The Capital Supply Channel in Peer Effects: The Case of SEOs

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

Current draft: June 2022

ABSTRACT

We document a capital supply channel in peer effects, through the lens of SEOs. Firms accelerate their SEOs – they have higher SEO hazards – when more of their peers conducted an SEO within the prior six months. The effect is stronger among older yet constrained firms than among younger yet unconstrained firms. It is also stronger after Russell index shocks that likely reduce indexer demand for a firm's equity. We document evidence of a potential underlying mechanism; information conveyed by underwriters that recently marketed SEOs of peers, thus reducing asymmetric information costs.

We thank Wolfang Bessler, Azi Ben-Rephael, Redouane Elkamhi, Janet Gao, Nandini Gupta, Isaac Hacamo, Kai Li, Dave Mauer, Gordon Phillips, Jay Ritter, Tong Yao, Yilei Zhang, two anonymous referees as well as an Associate Editor, and seminar participants at Bilkent University, City University of Hong Kong, Clemson University, Florida International University, 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 Illinois Chicago, University of New Hampshire, University of North Carolina-Charlotte, University of Saskatchewan, University of Toronto, as well as the 2014 FMA conference, 2017 CICF conference, and 2018 MFA conference for many helpful comments and suggestions. This paper previously circulated under the titles: "The Role of Financial Intermediaries in the Transmission of Peer-to-Peer Financial Policies" and "Capital Supply, Financial Intermediaries, and Corporate Peer Effects."

[a] Richard E. Jacobs Chair in Finance, Kelley School of Business, Indiana University, mbillett@indiana.edu
[b] Henry B. Tippie Research Professor of Finance, 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

1. Introduction

Numerous studies document common financial policies and actions among peer firms. Explanations for these connections are varied. There are so-called “true peer effects”, where one firm may simply observe and mimic others (e.g. Kaustia and Rantala (2015)). There are learning-based peer effects where a firm may become informed about industry investment or financing opportunities and respond accordingly (Foucault and Fresard (2014), Leary and Roberts (2014)). There are examples of firm responses to sudden shocks that potentially alter the competitive landscape (Hoberg and Phillips (2015), Aslan and Kumar (2016), Servaes and Tamayo (2014), Billett, Esmer, and Yu (2018)). To date however, there have been few studies that recognize the potential importance of peer financing as a channel that helps sunder capital supply barriers, enabling followers to mimic. Indeed, Leary and Roberts (2014) provide preliminary evidence consistent with such barriers. They document that “following firms” have the usual markings of financially constrained firms.[1] We explore the potential existence of a capital supply channel that results in the appearance of peer effects in SEO issuance. We also provide evidence on a potential mechanism – that prior SEOs by peers reduce asymmetric information costs. Our work is the first to contemplate the capital supply channel of peer effects in SEOs.[2]

We begin by offering a timing-based perspective on Leary and Roberts’ (2014) peer effects result. Splitting our sample of SEOs into financially constrained and unconstrained groups and using a hazard model, we show that constrained firms ‘follow’ their peers’ SEOs. Specifically, we find that constrained firms’ SEO hazards increase in the *number of their peers* that conducted SEOs within the *prior* six months. Financially unconstrained firms show less than half the sensitivity that constrained firms do (and the difference in covariates’ effects across the samples is significant). Put simply, prior SEOs by peers appear to encourage SEOs by constrained focal firms.

[1] They tend to be small, unrated, with no payout and high values of the Whited-Wu index of financial constraints.
[2] Brauner, Lee, and Naranjo (2018) and Francis, Hasan, and Kostova (2016) cite our work as antecedent.

However, this result carries multiple interpretations. As Leary and Roberts (2014) emphasize, followers may learn about optimal capital structure or financing model by observing peer financing. Alternatively, the learning could be about industry growth opportunities (investment opportunity set). Both types of learning can encourage mimicry, with constrained firms responding later possibly because constraints naturally slow responses via typical frictions. To distinguish such learning-driven mimicry from a capital supply channel, we require more direct measures of either the learning aspect (as control) or of the channel itself. We offer two approaches to such distinguishment.

First, we submit that learning is much more likely among younger firms than older firms.[3] This motivates us to create sub-samples to isolate the likely drivers of observed mimicry. We create one subsample of young unconstrained[4] firms where the learning channel should be pronounced and capital supply effects should be muted. We create a contrasting subsample of old constrained firms where learning is muted but capital supply sensitivity is high. We find that the influence of prior peer SEO count on follower SEO hazards is more than 20 times larger for the old and constrained firm sub-sample, than it is for the young and unconstrained firm sub-sample. This first approach is consistent with a capital supply channel at work in the observed peer mimicry of SEOs by constrained firms.

Our second approach begins with the plausibly exogenous shocks to stock index membership described in Chang, Hong and Liskovich (2015). Migration of a firm's membership between the Russell 1000 and 2000 indices, shocks index funds' willingness to provide equity capital during an SEO (see our discussion in section 2.2).[5] Financial constraints are exacerbated for negatively shocked firms. These negative shocks concomitantly affect constrained firms' SEO hazards in a way that suggests our hypothesized capital supply channel is at work: it *increases* the hazard sensitivity to prior peer SEO activity.

[3] See discussion in section 2.2.
[4] By Whited-Wu index.
[5] Firms that migrate from the bottom of the Russell 1000 to the top of the Russell 2000 experience positive shocks to equity capital supply; and vice-versa.

In other words, there is substitution: financially constrained firms rely on prior peer SEOs to reduce barriers to their own SEO, when the shock raises such a barrier.[6]

We then explore one potential mechanism behind this capital supply channel. Specifically, we hypothesize a reduction in asymmetric information costs, driven by investment bank learning from prior peer SEOs that they executed. This thinking calls upon Benveniste, Ljungqvist, Wilhelm, and Yu (2003) who show that investment banks tend to bundle offerings that are subject to a common valuation factor (e.g. SEOs by peers). Thus bundling enhances information acquisition, reducing asymmetric information problems and costs – key drivers of financial constraints. This effect is likely concentrated where more peer SEOs are underwritten by the *same* underwriter that the following firm uses on its SEO. We find that hazards increase in the count of prior peer SEOs that were marketed by the focal firm's underwriter.

We provide confirming evidence of reduced asymmetric information costs with exploration of two proxies common to that literature. The average spread an underwriter charges the focal firm decreases in the number of (recent) SEOs that the common underwriter did for the focal firm's peers. Second, the focal firm's own SEO event return increases in the same common-underwriter experience variable. Finally, all of these effects are stronger when the investment bank is more highly-ranked, consistent with Carter and Manaster (1990) as well as Chemmanur and Fulghieri (1994).

Overall, we offer a new channel behind observed peer effects in financing and specifically SEOs. This capital supply channel is separate and distinct from demand-based peer effects and complements Leary and Roberts' (2014) result that peer mimicry is pronounced among financially constrained firms. Finally, we support the information acquisition via bundling theory of Benveniste et al. (2003), in two ways. The commonality of underwriter (who marketed the SEOs) between the focal firm and its peers

[6] We also find the reverse for firms experiencing positive exogenous shocks to equity capital supply. Firms migrating "down" from the Russell 1000 to the Russell 2000 see an increase in SEO hazard, but also weaker sensitivity to prior peer SEOs.

empirically raises SEO hazards, while this overlap also reduces spreads charged and improves event returns around constrained firm SEOs.

2. Drivers of Peer Effects in Corporate Behavior

This section further develops the logic underlying our measurement of a capital supply channel in peer effects. It also positions our work in the related extant literatures.

2.1 Prior Analyses of Peer Effects

Extant literature on corporate peer effects takes an essentially demand-oriented view; firms observe peer actions or characteristics, and this *motivates* the firm's own behavior. Examples include the major corporate finance decision arenas: investment, financing, compensation, as well as others. But all of this work is essentially silent on the relevance of the supply of capital to the manifestation of peer effects. A brief sampling of these papers is as follows.

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. When an investing firm's peers have higher valuations, the firm invests significantly more. Hoberg and Phillips (2016) examine shocks to two industries (military goods and services, and software), and show that firms respond to their product-market peers when making product offering decisions. Faulkender and Yang (2010) illustrate a strong peer influence on CEO compensation policy.[7] Kaustia and Rantala (2015) show that firms are more likely to split their stock when peers have done so. Armstrong et al. (2010) review peer-sharing of lenders, while De Franco et al. (2020) highlight the trade-off concern of proprietary information leakage in such cases. Perhaps most closely related to our work is that of Leary and Roberts (2014).[8] They document sensitivity of firm leverage and financing decisions to peers'

[7] See also Bizjak, Lemmon and Nguyen (2011).
[8] We view their paper as a starting point for our analysis. They call for identification of channels in peer effects.

exogenous variation in characteristics or behaviors.[9] They further distinguish between the influence of characteristics or behavior by showing that focal firm leverage changes are primarily driven by peer leverage changes across all peer shock rankings, while the converse is not true. Our research complements the above papers in two ways: we study SEOs specifically, which entail demonstrative capital structure decisions that require the participation of outside intermediaries; and we document a distinct capital supply channel.

