	(0.141)	[-0.835]
Mktret	0.028	-0.268	0.296
	(0.203)	(0.353)	[0.726]
Cashneeds	-0.028	-0.556***	0.528***
	(0.021)	(0.097)	[5.311]
Dinstidem	0.193***	0.256***	-0.063
	(0.055)	(0.059)	[-0.787]
Ln(MV)	-0.022**	-0.019	-0.003
	(0.012)	(0.020)	[-0.116]
Proceeds	0.001***	0.000	0.001
	(0.000)	(0.001)	[0.952]
Log Likelihood	-27353.129	-17442.259	
Likelihood Ratio test	297.026***	247.407***	

Panel D. Duration Analysis of the Time between Offerings (Use Whited-Wu index)

	Constrained	Unconstrained	Difference
Ln(Peer SEO)	0.186***	0.059	0.127**
	(0.036)	(0.024)	[2.120]
Ln(Market SEO)	0.034**	0.005	0.029*
	(0.014)	(0.008)	[1.733]
Book-to-market	-1.405***	-0.149**	-1.256***
	(0.092)	(0.073)	[-10.710]
Firm_indret	0.229***	0.026	0.203**
	(0.048)	(0.067)	[2.441]
Ind_mktret	0.913***	-0.324**	1.237***
	(0.137)	(0.126)	[6.653]
Mktret	-0.044	0.011	-0.054
	(0.406)	(0.189)	[-0.121]
Cashneeds	-0.013	-0.361***	0.349***
	(0.021)	(0.064)	[5.196]
Dinstidem	0.487***	0.155***	0.332***
	(0.069)	(0.054)	[3.802]
Ln(MV)	-0.171***	0.103***	-0.273***
	(0.017)	(0.016)	[-11.622]
Proceeds	0.004***	-0.002**	0.006***
	(0.001)	(0.001)	[4.118]
Log Likelihood	-15044.411	-23825.647	
Likelihood Ratio test	570.724***	171.503***	

Panel E. Duration Analysis of the Time between Offerings (Use Credit ratings)

	Constrained	Unconstrained	Difference
Ln(Peer SEO)	0.149***	0.010	0.139***
	(0.023)	(0.027)	[3.916]
Ln(Market SEO)	0.020**	-0.040***	0.060***
	(0.009)	(0.009)	[4.778]
Book-to-market	-1.068***	-0.274***	-0.794***
	(0.068)	(0.067)	[-8.300]
Firm_indret	0.119***	0.406***	-0.287***
	(0.043)	(0.084)	[-3.049]
Ind_mktret	0.635***	-0.096	0.731***
	(0.101)	(0.138)	[4.271]
Mktret	-0.741**	-0.008	-0.733**
	(0.300)	(0.178)	[-2.103]
Cashneeds	-0.014	-0.769***	0.755***
	(0.018)	(0.090)	[8.299]
Dinstidem	0.321***	0.270***	0.050
	(0.054)	(0.043)	[0.727]
Ln(MV)	-0.089**	-0.133***	0.044**
	(0.015)	(0.013)	[2.155]
Proceeds	0.001***	0.000	0.001***
	(0.001)	(0.001)	[7.320]
Log Likelihood	-30845.775	-31935.986	
Likelihood Ratio test	536.899***	370.891***	

Table V. Information Communicated by Peers' SEOs

This table reports the industry-peer reactions for unconstrained and constrained firms separately based on whether the issuer is constrained or unconstrained. *3-day CAR* is the SEO 3-day announcement period abnormal returns calculated using standard market model over the event days –1, 0, and +1, where day 0 is the filing date. *Constrained firms* are firms that have a consistent history of zero distribution & share repurchase since their previous issue. *Unconstrained firms* refer to the complement sample. Panel A reports the univariate results. Panel B reports the regression results with SEO *3-day CAR* as the dependent variable. *Prior 6, 9 or 12 month issue* is a dummy variable that equals to one if a constrained firm issue SEO in prior 6, 9, or12 month for column (1)-(4); and that equals to one if a unconstrained firm issue SEO in prior 6, 9, or12 month for column (5)-(8) in Panel B. In Panel A, assumed independence *t*-statistics are in the square brackets, while t-statistics under clustered standard errors (per SEO event) are in {curly brackets}. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Univariate results (pooled)

	Constrained firms (when unconstrained firms issue SEO)	Unconstrained firms (when constrained firms issue SEO)	Difference
3-day CAR (%)	0.35***	0.07	
	[22.74]	[6.22]	
	{3.35}	{1.33}	
# of firm-year obs	288977	233296	

	Constrained firms who did SEO in the prior 6 months (when unconstrained firms issue SEO)	Unconstrained firms who did SEO in the prior 6 months (when constrained firms issue SEO)	Difference
3-day CAR (%)	0.10	0.05	
	[1.12]	[0.26]	
	{0.54}	{0.24}	
# of firm-year obs	6360	1212	

	Constrained firms who did no SEO in the prior 6 months (when unconstrained firms issue SEO)	Unconstrained firms who did no SEO in the prior 6 months (when constrained firms issue SEO)	Difference
3-day CAR (%)	0.36***	0.07	
	[22.77]	[6.22]	
	{3.33}	{1.33}	
# of firm-year obs	282617	232084	