2.2 Identifying a Capital Supply Channel in Peer Effects

The main challenge of illustrating a financial capital supply channel as driver of SEO mimicry is endogeneity. Constrained firms' sensitivity of issuance timing to prior peer-SEO activity can be driven by multiple factors. One is the capital supply channel we seek to document; the constrained firm's SEO is facilitated by [elements in the process of] their peers' SEOs. Alternatively, the sensitivity could be due to an omitted common factor with no facilitation attributable to peers. For example, if an industry experiences a positive shock to investment opportunities, and constrained firms are naturally slower to respond through their own issuance, then we could observe the documented sequencing.

To identify the former – our hypothesized capital supply channel – we first attempt to isolate two sub-samples with polar opposite explanations for the followers' SEO sensitivity to prior peer SEOs. At one end we expect that younger yet (financially) unconstrained firms would be most subject to demand-side motivations for an SEO. Younger firms have less experience in their industry, with comparatively less information about the IOS.[10] Observing the SEOs of industry peers is likely to communicate positive information about the industry's opportunities, encouraging capital-raising. At the same time, their unconstrained status makes it less likely that a follow-on SEO is driven by the capital supply channel we

---

[9] 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 augmented market model), have a significant influence on firms' leverage and financing policies.

[10] Leary and Roberts (2014) conclude that learning and reputation are potential motives for mimicry when they note that it is found amongst younger firms.

contemplate. By contrast, our other sub-sample contains older yet (financially) constrained firms. If these firms follow the SEOs of peers, it is less likely due to learning about the industry's opportunities (since older firms are more established/experienced in their product market). Combined with the financial constraints inherent in the sub-sample, this loads the explanatory power towards our hypothesized capital supply channel.

Our second approach to identifying a capital supply channel uses plausibly exogenous changes to investor willingness to supply equity capital. We study such shocks to test whether treated firms show different sensitivities of constrained firms' SEO timing to recent peer-SEO activity. If exogenously increased (decreased) capital supply associates with reduced (heightened) focal firm SEO sensitivity to prior peer SEOs, this suggests substitution between the shock and the peer sensitivity. The corollary is that our hazard-measured sensitivity to peer SEOs proxies for investor receptivity towards equity issuance (a peer capital supply channel).

The plausibly exogenous shocks we use are from Chang, Hong, and Liskovich (2015). They find that firms migrating from the (bottom of the) Russell 1000 to the (top of the) Russell 2000 experience a significant increase in indexers' demand for the firm's shares, and vice-versa. This is because the indices are value-weighted, so the weights of the largest stocks in the Russell 2000 are much larger than the weights of the smallest stocks in the Russell 1000. While this shock to indexer demand is measured in the secondary market, it is very likely to present in the primary market as well. Blume and Edelen (2002) show that tracking error is both pronounced and highly volatile when a fund does not exactly replicate the index (holdings). They further argue that tracking error reflects agency problems with attendant costs, and this creates an incentive to avoid it. They find that index funds forego potential return benefits by reducing tracking error through exact replication. Therefore, equity issuance by an index member-firm must be bought in exact proportion to its weight in the index, by index funds that wish to minimize tracking error.

For purposes of our analysis, changes in index membership are therefore good proxies for exogenous variation in equity capital supply. In the context of SEOs by constrained firms, the "requirement" that index funds closely track the index's performance, implies a ready and willing participant in the firm's SEO. This implies a changing barrier-height for migrating constrained firms. Take the example of firm movement down from the Russell 1000 to the Russell 2000. The exogenously driven increase in indexer demand (i.e. equity capital supply) should reduce a constrained focal firm's reliance on prior peer SEOs to catalyze its own SEO. Notably, this substitution effect should only appear if the prior peer SEOs were important because of the capital supply channel we contemplate.

The effect of opposite direction migration (from Russell 2000 to Russell 1000) is expected to present as follows. Chang et al. (2015) document that such migration "up", reduces the firm's weight in the index and thereby decreases indexers' demand. This negative shock to equity capital supply should increase the constrained focal firm's SEO hazard sensitivity to its peers' recent SEOs.

This second approach using shocks, also raises the question of whether focal (i.e. follower) firms are reacting to a peer's characteristic change or peer action. In particular, index shocks can ostensibly encourage SEOs. Therefore, peer SEOs may be in response to index shocks, the same way that focal firms' SEOs are. But in the case of peer SEOs after shocks, the question now arises of whether it is those index shocks *as a characteristic* – perhaps an indicator of changed industry investment opportunities – which drive the follow-on focal firm SEO. This classic tension between characteristic and action is addressed by including measures of both in our hazard. We find that both characteristics and actions of peers influence focal firm SEO hazards, but only the latter is apparent strictly among constrained firms – the former is apparent across all firms.

2.3 Constrained Focal Firm Usage of the Same Underwriter that Peers Used

How do recent prior SEOs by peer firms ease financial constraints for 'following' firms? Benveniste et al. (2003) provide a model that suggests this can result from underwriters 'bundling' securities offerings by related firms. In particular, firms in the same industry share a common valuation factor (while also individually having an idiosyncratic one). The common valuation factor is learned through the underwriting of earlier issuances. Therefore, asymmetric information costs are reduced for later issuers in the same industry (because the common valuation factor is better-understood), particularly when the underwriter is the same for the earlier and later issuing firms. The information production role is also likely to be pronounced when the underwriter is more highly ranked (e.g. Carter and Manaster (1990) and Chemmanur and Fulghieri (1994)). We therefore include underwriter rank both stand-alone and interacted with common underwriter, in our analyses.

We assess the importance of commonality of underwriter between the focal firm and peers in two ways. First, beneficial effects of more (common) underwriter experience should generally increase the constrained firm's SEO hazard. Second, we focus more precisely on the specific mechanism of asymmetric information reduction. Prior work characterizes underwriter spreads as compensation for asymmetric information (e.g. Lee and Masulis (2009)). The common underwriter's reduction of asymmetric information should reduce spreads. Furthermore, constrained firms' own SEO event returns should be higher when asymmetric information costs are mitigated by underwriter overlap (again similar to Lee and Masulis (2009)).

3. Data and Methods

3.1 Base Sample of SEOs

Our analysis revolves around SEOs. We begin with Thomson Financial's Securities Data Company (SDC) Global New Issues database to identify firms that conduct IPOs/SEOs during 1999–2020. For a firm to be included in the sample, it must have conducted either an IPO or an SEO during the sample period 1999-2020. We start the sample in 1999 because our definition of peers is based on the 6-digit Global Industry Classification Standard (GICS) code. We use GICS because of its prevalence in the investment community as we seek to identify capital supply-linked peer firms. The GICS was constructed by Standard and Poor's and MSCI to help capital market participants identify firms within the same sector/industry for investment purposes. As described by S&P:

> The GICS methodology aims to enhance the investment research and asset management process for financial professionals worldwide. It is the result of numerous discussions with asset owners, portfolio managers and investment analysts around the world. It was designed in response to the global financial community's need for accurate, complete and standard industry definitions. (page 3, GICS, S&P Global Market Intelligence, 2018)

Companies are assigned to a sector, industry group, industry, and sub-industry. The 6-digit code we use identifies peers based on the sector, industry group, and industry. An example illustrates.

The 2-digit GICS code 35 is for the health care sector. The 4-digit codes 3510 and 3520 split this sector into two industry groups: healthcare equipment and services (3510), as well as pharmaceuticals and biotechnology & life sciences (3520). There are three 6-digit codes for each industry group, identifying a total of 6 industries within the sector (e.g., 3520 is divided into biotechnology (352010), pharmaceuticals (352020), and life sciences tools & services (352030)).

Our sample firms further 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 banks, insurance companies 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[11]; (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 require sufficient data to calculate the Whited-Wu constraint index (see below). The resulting sample consists of 2,892 SEOs.

---

[11] 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.

We define financial constraints on the basis of a company's Whited-Wu index value. Whited and Wu (2006) show that their index carries greater explanatory power for firm returns than firm size does. They also document correlation between their index and common indicators for difficulty accessing external finance, such as lack of bond rating and less analyst coverage, more cash and less debt, and low sales growth despite belonging to industries with high sales growth. We split our sample at the median Whited-Wu index value. Firms with index value above the median are labeled *constrained firms*. *Unconstrained firms* refer to the complement sample.

3.2 Construction of Exogenous Shock Variables

Our shock-based identification strategy relies on exogenous shocks to investors' demand for a firm's equity. We utilize the shocks (and procedures to measure them) described in Chang et al. (2015) as well as Schmidt and Fahlenbrach (2017). To set expectations, we label shocks that exogenously increase (decrease) investor demand for a firm's equity as ***Index Shock Pos*** (***Index Shock Neg***) respectively.

First we build the theoretical Russell 1000 and 2000 based on raw market capitalizations of firms. Prior to 2007, index membership is strictly classified on the basis of ranked market value of equity. For the top 3000 stocks that meet Russell's index inclusion criteria, the largest 1000 are assigned to the Russell 1000 and the next largest 2000 stocks are assigned to the Russell 2000. These assignments are made once per year, on the basis of end-of-May market values of equity.

Stocks that move "down" from the Russell 1000 to the Russell 2000 based on these end-of-May (year t) rankings, are given a value of one for ***Index Shock Pos*** over the ensuing year (June 1 of year t through May 31 of year t+1). All other stocks receive a zero for ***Index Shock Pos*** over the same period. Per Chang, Hong, and Liskovich (2015) (see our section 2.2), stocks that migrate "down" become a much larger component of an index and thus experience a positive shock to indexer demand for their shares. Stocks that move "up" from the Russell 2000 to the Russell 1000 have ***Index Shock Neg*** = 1 over the ensuing year (June 1 of year t through May 31 of year t+1), zero otherwise. These stocks become a much smaller component of an index and experience a negative shock to indexer demand for their equity. Stocks that do not "migrate" between indices based on the May 31 ranking date, are assigned a value of zero for both shock dummies.

Given our proxies for exogenous variation in equity capital demand (***Index Shock Pos*** and ***Index Shock Neg***), we construct indicators of peer effects in SEO actions as follows. The interactive ***Ln(Peer SEO)*Index Shock Pos*** should carry a negative coefficient in the hazard. This is because a positive exogenous shock to equity demand (via indexer behavior) reduces the importance of prior peer SEOs as a facilitating mechanism for a constrained firm's SEO. The vice-versa argument also applies. Negative exogenous shocks to equity demand raise the importance of prior peer SEOs as a mechanism to facilitate constrained firm SEOs; the interactive ***Ln(Peer SEO)*Index Shock Neg*** should carry a positive coefficient in the hazard.

3.3 Descriptive Statistics

Table 1 reports ex-ante descriptive statistics for sample SEO firms classified by financial constraint status. For each group, we report mean, median, and standard deviation of firm characteristics at the fiscal year-end prior to the SEO, as well as issuance characteristics.[12] We also report several return characterizations: firm, industry, and market returns, as well as SEO announcement returns. Finally, we report the incidence of positive and negative capital supply shocks among our sample firms. We test the significance of differences in means and medians across groups. In general, the differences align with expectations.

Unconstrained firms are on average larger with higher book-to-market. Institutional investor demand is similar across constrained and unconstrained firms. Event study returns[13] indicate statistically worse SEO announcement effects for constrained firms compared to unconstrained firms (-1.9% vs. -1.5%). We explore determinants of constrained firm SEO event returns in Table 6.

[12] All variable definitions are defined in the Appendix Table A-1.
[13] Calculated using standard market model methodology over the 3-day window surrounding the SEO filing date.

Our variable *Peer SEO* equals the number of firms in the same GICS peer group that conduct an SEO in the prior six months preceding the event month. 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 preceding the event month. On average, there are 17.37 (21.38) firms in a peer group issuing SEOs in the six months preceding a constrained (unconstrained) firm's SEO announcement. The average number of SEOs conducted in the (rest of the) market in the prior six months is also significantly lower for constrained (36.16) than for unconstrained firms (41.35). One potential reason for the fewer peer SEOs before constrained firm SEOs is that constraints sensitize firms to triggers. We document such a pattern below through hazard estimation of firm equity issuance timing and its drivers.

3.4 Hazard

We use a hazard model to study the duration between SEO issuances. The main benefits of using a hazard in our setting resemble those described in Shumway (2001). The hazard model conditions on the length of time since the last issuance. This admits potential differences between a firm that issues equity soon after a prior issuance, and a firm with a much longer spell between. Since our research question is about the determinants of SEO issuance, it is natural to explore the time between issuances. A second benefit to hazards is the allowance for time varying covariates. Given that many SEOs occur during waves, the influence of SEO timing determinants likely vary over time.

The basic form of our specification (where i indexes firms and j indexes spells for firm i) is:

$$h_{ij}(t) = h_0(t)\exp[X_{ij}(t)'\beta] \quad (4)$$

where,

- t represents the survival time (time since the last issuance)
- $h_{ij}(t)$ is the hazard function determined by a set of covariates
- the coefficients (βs) measure the impact (i.e., the effect size) of covariates.
- the term $h_0(t)$ is called the baseline hazard. It corresponds to the value of the hazard if all the X_{ij} are equal to zero (the quantity exp(0) equals 1). The 't' in $h_{ij}(t)$ indicates that the hazard may vary over time.

In the above model, exp (β) is the hazard ratio. A value of β greater than zero, or equivalently a hazard ratio greater than one, indicates that as the value of the covariate increases, the event hazard (probability of SEO) increases and thus the length of survival (time since last issuance) decreases.

There are several important elements to our hazard estimation. First, we estimate a Cox proportional hazard model because it offers a number of advantages over other survival models (such as the exponential and the Weibull models). Cox requires minimal assumptions about the distribution of event times (in contrast to other that require a specified probability distribution of them). This is advantageous because time to event data tends to be non-normal (fat right tails); particularly in our study's context of both peer effects and SEOs (which often come in waves).[14] Cox also easily accommodates time-varying covariates. And the Cox model has the ability to handle both left-truncated and right-censored data (in both continuous and discrete form).

We adapt our Cox hazard estimation to control for time-invariant (potentially unobservable) firm characteristics on issuance timing. We include firm-level fixed effects, and we cluster standard errors at the firm level to recognize the non-independent nature of multiple spells (or events) for the same firm. As Kleinbaum and Klein (2005) note, Cox is a robust model so that results will "closely approximate (a) correct parametric model."

Hazard Panel and Variables

We form our dataset as a panel of firm-years to accommodate fiscal year data from Compustat as well as our construction of the Russell-based exogenous shocks to investor demand for SEO shares. Our sample sizes are 10,928 firm/years in the constrained firms sample, and 13,224 firm/years in the unconstrained firms sample.

The dependent variable in a hazard model consists of two parts: An event indicator (e.g., a binary indicator of whether an SEO occurs) and a measure of time from baseline (i.e. of time since previous

[14] This also motivates our use of a hazard as opposed to Tobit specification which assumes Gaussian errors.

event). This spell length is measures in years (e.g. 2.675 years). For example, assume that ABC company has an IPO in February 2010, an SEO in October 2018, and the data ends in December 2020. In 2018, the dependent variable is 1(SEO event indicator)*8.5(spell length)=8.5. In 2020, the data is right-censored, which arises when the event either never occurred or took place after the period of observation. The dependent variable is 0(SEO event indicator)*2.167(spell length)=0, indicating no SEO occurred in 2020.

According to Table 1 Panel B, unconstrained firms have longer average spells than constrained firms. This reflects the fact that unconstrained firms often have ample internally generated funds and/or access to debt markets, mitigating the need for external equity capital. This longer *Spell Length* for unconstrained firms highlights the concern with comparing *baseline* hazard rates across the two samples. This baseline probability of doing an SEO conditional on how long the spell has been, does not measure accelerants to the decision.

Rather, our focus is on the coefficients (the vector β) on the time-varying covariates. Positive coefficients indicate raised hazards or sped up SEOs, implying the covariate encourages the focal firm's SEO; and vice-versa. Our hazard covariates that we include in all specifications (tables) are:

> *Peer SEO*: the number of firms conducting SEOs in the same 6-digit GICS industry in the 6 months prior to the event date, or prior to the time of censoring (in the case of no event). Using the example above, Peer SEO is the number of SEOs among all 6-digit GICS industry peers between April 2018 and September 2018 (inclusive). For the censored observation, the Peer SEO value equals the number of SEOs by 6-digit GICS industry peers between June 2020 and November 2020 (inclusive).
>
> *Market SEO*: the number of firms conducting SEOs across all industries (i.e. the market), as opposed to just by 6-digit GICS industry peers, minus the number of peer firms conducting SEOs in the prior 6 months (both measured in the 6 months prior to the event date or prior to time of censoring).
>
> *Book-to-market*: the ratio of book equity for the fiscal year ending in calendar year t-1 relative to event year (or censoring year), scaled by market equity (from CRSP) at the end of December of year t-1.
>
> *Lnmv*: the natural logarithm of market capitalization, computed as share price times shares outstanding (both from CRSP) measured at the end of December of year t-1.

Firm_indret: the firm's cumulative return in the prior 6 months, minus industry cumulative return in the prior six months before the event date (i.e., SEO filing date), or before the time of censoring in the case of no event.

Ind_mktret: the industry cumulative return in the prior 6 months, minus NYSE/Amex value-weighted cumulative return in the six months prior to the event date, or before the time of censoring in the case of no event.

Mktret: the NYSE/Amex value-weighted cumulative return in the prior 6 months before the event date or before the time of censoring in the case of no event.

Our main tests for the presence of peer effects and our hypothesized capital supply channel, focus on the coefficients on the peer SEO counts and their interaction with proxies for exogenous variation in capital supply. Again, these are (respectively): ***Ln(Peer SEO)***; and the interactives ***Ln(Peer SEO)*Index Shock Pos***, and ***Ln(Peer SEO)*Index Shock Neg***.