Panel B: Regression analysis

	When unconstrained firms issue SEO				When constrained firms issue SEO			
	Dependent variable: 3-day CAR (%) of constrained firms				**Dependent variable: 3-day CAR (%) of unconstrained firms**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.352***	0.358***	0.361***	0.362***	0.066	0.066	0.066	0.066
	(3.35)	(3.33)	(3.35)	(3.34)	(1.33)	(1.33)	(1.34)	(1.33)
Prior 6 month issue		-0.261*				-0.019		
		(-1.81)				(-0.10)		
Prior 9 month issue			-0.273**				-0.109	
			(-2.02)				(-0.68)	
Prior 12 month issue				-0.248*				-0.011
				(-1.88)				(-0.08)
No. of obs	288977	288977	288977	288977	233296	233296	233296	233296
No. of clusters in event date	2284	2284	2472	2572	2330	2330	2731	3127

Table VI. Information Producers' Participation Changes around Peers' SEOs

Table reports the regression results for constrained firms that have not done an SEO in the prior 6 months when unconstrained firms conduct SEOs. In column (1), the dependent variable is the *change in analyst coverage*, defined as the number of analysts covering the constrained firm in the month after an unconstrained firm SEO, minus analyst coverage of the constrained firm in the month before. In column (2), the dependent variable is the *change in institutional holdings*, defined as the percentage of shares outstanding held by institutional investors of constrained firms after an unconstrained SEO, minus the percentage of shares outstanding held by institutional investors of constrained firms in the month before. All other variables are defined as in Table 2, including industry and year effects. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Change in Analyst coverage	Change in Institutional holdings
Intercept	1.357***	16.009
	[10.93]	[0.61]
Ln(Peer SEO)	0.515***	30.433***
	[11.87]	[3.31]
Ln(Market SEO)	0.122***	9.062
	[4.37]	[1.53]
Book-to-market	-0.024	-3.232
	[-1.33]	[-0.84]
Firm_indret	0.067***	1.773
	[2.98]	[0.37]
Ind_mktret	0.278***	5.192
	[6.73]	[0.59]
Mktret	-0.253	-34.192*
	[-0.74]	[-1.75]
Cashneeds	-0.079***	-3.909
	[-3.88]	[-0.91]
Ln(MV)	0.004	0.650
	[0.54]	[0.47]
Proceeds	0.001	-0.021
	[0.24]	[-1.07]
# of observations	249904	249904
No. of clusters in event date	1872	1872

Table VII. Information Production Around Peers' SEOs

Table reports the regression results for constrained firms that have not done an SEO in the prior 6 months when unconstrained firms conduct SEOs. In column (1), the dependent variable is the *change in analyst forecast dispersion*, defined as the difference in the forecast dispersion after and before the SEO announcement. *Forecast dispersion* is defined as the cross-sectional standard deviation of analyst forecasts on earnings per share, divided by the stock price at the end of the month. The data are from IBES. In column (2), the dependent variable is the *change in bid-ask spread*. We calculate ([ask minus bid]/closing price) on each day of the month, and then average across the days in the month. The *change in bid-ask spread* is defined as the change between two monthly values of average bid-ask spread. All other variables are defined as in Table 2, including industry and year effects. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Change in analyst forecast dispersion	Change in bid-ask spread
Intercept	-0.068	-0.061
	[-0.35]	[-0.33]
Ln(Peer SEO)	-0.122*	-0.125**
	[-1.87]	[-2.01]
Ln(Market SEO)	0.015	0.005
	[0.36]	[0.01]
Book-to-market	0.014	0.014
	[0.51]	[0.55]
Firm_indret	0.001	0.001
	[0.02]	[0.02]
Ind_mktret	-0.009	-0.015
	[-0.15]	[-0.25]
Mktret	-0.061	-0.063
	[-0.44]	[-0.47]
Cashneeds	-0.041	-0.037
	[-1.34]	[-1.28]
Ln(MV)	0.002	0.002
	[0.17]	[0.25]
Proceeds	-0.002	-0.003
	[-0.32]	[-0.40]
# of observations	157925	157925
No. of clusters in event date	1644	1644

Table VIII. "Common" Underwriter, Analyst, and Institutional Owners Influence on Issuance Activity

The table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1970-2010. Cox regression model with time-dependent covariates is specified as $h_i(t)=h_0(t)e^{x(t)\beta}$.The dependent variable is the number of days between IPOs and first SEOs and between consecutive SEOs. *Common Underwriter* is defined as the number of "same industry" firms that used the same lead underwriter as the issuing firm in the prior 6 months. *Common Analyst* is defined as the number of analysts providing EPS forecasts for an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of analysts covering the SEO firms. The data are from the IBES Detailed History File. *Common institutional holdings* is the number of institutional investors reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of institutional investors holding the SEO firms. The data are from Thomson-Reuters institutional holdings (i.e., 13F). *Common mutual fund holdings* is the number of actively-managed equity mutual funds reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of actively-managed equity mutual funds holding the SEO firms. The data are from Thomson-Reuters mutual fund holdings. *Ln(Common Underwriter)* is the natural logarithm of (1+*Common Underwriter*). All other variables are defined as in Table 2, including industry and year effects. The sample period is 1982–2010 for the analysis involving common analyst coverage and 1980–2010 for the analysis involving common mutual fund holdings and common institutional holdings. Panel A reports the hazard model estimation of the time between offerings based on common leader underwriter. Panel B and C report the results for common analysts and common institutional owners. Standard errors are in parentheses. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Duration Analysis of the Time between Offerings-Common Lead Underwriter