A hazard model incorporates time-varying covariates, or explanatory variables that change with time. A firm's probability of SEO changes through time and may depend on how long it has been since its last equity raising activity. The hazard model allows the probability of an SEO to depend on recent characteristics (i.e., is a function of its latest financial data and peers' SEO activity) as well as on the length of time since the last equity raising event (the baseline hazards may differ across spell lengths). The independent variables are measured relative to the end of the spell. For example, the Peer SEO count is measured over the 6 months preceding the event month. These covariates affect the change in SEO probability *from the baseline*, so their influence will differ conditional on spell length. For example, recent high stock returns is a well-known predictor of SEO activity. However, a firm that did an SEO in December 2018 will be unlikely to do an SEO in January of 2019, regardless of its returns, while a firm that last did an SEO in January of 2014 may be ripe for an SEO (in January of 2019). This would not be captured by a logit, which does not condition on spell length; however, the hazard would control for this. For example, a spell length of one-month (December 2018 to January 2019) could have a baseline prob(SEO) of 0.000001 while the 60 month spell length could have a prob(SEO) of, say, 0.10. This allows the covariates to explain variation in pr(SEO) around different baselines.[15]

As noted above, our estimation accounts for left-truncation and right-censoring.[16] The sample shows a non-trivial incidence of each. Right-censored observations include all firms who did not conduct an SEO in December 2020. For example, if a firm went IPO in June 2014, if it never issues SEO and the data on the firm end in December 2020, the censoring time is 6.5 years. Right-censored observations also include firms who didn't survive through December 2020. For example, if a firm went IPO in June 2014, if it never issues SEO and the data on the firm end in December 2018, the censoring time is 4.5 years. In Table 1 Panel B, 71.3% (28.7%) spells are uncensored (censored) for constrained firms, which compares to 68.9% (31.1%) uncensored (censored) spells for unconstrained firms. The average uncensored (censored) spell lengths are 4.25 (9.61) years for constrained firms. The unconstrained firms have longer average uncensored and censored spells than constrained firms. We left-truncate our sample for firms whose IPO dates precede 1999. For example, if a firm's SEO date is June 2003, and the IPO date is 1965, then the spell length is 4.5 years (because our data begin in 1999). Table 1 Panel B indicates that there are 2.7% (3.9%) truncated SEOs for constrained (unconstrained) firms.

4. Results

Our results are presented as follows. Table 2 provides evidence of sequencing in SEOs. Panel A splits the sample into constrained vs. unconstrained firms, while Panel B focuses on young and unconstrained firms as one sub-sample vs. old and constrained firms as another sub-sample. Table 3 uses the exogenous capital supply shocks of Chang et al. (2015) to identify peer SEO capital supply effects via substitution

---

[15] Fisher,L. and D. Y. Lin, 1999, Time-Dependent Covariates in the Cox Proportional-Hazards Regression Model, *Annual Review of Public Health* 20:1, 145-157

[16] See Allison (1995) for details.

inference. Table 4 distinguishes between peer characteristics (being positively shocked via index migration) and peer actions (doing an SEO after such migration), on focal firm SEO hazards. Table 5 emphasizes the importance of shared underwriter (between focal firm and peers) to propel peer effects. Table 6 illustrates reduced asymmetric information costs attributable to such shared underwriters.

4.1 SEO Sequencing (Hazard) Results

Table 2 presents estimates from hazard analysis of SEO issuance decisions in two panels. Panel A splits our full sample into two collectively-exhaustive sub-samples of constrained and unconstrained firms. The former have Whited-Wu (2006) index value above the [full sample] median, while the latter are the complement sample.[17] Dependence of constrained firms' SEO hazards on prior peer SEO activity indicates sequencing that may reflect constrained firms' responses to peers.

The hazard for constrained firms in the first column of Panel A indicates that sequencing is indeed evident in our data. Constrained firms' SEO decisions are highly sensitive to prior issuance activity by peers; the coefficient on ***Ln(Peer SEO)*** is positive and significant. In the spirit of Whited (2006), a factor that raises the hazard aids in / speeds up the process of overcoming barriers (such as financial constraints) to the event. More peer-SEO activity recently, associates with earlier SEOs by firms in the constrained sample – i.e. the spells between issues are shorter.

This result is incremental to more typical results found in the literature; in particular that firms' SEO hazards increase in stock returns. It is also noteworthy that the coefficients on prior peer vs. market issuance activity differ significantly. Prior peer issuance activity has a stronger influence on the hazard (0.415) than prior market activity does (0.009); the coefficients are statistically different at the 1% level. In other words, constrained firms' SEO timing is reliably correlated with peer SEO activity much more so than its correlation with the rest of the market's SEO activity. The incremental importance of prior peer

[17] Table A-2 (in the Internet Appendix) illustrates the robustness of results to alternative definitions of 'financially constrained' firms.

issuance activity to a firm's own SEO decision is an important perspective on SEOs, and supports the *potential* role of peer actions (not just characteristics) for financing policy.[18]

The second column presents hazard estimates for our sample of unconstrained firms (those with below-the-median Whited-Wu index values). There is markedly weaker evidence of sensitivity to prior peer activity or returns in this sample. The coefficient on ***Ln(Peer SEO)*** in this sample is 0.122, which is significantly smaller than in the constrained sample hazard (t-statistic on difference equals 4.032). We also observe a different sensitivity to market SEO activity. The coefficient on prior market equity issuance activity is now significantly positive, unlike in the constrained sample. Finally, there is no significant difference between the influences of prior market SEO activity and prior peer SEO activity on the unconstrained sample's SEO timing. Overall, unconstrained firms are less reliant on prior peer SEO activity by several measures.

Economic interpretation of non-linear models relies on additional assumptions. We therefore use linear probability model (LPM) regressions – with regressors that mirror the hazard covariates – to gauge the economic import of prior peer SEOs on constrained firm issuance probability. Economically, the influence of prior peer SEO activity on constrained firms' SEO decisions appears reasonable. In Appendix Table A-2 LPM results, the regression on the constrained firms sample yields a coefficient on ***Ln(Peer SEO)*** of 0.0229. Moving ***Ln(Peer SEO)*** from 0 to 2.30 (the median value of this variable) increases the probability of an SEO by 5.273%.

Panel B of Table 2 presents SEO hazard estimates for two sub-samples at the poles of demand-driven vs. capital supply-driven (likely) motivation for the SEO. Again the logic follows the conclusions of Leary and Roberts (2014), with older firms already having both good knowledge about industry opportunities as well as an established reputation. This mitigates the learning or demand-side channel to

[18] We revisit the difference between characteristics and actions of peers as driver of focal firm SEOs, in Table 4.

mimicry, while the constrained status emphasizes the capital supply channel's potential role in mimicry. The coefficient on ***Ln(Peer SEO)*** (.488) is significant at the 1% level.

On the other hand, younger firms are likely to learn more about the industry's investment opportunity set by observing peer financing, than older firms would. Coupled with lower value of Whited-Wu that suggests financial constraint / capital supply motives are muted, the sub-sample in the second column should show much weaker effect of prior peer SEOs on focal firm SEO hazards. Indeed it does. Although significant, the coefficient on ***Ln(Peer SEO)*** (.019) is demonstrably smaller than the coefficient in the first column.

4.2 The Mediating Role of Index Migration Shocks on SEO Hazards

Table 3 presents results from estimating hazards including capital supply shocks built on Chang et al.'s (2015) approach. Again, we expect that constrained firms migrating "up" from the Russell 2000 to the Russell 1000 will show increased SEO hazard sensitivities to peer SEOs, and vice-versa. We augment the model from Table 2 with several key variables: the two dummies for positive and negative exogenous capital supply shocks, and each dummy's interactives with prior peer SEO activity.

The results again suggest that capital supply is a key channel in peer effects. Among constrained focal firms, we still observe a significantly positive coefficient on ***Ln(Peer SEO)***. Moreover, we see a positive coefficient on ***Index Shock Pos***, indicating that greater capital supply accelerates constrained firms' SEOs, and vice-versa (negative coefficient on ***Index Shock Neg*** indicating that a dearth of indexer demand acts to slow these firms' SEOs). Most importantly, the coefficients on both interactives of the index shocks with prior peer activity are of the expected sign and significant. For example, the coefficient on ***Ln(Peer SEO)*Index Shock Pos*** is -.029 and significant at the 1% level. When the capital supply shock is positive, prior peer SEO activity has a (significantly) less positive influence on constrained firms' SEO hazards. The positive capital supply shock <u>substitutes</u> for the facilitation effect of prior peer equity issuance, on constrained firms' ability to bring seasoned equity to market.[19] Finally, we note that in column two, neither of the shock dummies nor their interactives appear to influence *un*constrained firms' SEO timing decisions. Overall, our results support the channel of capital supply in SEO peer effects.

Again for assessment of economic effects we turn to a linear probability model.[20] In the LPM regression mimicking the Table 3 hazard on the constrained firms sample, the coefficient on *Index Shock Neg* is -0.196. This implies that migration "up" from the Russell 2000 to the Russell 1000 (a negative capital supply shock as indexers reduce their demand for the firm's shares), reduces SEO likelihood for constrained firms by 19.63%. This is a resounding effect. When firms lose the effectively guaranteed indexer demand for their shares (to be issued in an SEO), they are far less likely to do one.

However, as noted in the above discussion of hazard results, this serves to raise the importance of prior peer SEOs to a constrained (and negatively shocked) firm's SEO likelihood. The coefficient on the interactive of *Index Shock Neg* with *Ln (Peer SEO)* is 0.040. Economically, 11 more peer SEOs (implying *Ln (Peer SEO)* increases by 2.5) raises the likelihood of a constrained and negatively shocked firm's SEO by 10.25%. While this does not completely offset the negative shock's effect, it is still substantial. Overall, the LPM results suggest that prior peer SEO activity has an economically meaningful influence on constrained firms' SEO likelihood, particularly when the constrained firm was recently negatively shocked.

4.3 Peers' SEOs after Index Shocks, and Mimicry of Characteristics or Actions

The previous results show focal firm SEOs are encouraged by index shocks that move firms from the (bottom of the) Russell 1000 to the (top of the) Russell 2000. Such migration among peer firms could have the same effect. This implies another layer of question about the influence of prior peer SEOs on focal firm SEO hazards: is the influence of prior peer SEOs due to characteristic – related to the shock – or due to action (the peer SEO that followed the shock)?

[19] And again, vice-versa for negative capital supply shocks due to index migration "up".

[20] We focus on the negative shock (dummy and interactive) variables where the economic effects are quite pronounced. The economic effects of positive shocks (and their interactives) are about one fourth the size.

To address this question, we re-run our standard Table 2 hazard but with two added variables: the number of peers shocked positively (i.e. that migrated from the bottom of the Russell 1000 to the top of the Russell 2000) at the last index rebalancing date; and the number of these shocked peers that conducted an SEO within six months of the shock. Note that we retain the variable ***Ln(Peer SEO)*** in our estimation, to capture the influence of prior peer SEOs that were not preceded by a positive index shock at the last rebalancing.

Table 4 presents the results. Focusing first on the constrained firms sample hazard, we continue to see a significant positive coefficient on ***Ln(Peer SEO)***. We also observe significantly positive coefficients on the two new variables: the number of positively shocked peers; and the number of those which followed it with an SEO, respectively. Notably, the coefficient on the latter is incremental to the usual coefficient (on ***Ln(Peer SEO)***). That incremental effect is of similar magnitude to the stand-alone effect of ***Ln(Peer SEO)***). On the other hand, the coefficient on the variable that counts number of positively shocked peers, is about one-fifth the size. Thus actions of peers are important to constrained firm SEO hazards.

In the second column we present hazard results for the unconstrained sample. Like in Table 2, the influence of ***Ln(Peer SEO)*** is much smaller. Also, we see no effect of SEOs by recently shocked peers on the (unconstrained) focal firm hazard. Finally, there is no difference in effect of peer shock events (index migrations) across the constrained – unconstrained margin. Taken together, we conclude that mimicry is of peer actions.

4.4 The Importance of Common Underwriters in Propelling Peer Effects

When the bank that underwrites a focal firm's SEO has prior experience with peer SEOs, the information collected during prior activities can mitigate asymmetric information production costs on the current SEO (see Benveniste et al. (2003) for details). For constrained focal firms where asymmetric information is usually a costly barrier, the mitigation due to information spillover should lower barriers and encourage focal firm issuance. We test this using the hazard framework presented in Table 2, but with the inclusion of a new variable measuring the quantity of prior peer-SEO experience by the underwriter. The new variable, ***Ln(Common Underwriter)***, is the natural log of one plus the number of SEOs by peers that were underwritten by the same investment bank (that the focal firm uses) over the last six months. The effect of the ***Ln(Common Underwriter)*** variable is incremental to the effect of ***Ln(Peer SEO)***.

Table 5 presents the results. For constrained firms, we continue to see the importance of ***Ln(Peer SEO)***. Now we also see incremental importance of ***Ln(Common Underwriter)***. When the constrained firm's underwriter has led more peer SEOs to market recently, this further increases the hazard for the constrained firm. Notably, the effect is muted among unconstrained firms. The difference in coefficients suggests a more pronounced reduction in asymmetric information costs, among constrained firms. We explore this reduced asymmetric information cost view, shortly.

As noted in section 2.3, the information production role is likely to be pronounced when the underwriter is more highly ranked. Carter and Manaster (1990) argue that higher ranked underwriters are (exogenously) more adept at identifying issuer risk and communicating it to investors. They trade off higher fees for better issuer return outcomes. Chemmanur and Fulghieri (1994) show underwriters invest in reputation building to communicate their superior information production (about issuer quality) abilities. The higher ranked underwriters are compensated through higher fees from issuers that will benefit most from underwriter certification. We therefore include underwriter rank both stand-alone and interacted with common underwriter in our analyses.

We document results consistent with this among constrained issuers. The coefficient on the interactive of common underwriter and their rank is significantly positive in the constrained firms' SEO hazard. However it is not significant, and this is statistically different from the former, among unconstrained firms. It is only when barriers are likely higher (constrained firms) that the greater information production by highly ranked underwriters facilitates SEOs.

We next turn to more specific indicators of reduced asymmetric information costs associated with greater underwriter experience with recent peer SEOs We explore announcement returns to, and gross spreads charged on, SEOs by constrained firms.[21] If underwriters learn from their prior activities underwriting SEOs of the constrained firm's peers, then we expect asymmetric information related costs to decline in our common underwriter variable.

Table 6 presents regression results. Constrained firms' SEO announcement abnormal returns are increasing (less negative) in ***Ln(Common Underwriter)***. More underwriting of peers' SEOs recently, improves the bank's information set and this knowledge can be used to reduce asymmetric information related costs at the constrained firm's SEO. This also manifests in the gross spread fees charged on constrained firms' SEOs, which are decreasing in ***Ln(Common Underwriter)***. Finally, both effects are more pronounced when the underwriter is more highly ranked, consistent with Carter and Manaster (1990) as well as Chemmanur and Fulghieri (1994). Our results also provide support for the theory of Benveniste et al. (2003), which suggests underwriters reduce asymmetric information by learning more about common valuation factors via their bundling of related firms' securities offerings.

The common underwriter effect may suffer from a selection problem. If the constrained firm recognizes the value of using an underwriter that recently marketed an SEO of a peer, they may select said common underwriter. However, this selection concern is most likely pronounced when the selecting (constrained) firm switches from whomever underwrote their own previous equity issue (SEO or even IPO).[22] Therefore, to mitigate this potential selection effect, we re-run our hazard on the sub-sample of constrained firm SEOs that were underwritten by the same investment bank that the constrained firm used in their *previous* equity issue. See Table A-5 Panel A of the Internet appendix. The results are robust.

---

[21] We focus on the constrained firms sample because information production matters most to issuance there.
[22] See James (1992) for evidence on switching costs in underwriting services.

5. Conclusions

Peer effects are known to be influential in corporate finance policy. Investment, capital structure, executive compensation, all show some form of sensitivity to peer characteristics and/or actions. We are the first to explore a capital-supply channel through which peer effects may be influenced.

We study SEO timing decisions using hazards. Constrained firms' SEO hazards are increasing in prior SEO activity by peers. Two distinct approaches to identifying a capital supply channel behind this sensitivity also present consistent results. Those SEOs by focal firms with muted learning / reputation needs but simultaneously high financial constraints (old and constrained), show strong sensitivity. By contrast, SEOs by focal firms with high learning / reputation needs but without financial constraint (young and unconstrained), show lower sensitivity.

Our second approach uses plausibly exogenous shocks to capital supply generated by index migration (e.g. Chang et al. (2015)). Positive (negative) exogenous shocks to capital supply reduce (increase) constrained firms' hazard sensitivities to peer SEOs. This suggests that the sensitivity proxies for the importance of capital supply and that such shocks are substitutes for it.

The documented capital supply channel raises the question of what barriers to equity issuance are being overcome. Asymmetric information costs are a well-known driver. We test this by relying on the model of Benveniste et al. (2003) which suggests such costs will be reduced by underwriter bundling of issues by related firms. We find that underwriter commonality (across the focal firm and its peers that recently conducted SEOs) accelerates SEO timing by constrained firms. Two other results support the hypothesis that asymmetric information costs (faced by the constrained firm) are mitigated through common underwriter experience. Spreads charged on the SEO are decreasing in the common underwriter's experience with peers' SEOs. And constrained firms' own-SEO event returns are increasing in the same experience variable.

Overall, our research highlights the critical channel of capital supply in the transmittal of peer-to-peer financial policies. There are two important caveats to our inferences. First, our focus has been on equity issuance which is a significant capital raising event. Our inferences may be less applicable for peer effects that more closely resemble "pure mimicry". Second, the focus on SEOs also sidesteps the potential for peer effect transmittal in debt financing. De Franco et al. (2020) explore this in bank lending. Future research on peer effects in public debt financing may be fruitful. Recent work by Dathan and Davydenko (2020) may carry relevance here as they recognize the influence of index fund demand for debt capital in its pricing.

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.

Armstrong, C., Guay, W., Weber, J., 2010. The role of information and financial reporting in corporate governance and debt contracting. *Journal of Accounting and Economics* 50, 179–234.

Asker, J., Ljungqvist, A., 2010. Competition and the Structure of Vertical Relationships in Capital Markets. *Journal of Political Economy* 118, 599–647.