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.061***	-0.008	0.069*
	(0.023)	(0.027)	[1.941]
Ln(Market SEO)	0.046***	-0.007***	0.053***
	(0.009)	(0.001)	[6.009]
Ln(Common Underwriter)	0.028***	0.003	0.024***
	(0.003)	(0.002)	[6.209]
Book-to-market	-0.915***	-0.068	-0.847***
	(0.069)	(0.064)	[-8.973]
Firm_indret	0.031**	0.256***	-0.225***
	(0.013)	(0.039)	[-5.485]
Ind_mktret	0.299***	-0.153**	0.453***
	(0.046)	(0.075)	[5.163]
Mktret	-1.780***	-0.430***	-1.349***
	(0.151)	(0.099)	[-7.448]
Cashneeds	-0.079***	-0.047**	-0.032
	(0.023)	(0.019)	[-1.070]
Dinstidem	0.411***	0.145***	0.267***
	(0.048)	(0.048)	[3.931]
Ln(MV)	0.002	-0.077***	0.077***
	(0.015)	(0.012)	[4.039]
Proceeds	0.000	0.001**	-0.001
	(0.001)	(0.004)	[-0.923]
Log Likelihood	-30695.267	-30505.302	
Likelihood Ratio test	679.356***	359.242***	

Panel B. Duration Analysis of the Time between Offerings-Common Analysts

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.057**	0.002	0.055**
	(0.023)	(0.000)	[2.366]
Ln(Market SEO)	0.034***	-0.012	0.046***
	(0.009)	(0.009)	[3.608]
Common Analyst	0.011***	-0.006	0.017***
	(0.002)	(0.001)	[8.373]
Book-to-market	-1.002***	-0.075	-0.927***
	(0.069)	(0.064)	[-9.821]
Firm_indret	0.121	0.290***	-0.169*
	(0.042)	(0.086)	[-1.762]
Ind_mktret	0.624***	-0.095	0.719***
	(0.105)	(0.141)	[4.089]
Mktret	-0.441	0.012	-0.454
	(0.294)	(0.184)	[-1.310]
Cashneeds	-0.075***	-0.037**	-0.038
	(0.023)	(0.019)	[-1.279]
Dinstidem	0.404***	0.153***	0.251***
	(0.048)	(0.047)	[3.703]
Ln(MV)	-0.005	-0.066***	0.061***
	(0.015)	(0.011)	[3.222]
Proceeds	0.000	0.000***	-0.000
	(0.000)	(0.000)	[-0.142]
Log Likelihood	-30395.999	-31812.514	
Likelihood Ratio test	598.537***	358.575***	

Panel C. Duration Analysis of the Time between Offerings-Common Institutional Owners

	(1) Common Institutional Holdings			(2) Common Mutual Fund Holdings		
	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.047**	0.002	0.044*	0.045*	0.003	0.042*
	(0.023)	(0.000)	[1.917]	(0.023)	(0.000)	[1.838]
Ln(Market SEO)	0.044***	-0.012	0.055***	0.043***	-0.012	0.056***
	(0.009)	(0.009)	[4.314]	(0.009)	(0.009)	[4.328]
Common Ins/MF	0.011***	-0.007	0.018***	0.012***	-0.007	0.019***
	(0.001)	(0.009)	[11.500]	(0.001)	(0.009)	[12.225]
Book-to-mkt	-1.012***	-0.089	-0.923***	-1.022***	-0.091	-0.931***
	(0.069)	(0.064)	[-9.771]	(0.070)	(0.064)	[-9.843]
Firm_indret	0.122***	0.302***	-0.180*	0.121***	0.300***	-0.179*
	(0.042)	(0.086)	[-1.879]	(0.042)	(0.086)	[-1.871]
Ind_mktret	0.617***	-0.081	0.698***	0.621***	-0.076	0.697***
	(0.105)	(0.141)	[3.975]	(0.105)	(0.141)	[3.974]
Mktret	-0.428	0.036	-0.465	-0.456	0.039	-0.496
	(0.292)	(0.183)	[-1.350]	(0.292)	(0.183)	[-1.439]
Cashneeds	-0.079***	-0.035*	-0.043	-0.077***	-0.036*	-0.042
	(0.023)	(0.019)	[-1.467]	(0.023)	(0.019)	[-1.411]
Dinstidem	0.395***	0.168***	0.227***	0.398***	0.166***	0.232***
	(0.048)	(0.047)	[3.358]	(0.048)	(0.047)	[3.435]
Lnmv	0.004	-0.071***	0.075***	0.000	-0.070***	0.070***
	(0.015)	(0.012)	[3.931]	(0.015)	(0.012)	[3.660]
Offer size	0.000	0.000***	0.000	0.000	0.000***	0.000
	(0.000)	(0.000)	[-0.323]	(0.000)	(0.000)	[-0.243]
Log Likelihood	-30418.525	-31784.129		-30413.644	-31781.601	
Likelihood Ratio test	553.485***	442.344***		563.247***	447.401***	

Table IX. "Common" Underwriter Information Effects

Table reports the regression results for the sample of constrained firms. *Constrained firms* are firms that have a consistent history of zero distribution & share repurchase since their previous issue. In column (1), the dependent variable is the SEO *3-day announcement period abnormal returns*, calculated using standard market model over the event days –1, 0, and +1, where day 0 is the filing date. In column (2), the dependent variable is the *Gross spread*, calculated as the dollar amount of the underwriter gross spread scaled by the principal amount, multiplied by 100 to be a percentage. *Common Underwriter* is defined as the number of "same industry" firms that used the same lead underwriter as the issuing firm in the prior 6 months. *Ln(Common Underwriter)* is the natural logarithm of (1+*Common Underwriter*). All other variables are defined as in Table 2, including industry and year effects. The *t*-statistics are in the square brackets. A ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Announcement abnormal return	Gross spread
Intercept	-0.013	2.111***
	[-1.08]	[5.37]
Ln(Peer SEO)	0.331*	-0.437***
	[1.88]	[-8.52]
Ln((Market SEO)	-0.017	0.013
	[-0.17]	[0.45]
Ln(Common Underwriter)	0.286**	-0.669***
	[2.25]	[-9.32]
Book-to-market	0.013***	-0.112
	[2.86]	[-0.89]
Firm_indret	0.031***	0.063
	[8.30]	[0.55]
Ind_mktret	0.028***	0.415
	[3.33]	[1.61]
Mktret	0.016	0.564
	[0.74]	[0.92]
Cashneeds	0.005**	-0.094
	[2.04]	[-0.97]
Dinstidem	0.005	0.021
	[1.47]	[1.24]
Ln(MV)	0.003***	-0.065*
	[2.65]	[-1.78]
Proceeds	-0.001	-0.004
	[-0.65]	[-1.39]
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
No. of obs	4864	3853
R-squared	0.040	0.121

Table X. Duration Analysis and the Influence of "More" Versus "less" Related Peers and Financial Market Participant Effects

The table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms for the sample period 1970-2010. Cox regression model with time-dependent covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. *Ln(Peer SEO_More)* is the natural logarithm of one plus the number of firms conducting SEOs in the industry in the prior 6 months that has the same 2-digit SIC code as the issuing firm in Columns (1), same 3-digit SIC code as the issuing firm in Columns (2), and more related TNIC score to the issuing firm in Columns (3). *Ln(Peer SEO_Less)* is the natural logarithm of one plus the number of firms conducting SEOs in the industry in the prior 6 months that has different 2-digit SIC code as the issuing firm in Columns (1), different 3-digit SIC code as the issuing firm in Columns (2), and less related TNIC score to the issuing firm in Columns (3). *Common Undwrt_More/Less* is the number of "same-industry" peer firms that used the same lead underwriter as the issuing firm in the prior 6 months. Those peers also have the same/different 2-digit code as the issuing firm in columns (1), same/different 3-digit code as the issuing firm in columns (2), and more/less related TNIC score to the issuing firm in columns (3). *Ln*(*Common Undwrt_More/Less*) is the natural logarithm of one plus *Common Undwrt_More/Less*. *Common Insti_More/Less* is the number of institutional investors reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of institutional investors holding the SEO firms. Those peers also have the same/different 2-digit code as the issuing firm in columns (1), same/different 3-digit code as the issuing firm in columns (2), and more/less related TNIC score to the issuing firm in columns (3). *Common MF_More/Less* is the number of actively-managed equity mutual funds reporting holdings on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of actively-managed equity mutual funds holding the SEO firms. Those peers also have the same/different 2-digit code as the issuing firm in columns (1), same/different 3-digit code as the issuing firm in columns (2), and more/less related TNIC score to the issuing firm in columns (3). *Common Analyst_More/ Less* is the number of analysts reporting coverage on an SEO firm as well as on any of the "same-industry" Peers that issued an SEO in the prior 6 months, divided by the number of analysts covering the SEO firms. Those peers also have the same/different 2-digit code as the issuing firm in columns (1), same/different 3-digit code as the issuing firm in columns (2), and more/less related TNIC score to the issuing firm in columns (3). Peer firms are more/less related to the SEO issuing firms when their TNIC sore is above/below the median of the TNIC score of all peers that are deemed related to the issuing firm using this TNIC data. The sample period is 1982–2010 for the analysis involving common analyst coverage and 1980–2010 for the analysis involving common mutual fund holdings and common institutional holdings. The sample period is 1996-2010 for the analysis involving TNIC score. All other variables are defined as in Table 2, including industry and year effects. Standard errors are in parentheses. The *t*-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Duration Analysis of the Time between Offerings-Common Lead Underwriter