Aslan, H., Kumar, P., 2016. The product market effects of hedge fund activism. Journal of Financial Economics 119, 226–248.

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.

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

Benveniste, L., Ljungqvist, A., Wilhelm, W., Yu, X., 2003. Evidence of Information Spillovers in the Production of Investment Banking Services. The *Journal of Finance* 58, 577-608.

Billett, M., Esmer, B., Yu, M. 2018. Creditor Control and Product Market Competition. *Journal of Banking and Finance*, 86, 87-100.

Billett, M., Floros, I., Garfinkel, J., 2019. At-the-Market (ATM) Offerings. *Journal of Financial and Quantitative Analysis* forthcoming.

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

Blume, M., Edelen, R., 2001. On replicating the S&P500 Index, University of Pennsylvania Wharton School Rodney White Center. *Working paper*.

Bolton, P., Scharfstein, D., 1990. A theory of predation based on agency problems in financial contracting, *American Economic Review* 80, 93-106.

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

Brauner, A., Lee, J., Naranjo, A., 2018. Peer Effects in Corporate Capital Structure Around the World. *Working paper*.

Chang, YC., Hong, H., Liskovich, I., 2015. Regression Discontinuity and the Price effects of Stock Market Indexing, *Review of Financial Studies* 28, 212-246

Choe, H., Masulis, R., Nanda, V., 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.

Dathan, M., Davydenko, S., 2020. Debt Issuance in the Era of Passive Investment. *Working paper*.

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

De Franco, G., Edwards, A., Liao, S., 2020. Product Market Peers in Lending: Information Processing Efficiencies and Proprietary Costs. *Management Science* forthcoming.

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

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

Farre-Mensa, J., Ljungqvist, A., 2016. "Do measures of financial constraints measure financial constraints?" *Review of Financial Studies* 29, 271-308.

Fazzari, S., Hubbard, R., Petersen, B., 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.

Francis, B., Hasan, I., Kostova, G., 2016. When do peers matter? A cross-country perspective. *Journal of International Money and Finance* 69, 364–389.

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

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

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

Hoberg, G., Phillips, G., 2016. Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423-1465.

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

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

Lee, G., Masulis, R., 2009. Seasoned equity offerings: Quality of accounting information and expected flotation costs, Journal of Financial Economics 92, 443-469.

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

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

Lys, T., Sohn, S., 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., Yeung, B., Yu, W., 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.

Schmidt, C., Fahlenbrach, R., 2017. Do exogenous changes in passive institutional ownership affect corporate governance and firm value?, *Journal of Financial Economics* 124, 285-306.

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.

Shumway, T., 2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *Journal of Business* 74, 101-124.

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

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

Table 1. Descriptive Statistics

The table reports descriptive statistics for sample SEO firms classified by finance constraints over 1999-2020. Firms are classified into 69 industries based on 6-digit Global Industry Classification Standard (GICS) codes. Constr*ained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. Appendix Table A-1 contains all variable definitions. Panel A reports the firm and deal characteristics for constrained and unconstrained SEOs separately. Panel B reports the spell characteristics. Asterisks indicate significant differences 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 firm SEOs			Unconstrained firm SEOs		
	Mean	Median	Std.	Mean	Median	Std.
Panel A. Firm and Deal Characteristics						
Firm_indret (%)	1.53	0.06	0.16	1.44	0.04	0.17
Ind_mktret (%)	1.42	0.78	4.63	1.58	0.86**	6.35
Mktret (%)	1.51	0.87	4.67	1.67	0.95*	6.40
Ln(MV)	6.68	6.45	1.54	7.46***	7.34***	1.29
Book-to-market	0.60	0.59	0.25	0.65***	0.67***	0.26
Dinstidem	0.43	0.00	0.50	0.45	0.00	0.49
Event abnormal return (%)	-0.019	-0.016	0.074	-0.015***	-0.013***	0.065
Peer SEO	17.37	10.00	13.62	21.38***	20.00***	9.79
Market SEO	36.16	34.00	6.85	41.35***	41.00***	7.19
% sample with Index Shock Pos	3.18%			2.63%		
% sample with Index Shock Neg	2.56%			2.00%		
Number of obs.	1,446			1,446		
Panel B. Spell Characteristics						
Spell Length (years)	5.72	3.66	2.23	7.12***	5.28***	3.86
Spell Length (years) Uncensored	4.25	3.02	2.18	5.78***	3.65*	3.91
Spell Length (years) Censored	9.61	7.76	2.51	10.14	8.75	3.30
Fraction Uncensored	0.713			0.689		
Fraction Censored	0.287			0.311		
Fraction Left-Truncated	0.027			0.039		

Table 2. Firm's SEO Sensitivity to Recent Peer SEOs

Table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms (Panel A), and old-constrained versus young-unconstrained firms (Panel B) over 1999-2020. The hazard model with time-varying covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. The dependent variable is the number of years between consecutive SEOs or between IPO and first SEO. *Constrained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. *Firm age* is the number of years since founding. *Young/old firms* are firms whose firm age are below/above the sample median. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Constrained vs. Unconstrained firms

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.415***	0.122***	0.293***
	(0.069)	(0.021)	[4.032]
Ln(Market SEO)	0.009***	0.023***	-0.014***
	(0.003)	(0.004)	[-2.649]
Book-to-market	-0.641***	-0.484***	-0.157
	(0.125)	(0.124)	[-0.891]
Firm_indret	0.413**	0.540***	-0.127
	(0.163)	(0.169)	[-0.541]
Ind_mktret	0.528**	0.575**	-0.047
	(0.217)	(0.236)	[-0.146]
Mktret	0.513**	0.564**	-0.051
	(0.215)	(0.235)	[-0.161]
Dinstidem	0.521***	0.734***	-0.214**
	(0.065)	(0.068)	[-2.260]
Ln(MV)	-0.189***	-0.241***	0.052
	(0.027)	(0.022)	[1.493]
Log Likelihood	-8486.374	-8007.354	
Likelihood Ratio test	198.929***	275.854***	
Diff test: Peer SEO	0.406***	0.099	
−Market SEO	(0.005)	(0.644)	

Panel B. Old & Constrained vs. Young & Unconstrained firms

	Old & Constrained Firms	Young & Unconstrained firms	Difference
Ln(Peer SEO)	0.488***	0.019**	0.469***
	(0.105)	(0.008)	[4.471]
Ln(Market SEO)	-0.005	0.012***	-0.016**
	(0.007)	(0.003)	[-2.067]
Book-to-market	-0.262	0.468*	-0.731**
	(0.161)	(0.251)	[-2.450]
Firm_indret	0.966***	0.347	0.619
	(0.323)	(0.424)	[1.162]
Ind_mktret	0.708***	0.894**	-0.187
	(0.254)	(0.359)	[-0.424]
Mktret	0.955***	0.335	0.619
	(0.320)	(0.419)	[1.174]
Dinstidem	0.898***	0.642***	0.257*
	(0.083)	(0.121)	[1.746]
Ln(MV)	-0.239***	-0.053	-0.186***
	(0.027)	(0.048)	[-3.376]
Log Likelihood	-4947.851	-4401.909	
Likelihood Ratio test	263.597***	109.253***	
Diff test: Peer SEO	0.493***	0.007	
–Market SEO	(0.004)	(0.286)	

Table 3. Firm's SEO Sensitivity to Recent Peer SEOs: Identification via Capital Supply Shocks

Table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms (Panel A), and old-constrained versus young-unconstrained firms (Panel B) over 1999-2020. The hazard model with time-varying covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. The dependent variable is the number of years between consecutive SEOs or between IPO and first SEO. *Constrained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. *Firm age* is the number of years since founding. *Young/old firms* are firms whose firm age are below/above the sample median. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Constrained vs. Unconstrained firms

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.276***	0.026	0.250**
	(0.093)	(0.034)	[2.516]
Ln(Market SEO)	0.010	0.011***	-0.002
	(0.108)	(0.004)	[-0.015]
Book-to-market	-0.727***	-0.816***	0.089
	(0.168)	(0.150)	[0.396]
Firm_indret	0.114	0.143	-0.029
	(0.213)	(0.164)	[-0.108]
Ind_mktret	0.454*	0.074***	0.381
	(0.275)	(0.026)	[1.379]
Mktret	0.437	0.722***	-0.285
	(0.272)	(0.256)	[-0.764]
Dinstidem	0.399***	0.360***	0.039
	(0.087)	(0.091)	[0.308]
Ln(MV)	-0.135***	-0.281***	0.147***
	(0.038)	(0.036)	[2.795]
Index Shock Pos	0.547*	0.001	0.546*
	(0.300)	(0.119)	[1.695]
Ln(Peer SEO) * Index Shock Pos	-0.029***	0.009	-0.038
	(0.010)	(0.051)	[-0.723]
Ind_mktret * Index Shock Pos	-0.059*	0.002	-0.061*
	(0.032)	(0.001)	[-1.925]
Index Shock Neg	-0.614**	0.136	-0.750**
	(0.279)	(0.135)	[-2.417]
Ln(Peer SEO) * Index Shock Neg	0.025***	-0.034	0.059*
	(0.010)	(0.034)	[1.648]
Ind_mktret * Index Shock Neg	-0.006	0.000	-0.006
	(0.018)	(0.001)	[-0.329]
Log Likelihood	-4545.191	-4464.864	
Likelihood Ratio test	77.385***	129.545***	
Diff test: Peer SEO	0.266***	0.015	
−Market SEO	(0.003)	(0.437)	