	(1) 2-digit SIC code			(2) 3-digit SIC code			(3) TNIC		
	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference
Ln(Peer SEO_more)	0.017***	0.014	0.003	0.018***	0.022***	-0.004	0.010*	-0.004	0.014
	(0.006)	(0.008)	[0.332]	(0.005)	(0.008)	[-0.395]	(0.006)	(0.008)	[1.420]
Ln(Peer SEO_less)	0.076***	0.005	0.071***	0.076***	0.004	0.071***	0.084***	0.014	0.070***
	(0.013)	(0.009)	[4.433]	(0.013)	(0.009)	[4.440]	(0.013)	(0.009)	[4.373]
Ln(Market SEO)	0.045***	-0.108***	0.152***	0.042***	-0.108***	0.150***	0.044***	-0.110***	0.154***
	(0.010)	(0.010)	[10.863]	(0.010)	(0.010)	[10.690]	(0.010)	(0.009)	[11.138]
Ln(Common undwrt_more)	0.687	0.029	0.657	0.664	0.031	0.633	0.520	0.019	0.501
	(0.433)	(0.021)	[1.518]	(0.434)	(0.021)	[1.459]	(0.433)	(0.021)	[1.156]
Ln(Common undwrt_less)	0.237***	0.040	0.197***	0.236***	0.036	0.200***	0.318***	0.061	0.258***
	(0.015)	(0.024)	[12.869]	(0.015)	(0.023)	[13.258]	(0.018)	(0.026)	[14.332]
Book-to-mkt	-0.823***	0.070	-0.893***	-0.829***	0.059	-0.889***	-0.768***	0.092	-0.859***
	(0.069)	(0.064)	[-9.499]	(0.069)	(0.064)	[-9.446]	(0.069)	(0.063)	[-9.205]
Firm_indret	0.136***	0.170**	-0.034	0.136***	0.183**	-0.048	0.139***	0.137*	0.003
	(0.044)	(0.084)	[-0.359]	(0.044)	(0.084)	[-0.506]	(0.044)	(0.080)	[0.030]
Ind_mktret	0.351***	-0.287**	0.638***	0.357***	-0.276*	0.633***	0.317***	-0.383***	0.701***
	(0.110)	(0.141)	[3.575]	(0.110)	(0.141)	[3.545]	(0.110)	(0.139)	[3.955]
Mktret	-0.365	-0.272	-0.093	-0.361	-0.267	-0.095	-0.372	-0.346*	-0.027
	(0.294)	(0.182)	[-0.269]	(0.294)	(0.183)	[-0.273]	(0.291)	(0.180)	[-0.078]
Cashneeds	-0.051**	-0.041*	-0.010	-0.051**	-0.041**	-0.011	-0.045*	-0.033	-0.011
	(0.024)	(0.021)	[-0.320]	(0.024)	(0.021)	[-0.334]	(0.024)	(0.024)	[-0.328]
Dinstidem	0.374***	0.137**	0.237***	0.376***	0.142***	0.234***	0.387***	0.115***	0.272***
	(0.048)	(0.048)	[3.492]	(0.048)	(0.047)	[3.457]	(0.048)	(0.048)	[4.014]
Lnmv	0.001	-0.070***	0.071***	-0.001	-0.073***	0.073***	0.002	-0.059***	0.062***
	(0.015)	(0.012)	[3.675]	(0.015)	(0.012)	[3.776]	(0.015)	(0.012)	[3.169]
Offer size	0.000	0.000*	0.000	0.000	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	[-0.867]	(0.000)	(0.000)	[-0.925]	(0.000)	(0.000)	[-0.851]
Log Likelihood	-30304.821	-31705.541		-30302.358	-31716.753		-30272.738	-32005.302	
Likelihood Ratio test	780.892***	609.522***		785.818***	577.098***		845.057***	807.432***	

Panel B. Duration Analysis of the Time between Offerings-Common Analysts

	(1) 2-digit SIC code			(2) 3-digit SIC code			(3) TNIC		
	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference
Ln(Peer SEO_more)	0.006**	0.003	0.004	0.003	-0.001***	0.004	0.004	-0.005***	0.008
	(0.003)	(0.004)	[0.745]	(0.003)	(0.001)	[1.255]	(0.006)	(0.001)	[1.278]
Ln(Peer SEO_less)	0.074***	0.011	0.063***	0.075***	0.014	0.061***	0.070***	0.010	0.060***
	(0.012)	(0.010)	[3.439]	(0.012)	(0.011)	[3.277]	(0.012)	(0.009)	[3.814]
Ln(Market SEO)	0.053***	-0.077***	0.131***	0.054***	-0.059***	0.114***	0.054***	-0.032***	0.087***
	(0.011)	(0.010)	[9.088]	(0.010)	(0.010)	[8.710]	(0.010)	(0.005)	[7.563]
Common Analyst_more	0.003	0.004	-0.001	0.006	0.003	0.003	0.010	0.020*	-0.010
	(0.002)	(0.011)	[-0.570]	(0.005)	(0.003)	[1.216]	(0.017)	(0.010)	[-0.943]
Common Analyst_less	0.038***	0.008	0.029***	0.026***	0.009	0.016**	0.087***	0.018	0.069***
	(0.005)	(0.007)	[5.677]	(0.007)	(0.011)	[2.336]	(0.011)	(0.013)	[6.313]
Book-to-mkt	-0.944***	-0.044	-0.900***	-0.999***	-0.111	-0.889***	-0.955***	-0.127*	-0.827***
	(0.070)	(0.066)	[-9.343]	(0.071)	(0.066)	[-9.190]	(0.069)	(0.065)	[-8.702]
Firm_indret	0.129***	0.341***	-0.213**	0.129***	0.344***	-0.215**	0.129***	0.323***	-0.195**
	(0.043)	(0.087)	[-2.191]	(0.042)	(0.087)	[-2.216]	(0.043)	(0.088)	[-1.993]
Ind_mktret	0.599***	-0.069	0.668***	0.612***	-0.079	0.691***	0.575***	-0.109	0.683***
	(0.107)	(0.142)	[3.755]	(0.106)	(0.143)	[3.895]	(0.107)	(0.143)	[3.830]
Mktret	-0.207	-0.001	-0.206	-0.291	-0.045	-0.246	-0.276	-0.023	-0.254
	(0.295)	(0.182)	[-0.595]	(0.295)	(0.183)	[-0.708]	(0.295)	(0.182)	[-0.732]
Cashneeds	-0.080***	-0.045**	-0.035	-0.084***	-0.052***	-0.032	-0.079***	-0.051***	-0.028
	(0.023)	(0.020)	[-1.171]	(0.023)	(0.019)	[-1.062]	(0.024)	(0.019)	[-0.918]
Dinstidem	0.391***	0.131***	0.260***	0.410***	0.139***	0.270***	0.392***	0.127***	0.265***
	(0.048)	(0.048)	[3.829]	(0.048)	(0.048)	[3.982]	(0.048)	(0.048)	[3.901]
Lnmv	0.005	-0.066***	0.071***	0.007	-0.068***	0.075***	-0.003	-0.067***	0.064***
	(0.015)	(0.012)	[3.672]	(0.015)	(0.012)	[3.892]	(0.015)	(0.012)	[3.303]
Offer size	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	[0.180]	(0.000)	(0.000)	[0.056]	(0.000)	(0.000)	[0.303]
Log Likelihood	-30334.179	-31655.156		-30357.927	-31688.334		-30310.750	-31669.959	
Likelihood Ratio test	722.157***	700.292***		674.676***	633.934***		769.036***	670.685***	