Table 4. Firm's SEO Sensitivity to Recent Peer SEOs: distinguish between mimic action vs characteristic of Peers

Table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1999-2020. The hazard model with time-varying covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. The dependent variable is the number of years between consecutive SEOs or between IPO and first SEO. Constr*ained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Constrained Firms	unconstrained firms	Difference
Ln(Peer SEO)	0.293***	0.091***	0.202***
	(0.073)	(0.023)	[2.656]
nINDEX_SHK_POS	0.068**	0.039*	0.029
	(0.029)	(0.022)	[0.784]
nINDEX_SHK_POS_SEO	0.315**	-0.309	0.624**
	(0.146)	(0.217)	[2.385]
Book-to-market	-0.481***	-0.356***	-0.126
	(0.127)	(0.126)	[-0.702]
Firm_indret	0.363**	0.467***	-0.104
	(0.161)	(0.156)	[-0.463]
Ind_mktret	0.423**	0.632***	-0.209
	(0.215)	(0.229)	[-0.663]
Mktret	-0.408*	0.623***	-1.030***
	(0.213)	(0.228)	[-3.304]
Dinstidem	0.520***	0.746***	-0.226**
	(0.065)	(0.068)	[-2.395]
Ln(MV)	-0.177***	-0.245***	0.068*
	(0.027)	(0.022)	[1.948]
Log Likelihood	-8375.225	-8102.312	
Likelihood Ratio test	237.378***	357.163***	

Table 5. "Common" Underwriter Influence

This table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1999-2020. The hazard model with time-varying covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. The dependent variable is the number of years between consecutive SEOs or between IPO and first SEO. *Constrained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

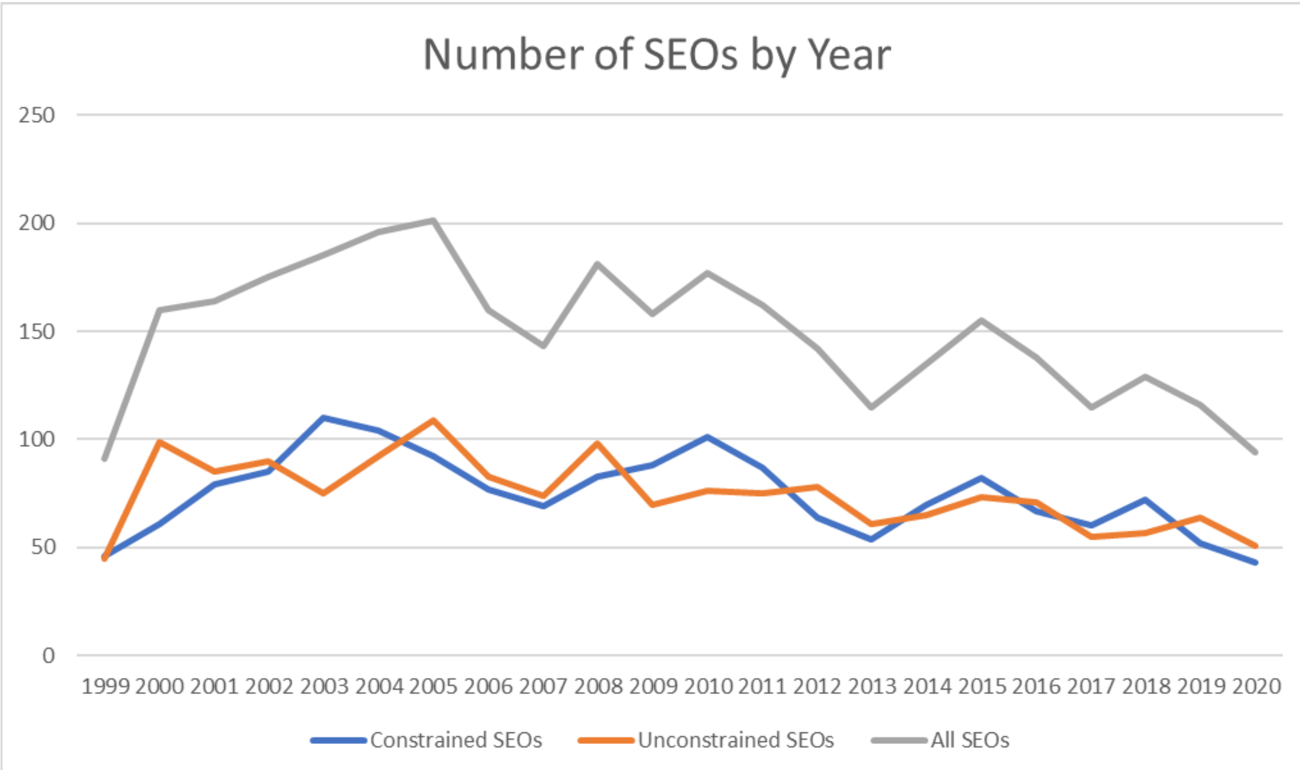
	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.194**	0.033	0.161*
	(0.092)	(0.029)	[1.674]
Ln(Market SEO)	0.005	0.049	-0.044
	(0.004)	(0.044)	[-0.981]
Ln(Common Underwriter)	0.039**	0.010*	0.028*
	(0.016)	(0.006)	[1.683]
UWrank	0.015	-0.004	0.019
	(0.012)	(0.005)	[1.463]
Ln(Common Underwriter) * UWrank	0.011***	0.001	0.010**
	(0.004)	(0.002)	[2.154]
Book-to-market	-0.695***	-0.853***	0.158
	(0.169)	(0.151)	[0.697]
Firm_indret	0.122	0.114	0.008
	(0.218)	(0.179)	[0.029]
Ind_mktret	0.568**	0.090***	0.478*
	(0.272)	(0.027)	[1.750]
Mktret	0.553**	0.877***	-0.324
	(0.269)	(0.270)	[-0.849]
Dinstidem	0.308***	0.457***	-0.149
	(0.088)	(0.092)	[-1.172]
Ln(MV)	-0.100**	-0.244***	0.144***
	(0.039)	(0.036)	[2.708]
Log Likelihood	-4372.401	-4230.822	
Likelihood Ratio test	60.119***	113.598***	
Diff test: Peer SEO	0.189***	-0.016	
−Market SEO	(0.004)	(0.197)	

Table 6. Asymmetric Information Indicators

The panel reports regression results for the sample of constrained firms. *Constrained firms* refer to a sample of firms that have above median Whited-Wu index. 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. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level. T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Announcement abnormal return	Gross spread
Intercept	-2.179***	2.399***
	[-6.43]	[6.22]
Ln(Peer SEO)	0.242***	-0.436***
	[4.50]	[-8.49]
Ln((Market SEO)	-0.034*	0.011
	[-1.70]	[0.38]
Ln(Common Underwriter)	0.397***	-0.526***
	[3.59]	[-5.76]
UWrank	0.034	-0.037
	[0.25]	[-0.46]
Ln(Common Underwriter) * UWrank	0.017*	-0.029**
	[1.79]	[-2.50]
Book-to-market	0.318**	-0.148
	[2.10]	[-1.19]
Firm_indret	0.136	0.061
	[0.95]	[0.52]
Ind_mktret	0.326	0.434*
	[1.08]	[1.69]
Mktret	3.838***	0.518
	[5.61]	[0.84]
Ln(MV)	0.461***	-0.096***
	[13.95]	[-3.20]
Year dummy	Yes	Yes
Industry dummy	Yes	Yes
No. of obs	1,446	1,446
R-squared	0.102	0.121

Figure 1. Number of all SEOs, Constrained SEOs, and Unconstrained SEOs by Year



Appendix

Table A-1: Variable Definitions

Age*:* the number of years since founding.

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

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.

Constrained firms**:** firms that have above median Whited-Wu index.

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).

Event Abnormal Return: 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.

Firm_indret: the firm's cumulative return in the prior 6 months, minus industry cumulative return in the prior six months before the event date or before the time of censoring in the case of no event.

Fraction Censored: the percentage of right-censored spells in the sample.

Index Shock Neg: Stocks that move "up" from the Russell 2000 to the Russell 1000 based on these end-of-May (year t) rankings, are given a value of one for ***Index Shock Neg*** over the ensuing year (June 1 of year t through May 31 of year t+1). All other stocks receive a zero for ***Index Shock Neg*** over the same period.

Index Shock Pos: Stocks that move "down" from the Russell 1000 to the Russell 2000 based on these end-of-May (year t) rankings, are given a value of one for ***Index Shock Pos*** over the ensuing year (June 1 of year t through May 31 of year t+1). All other stocks receive a zero for ***Index Shock Pos*** over the same period.

Length Censored (uncensored)**:** the spell length of the censored (uncensored) spells. Spell length is the number of fractional years between IPOs and first SEOs and between consecutive SEOs, or in the case of censored spells, between the last event (IPO or SEO) and the end of the data.

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

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

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

Ind_mktret: the industry cumulative return in the prior 6 months, minus NYSE/Amex value weighted cumulative return in the prior six months before the event date or before the time of censoring in the case of no event.

Lnmv: the Natural logarithm of market capitalization, computed as share price times shares outstanding (both from CRSP) measured at the end of December of year t-1.

Market SEO: the number of firms conducting SEOs across all industries (i.e. the market), as opposed to just by 6-digit GICS industry peers, over the prior 6 months, minus the number of peer firms conducting SEOs in the prior 6 months.

Mktret: the NYSE/Amex value weighted cumulative return in the prior 6 months before the event date or before the time of censoring in the case of no event.

nINDEX_SHK_POS: the count of the number of peers that experience a positive index shock at the most recent previous reconstitution date.

nINDEX_SHK_POS_SEO: the count of the number of peers that experience a positive index shock at the most recent previous reconstitution date and that did an SEO in the last 6 months.

Peer SEO: the number of firms conducting SEOs in the same 6-digit GICS industry in the 6 months prior to the event date, or prior to the time of censoring in the case of no event.

Spell Length: the number of fractional years between IPOs and first SEOs and between consecutive SEOs, or in the case of censored spells, between the last event (IPO or SEO) and the end of the data.

Unconstrained firms**:** Unconstrained firms are the complement sample to constrained firms.

UWrank: the underwriter prestige rankings which are on a 0 to 9 scale, with the 9 the highest/most prestigious. The underwriter ranking data is obtained from Jay Ritter's website (The underwriter reputation ranking from 1980-2020). The rankings are created based on Carter and Manaster (1990) and Carter, Dark, and Singh (1998) rankings.

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.

Internet Appendix

Table A-2. Robustness Checks: Alternative Proxies for Financial Constraints Hazard Model Estimates

Table reports semiparametric hazard parameter estimates for constrained versus unconstrained firms over 1999-2020. The hazard model with time-varying covariates is specified as $h_i(t)=h_0(t)e^{X(t)\beta}$. The dependent variable is the number of years between consecutive SEOs or between IPO and first SEO. In Panel A, Constr*ained firms* refer to a sample of firms that have below median firm age. *Unconstrained firms* refer to the complement sample that have above median firm age. In Panel B, Constr*ained firms* refer to a sample of firms that have below median firm size. *Unconstrained firms* refer to the complement sample that have above median firm size. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Proxy: Age

	Below median age	Above median age	Difference
Ln(Peer SEO)	0.392***	0.071***	0.321***
	(0.108)	(0.024)	[2.899]
Ln(Market SEO)	0.006	0.057***	-0.051***
	(0.006)	(0.004)	[-6.903]
Book-to-market	-0.124	-0.334**	0.210
	(0.160)	(0.167)	[0.908]
Firm_indret	0.453	0.570**	-0.117
	(0.364)	(0.275)	[-0.256]
Ind_mktret	0.766***	0.083	0.682**
	(0.261)	(0.174)	[2.173]
Mktret	0.449	0.535**	-0.086
	(0.360)	(0.269)	[-0.192]
Dinstidem	0.386***	0.507***	-0.121
	(0.087)	(0.096)	[-0.939]
Ln(MV)	-0.102***	-0.188***	0.086
	(0.032)	(0.042)	[1.625]
Log Likelihood	-4742.512	-4408.581	
Likelihood Ratio test	50.323***	163.017***	

Panel B. Proxy: Firm Size

	Below median firm size	Above median firm size	Difference
Ln(Peer SEO)	0.472***	0.091***	0.381***
	(0.071)	(0.020)	[5.142]
Ln(Market SEO)	0.016***	0.026***	-0.010**
	(0.004)	(0.003)	[-2.093]
Book-to-market	-0.090	-0.650***	0.560***
	(0.135)	(0.114)	[3.169]
Firm_indret	0.520***	0.535***	-0.016
	(0.191)	(0.147)	[-0.065]
Ind_mktret	0.994***	0.320	0.675**
	(0.249)	(0.225)	[2.009]
Mktret	0.977***	0.310	0.668**
	(0.247)	(0.222)	[2.009]
Dinstidem	0.793***	0.490***	0.303***
	(0.066)	(0.073)	[3.075]
Ln(MV)	-0.229***	-0.015	-0.214***
	(0.029)	(0.044)	[-4.055]
Log Likelihood	-8181.076	-8211.859	
Likelihood Ratio test	311.922***	226.279***	

Table A-3. Firm’s SEO Sensitivity to Recent Peer SEOs; Linear Probability Model (LPM)

Table reports estimates of a linear probability model for constrained versus unconstrained firms over 1999-2020. The dependent variable is a dummy variable equals to one if a firm did an SEO, and zero otherwise. *Constrained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. We include firm fixed effects and robust standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Constrained vs. Unconstrained firms

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.023*	-0.008	0.031**
	(0.012)	(0.007)	[2.213]
Ln(Market SEO)	-0.001	0.000	-0.001*
	(0.000)	(0.000)	[-1.745]
Book-to-market	-0.226***	-0.049*	-0.177***
	(0.035)	(0.028)	[-3.965]
Firm_indret	0.050	0.048	0.002
	(0.051)	(0.037)	[0.032]
Ind_mktret	0.044*	-0.041	0.085*
	(0.024)	(0.044)	[1.679]
Mktret	-0.166	-0.036	-0.130
	(0.113)	(0.046)	[-1.067]
Dinstidem	0.029	0.049***	-0.020
	(0.021)	(0.012)	[-0.811]
Ln(MV)	-0.042***	-0.012*	-0.030***
	(0.008)	(0.006)	[-2.940]
R-squared	0.177	0.165	

Table A-4. Firm's SEO Sensitivity to Recent Peer SEOs Mediated by Russell Shocks (LPM)

Table reports estimates of a linear probability model for constrained versus unconstrained firms over 1999-2020. The dependent variable is a dummy variable equals to one if a firm did an SEO, and zero otherwise. Constr*ained firms* refer to a sample of firms that have above median Whited-Wu index. *Unconstrained firms* refer to the complement sample that have below median Whited-Wu index. Appendix Table A-1 contains all variable definitions. We include firm fixed effects and robust standard errors clustered at the firm level (reported in parentheses). T-statistics are in the square brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Constrained vs. Unconstrained firms

	Constrained Firms	Unconstrained firms	Difference
Ln(Peer SEO)	0.021**	0.001	0.020*
	(0.010)	(0.003)	[1.844]
Ln(Market SEO)	-0.011***	0.003	-0.014***
	(0.003)	(0.003)	[-3.272]
Book-to-market	-0.021	-0.088**	0.067
	(0.037)	(0.040)	[1.228]
Firm_indret	-0.008	0.071**	-0.079**
	(0.017)	(0.030)	[-2.268]
Ind_mktret	0.084**	-0.008	0.092**
	(0.042)	(0.006)	[2.160]
Mktret	-0.221***	0.035	-0.256***
	(0.083)	(0.051)	[-2.616]
Dinstidem	-0.005	0.056***	-0.062**
	(0.016)	(0.018)	[-2.507]
Ln(MV)	-0.018***	-0.012	-0.006
	(0.007)	(0.011)	[-0.513]
Index Shock Pos	-0.053	0.021	-0.074
	(0.088)	(0.124)	[-0.487]
Ln(Peer SEO) * Index Shock Pos	-0.007	-0.008	0.001
	(0.026)	(0.008)	[0.040]
Ind_mktret * Index Shock Pos	0.068	0.018	0.049
	(0.099)	(0.103)	[0.347]
Index Shock Neg	-0.196**	0.043	-0.239*
	(0.088)	(0.106)	[-1.734]
Ln(Peer SEO) * Index Shock Neg	0.041*	0.003	0.037*
	(0.022)	(0.005)	[1.670]
Ind_mktret * Index Shock Neg	0.144	0.161	-0.017
	(0.092)	(0.115)	[-0.116]
R-squared	0.136	0.164	

Table A-5. Robustness of Common Underwriter Results

Table A-5 offers robustness checks of our constrained firm hazards in Table 5. We run the hazard model for the sub-sample of constrained firms that use the same underwriter for their current SEO that they used in their prior issuance event.

Sub-sample of SEOs brought to market by same underwriter that firm used in previous equity issue

	Constrained Firms
Ln(Peer SEO)	0.182***
	(0.067)
Ln(Market SEO)	-0.003
	(0.030)
Ln(Common Underwriter)	0.030***
	(0.010)
UWrank	0.017
	(0.078)
Ln(Common Underwriter) * UWrank	0.005*
	(0.003)
Book-to-market	-0.744***
	(0.112)
Firm_indret	0.108
	(0.135)
Ind_mktret	0.756***
	(0.189)
Mktret	0.738***
	(0.187)
Dinstidem	0.360***
	(0.063)
Ln(MV)	-0.171***
	(0.026)
Log Likelihood	-3369.273
Likelihood Ratio test	147.768***
Diff test: Peer SEO	0.185***
−Market SEO	(0.002)