Panel C. Duration Analysis of the Time between Offerings-Common Institutional Owners

	(1) 2-digit SIC code			(2) 3-digit SIC code			(3) TNIC		
	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference
Ln(Peer SEO_more)	0.010	-0.003*	0.013	0.008	-0.001	0.009	-0.008	-0.007	0.001
	(0.005)	(0.008)	[1.387]	(0.006)	(0.000)	[1.586]	(0.006)	(0.001)	[0.083]
Ln(Peer SEO_less)	0.076***	0.010	0.067***	0.073***	0.010	0.063***	0.087***	0.011	0.076***
	(0.013)	(0.002)	[4.950]	(0.014)	(0.002)	[4.611]	(0.013)	(0.002)	[5.667]
Ln(Market SEO)	0.050***	-0.075***	0.126***	0.057***	-0.060***	0.117***	0.057***	-0.060***	0.117***
	(0.010)	(0.010)	[8.838]	(0.010)	(0.010)	[8.279]	(0.010)	(0.009)	[8.371]
Common Insti_more	0.014	-0.010***	0.025	0.032*	-0.010	0.042	0.091	-0.010***	0.101
	(0.017)	(0.001)	[1.457]	(0.016)	(0.001)	[2.536]	(0.163)	(0.010)	[0.617]
Common Insti_less	0.045***	0.010	0.035***	0.051***	0.015	0.036***	0.115***	0.022	0.093***
	(0.004)	(0.000)	[9.060]	(0.005)	(0.001)	[6.913]	(0.009)	(0.001)	[10.685]
Book-to-mkt	-0.927***	-0.083	-0.844***	-0.913***	-0.091	-0.822***	-0.956***	-0.183***	-0.773***
	(0.070)	(0.065)	[-8.855]	(0.070)	(0.065)	[-8.632]	(0.070)	(0.066)	[-8.088]
Firm_indret	0.128***	0.381***	-0.253***	0.133***	0.369***	-0.236**	0.128***	0.341***	-0.213**
	(0.043)	(0.086)	[-2.614]	(0.043)	(0.086)	[-2.455]	(0.043)	(0.087)	[-2.187]
Ind_mktret	0.557***	0.004	0.553***	0.555***	0.023	0.532***	0.557***	-0.024	0.581***
	(0.108)	(0.142)	[3.099]	(0.108)	(0.141)	[2.999]	(0.108)	(0.142)	[3.263]
Mktret	-0.146	0.168	-0.315	-0.273	0.185	-0.457	-0.091	0.192	-0.283
	(0.294)	(0.179)	[-0.914]	(0.294)	(0.179)	[-1.328]	(0.293)	(0.178)	[-0.827]
Cashneeds	-0.081***	-0.050**	-0.031	-0.081***	-0.052**	-0.029	-0.090***	-0.061***	-0.029
	(0.023)	(0.020)	[-1.018]	(0.023)	(0.020)	[-0.942]	(0.023)	(0.020)	[-0.970]
Dinstidem	0.382***	0.135***	0.247***	0.386***	0.129***	0.258***	0.386***	0.126***	0.260***
	(0.048)	(0.048)	[3.634]	(0.048)	(0.048)	[3.786]	(0.048)	(0.048)	[3.821]
Lnmv	0.004	-0.061***	0.065***	0.005	-0.063***	0.068***	0.006	-0.060***	0.066***
	(0.015)	(0.012)	[3.362]	(0.015)	(0.012)	[3.514]	(0.015)	(0.012)	[3.395]
Offer size	0.000	0.000*	0.000	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	[0.337]	(0.000)	(0.000)	[0.369]	(0.000)	(0.000)	[0.319]
Log Likelihood	-30695.267	-32005.302		-30371.954	-31664.778		-30332.379	-31617.399	
Likelihood Ratio test	676.013***	757.507***		646.627***	721.047***		725.778***	775.804***	

Panel D. Duration Analysis of the Time between Offerings-Common Mutual Funds

	(1) 2-digit SIC code			(2) 3-digit SIC code			(3) TNIC		
	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference	Constrained firms	Unconstrained firms	Difference
Ln(Peer SEO_more)	0.010	-0.003	0.013	0.009	-0.005	0.014	-0.007	-0.008	0.000
	(0.005)	(0.008)	[1.362]	(0.009)	(0.001)	[1.466]	(0.006)	(0.001)	[0.064]
Ln(Peer SEO_less)	0.072***	0.010	0.062***	0.068***	0.011	0.058***	0.082***	0.028	0.053***
	(0.013)	(0.002)	[4.699]	(0.013)	(0.002)	[4.316]	(0.013)	(0.005)	[3.869]
Ln(Market SEO)	0.051***	-0.074***	0.125***	0.057***	-0.059***	0.116***	0.057***	-0.059***	0.116***
	(0.010)	(0.010)	[8.793]	(0.010)	(0.010)	[8.229]	(0.010)	(0.009)	[8.347]
Common MF_more	0.029	-0.011***	0.039	0.047	-0.010***	0.058*	0.239	-0.011***	0.250
	(0.025)	(0.001)	[1.577]	(0.016)	(0.001)	[1.687]	(0.163)	(0.001)	[1.530]
Common MF_less	0.046***	0.010*	0.036***	0.050***	0.015	0.035***	0.117***	0.022	0.094***
	(0.004)	(0.001)	[9.208]	(0.005)	(0.001)	[6.701]	(0.009)	(0.001)	[10.663]
Book-to-mkt	-0.931***	-0.091	-0.840***	-0.921***	-0.094	-0.827***	-0.963***	-0.184***	-0.779***
	(0.070)	(0.065)	[-8.806]	(0.070)	(0.065)	[-8.668]	(0.070)	(0.066)	[-8.145]
Firm_indret	0.128***	0.361	-0.234**	0.131***	0.361***	-0.231**	0.126***	0.325***	-0.199**
	(0.043)	(0.087)	[-2.404]	(0.043)	(0.086)	[-2.391]	(0.043)	(0.088)	[-2.030]
Ind_mktret	0.562***	-0.007	0.570***	0.559***	0.014	0.545***	0.562***	-0.038	0.600***
	(0.108)	(0.142)	[3.195]	(0.108)	(0.141)	[3.073]	(0.108)	(0.142)	[3.367]
Mktret	-0.166	0.160	-0.326	-0.300	0.175	-0.474	-0.101	0.176	-0.276
	(0.294)	(0.179)	[-0.947]	(0.294)	(0.179)	[-1.378]	(0.293)	(0.178)	[-0.806]
Cashneeds	-0.080***	-0.049**	-0.030	-0.080***	-0.051**	-0.028	-0.088***	-0.059***	-0.029
	(0.023)	(0.020)	[-0.985]	(0.023)	(0.020)	[-0.918]	(0.023)	(0.020)	[-0.963]
Dinstidem	0.382***	0.136**	0.246***	0.388***	0.129***	0.258***	0.387***	0.133***	0.254***
	(0.048)	(0.048)	[3.626]	(0.048)	(0.048)	[3.799]	(0.048)	(0.048)	[3.742]
Lnmv	0.001	-0.063**	0.064***	0.003	-0.063***	0.066***	0.003	-0.063***	0.066***
	(0.015)	(0.012)	[3.311]	(0.015)	(0.012)	[3.406]	(0.015)	(0.012)	[3.370]
Offer size	0.000	0.000*	0.000	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	[0.358]	(0.000)	(0.000)	[0.377]	(0.000)	(0.000)	[0.260]
Log Likelihood	-30354.659	-31625.773		-30371.117	-31644.043		-30330.498	-31618.191	
Likelihood Ratio test	681.215***	759.057***		648.318***	722.519***		729.539***	774.222***	

Table XI. Information Communicated by Peers' SEOs and Relatedness of Peers

This table reports the regression results of industry-peer reactions for unconstrained and constrained firms separately based on whether the peer is more or less related to the issuer, with SEO *3-day CAR* as the dependent variable. *3-day CAR* is the SEO 3-day announcement period abnormal returns calculated using standard market model over the event days –1, 0, and +1, where day 0 is the filing date. *Constrained firms* are firms that have a consistent history of zero distribution & share repurchase since their previous issue. *Unconstrained firms* refer to the complement sample. *Prior 6 month issue* is a dummy variable that equals to one if a constrained firm issue SEO in prior 6 months. *Less-related Peer* is a dummy variable that equals to one if constrained (unconstrained) firms have different 2-digit SIC code/different 3-digit SIC code/less-related TNIC as SEO issuing unconstrained (constrained firms) in the same industry in column (1)/column(2)/column(3). *Less-related Peer* Prior 6 month issue* is the interaction term of *Less-related Peer* and *Prior 6 month issue*. The *t*-statistics are in the brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	When unconstrained firms issue SEO **Dependent variable: 3-day CAR (%) of constrained firms**			When constrained firms issue SEO **Dependent variable: 3-day CAR (%) of unconstrained firms**		
	(1) SIC2	(2) SIC3	(3) TNIC	(1) SIC2	(2) SIC3	(3) TNIC
Intercept	0.185	0.212	0.158	0.119***	0.166***	0.109***
	(1.63)	(1.55)	(1.62)	(2.56)	(2.92)	(2.68)
Less-related Peer	0.277*	0.179*	0.364**	-0.074	-0.117	-0.066
	(1.68)	(1.72)	(1.96)	(-0.95)	(-1.51)	(-0.82)
Prior 6 month issue	-0.098	0.01	-0.05	0.144	0.293	0.033
	(-0.51)	(0.04)	(-0.29)	(0.43)	(0.58)	(0.11)
Less-related Peer*	-0.255*	-0.368**	-0.394*	-0.329	-0.425	-0.147
Prior 6 month issue	(-1.89)	(-1.98)	(-1.90)	(-0.95)	(-0.78)	(-0.39)
No. of obs	288977	288977	288977	233296	233296	233296
No. of clusters in event date	2284	2284	2284	2330	2330	2330

Figure I. Number of all SEOs, Constrained, and Unconstrained SEOs by Year

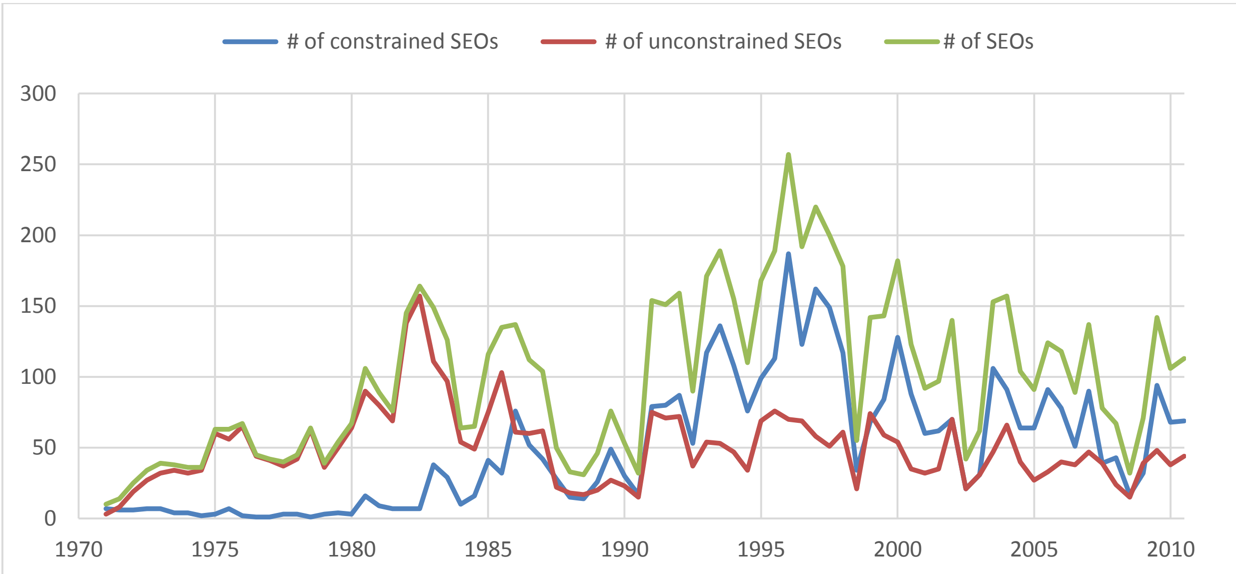
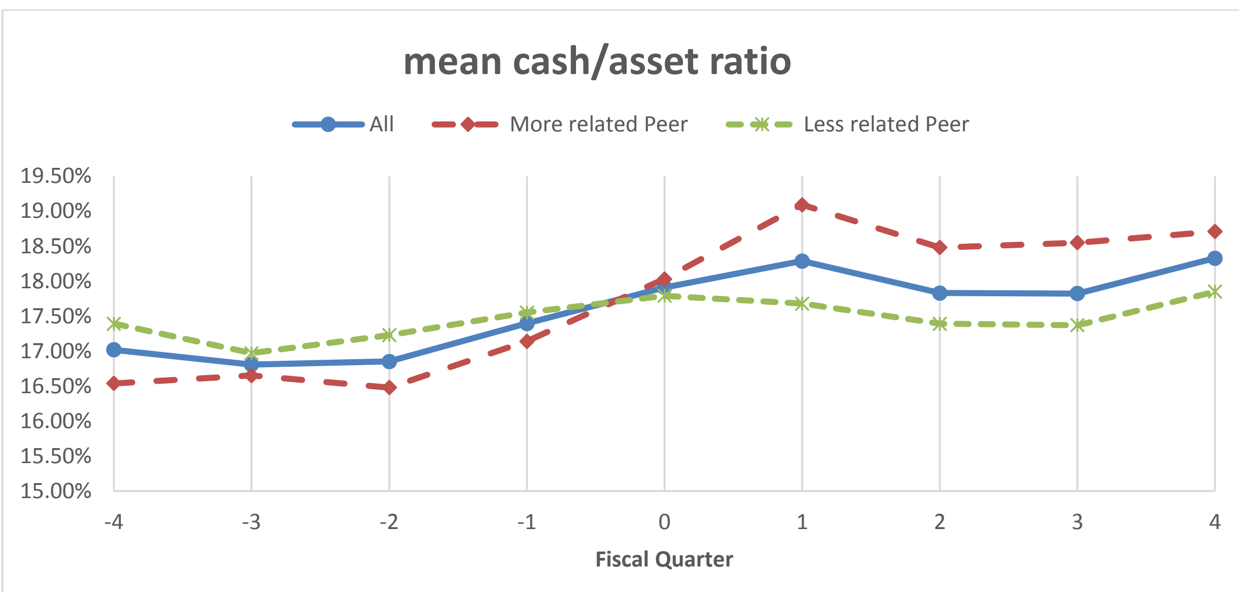


Figure II. The cash holdings of constrained firms in the four quarters before (-4 to -1) and four quarters after (+1 to +4) the unconstrained firms' SEO announcement (quarter t=0)



Appendix II. Censored and Uncensored SEOs

This table reports the number of censored and uncensored SEOs. *Uncensored SEOs* are SEOs whose issuing dates can be located in the sample period 1970-2010. *First time SEOs* have both IPO and SEO dates available during the sample period. *Follow-on SEOs* have consecutive SEO dates available during the sample period. We censor firms with IPO/SEO dates unavailable during the sample period 1970-2010. We left censor a firm whose IPO date is before 1970. For example, if a firm's SEO date is 1980, and the IPO date is 1965, then the censoring time is ten year. We right censor a firm whose SEO date is after 2010. For example, if a firm went IPO in 2004, if it never issues SEO and the data on the firm end in 2010, the censoring time is six years. We left and right censor a firm if the IPO date is before 1970 and the SEO date is after 2010.

Uncensored SEOs	
First time SEOs	2659
Follow-on SEOs	5314
Total # of uncensored SEOs	7973
Censored SEOs	
Left censored	844
Right censored	914
Left and Right Censored	847
Total # of censored SEOs	2605