Information Externalities Among Listed Firms [*] [†]

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Abstract

We establish the presence of sizeable information externalities across firms listed on U.S. stock exchanges. To identify externalities, we use staggered non-marginal increases in disclosure at peer firms that are unaccompanied by changes in mandatory disclosure at focal firms. We find that a peer firm's mandatory disclosure improves the focal firm's trading liquidity directly by reducing information asymmetry and indirectly by crowding in both voluntary disclosure and analyst information production at the focal firm. Positive information externalities, and the complementarities they operate through, support regulators' use of mandatory disclosure to improve the market-wide information environment.

Keywords: Mandatory disclosure, voluntary disclosure, information externalities, information environments, strategic interaction, liquidity.

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"Understanding disclosure externalities is essential in any debate over disclosure regulation."

Matsumoto and Shaikh (2017)

Disclosure spillovers are a main motivation for why securities market regulators mandate listed firms to disclose information to investors in the form of regular filings such as annual and quarterly reports and current-event updates (Vives 1984, Dye 1990, Easterbrook and Fischel 1991, Darrough 1993, Admati and Pfleiderer 2000, Kanodia et al. 2000, Hughes et al. 2002). In this paper, we quantify the presence of information externalities across firms listed on U.S. stock exchanges using staggered non-marginal increases in disclosure at peer firms that are unaccompanied by changes in mandatory disclosure at focal firms. Through a series of tests, we paint a comprehensive empirical picture of the channels through which firms influence each others' information environments.

The disclosure literature recognizes how challenging it is to identify disclosure spillovers.[1] A firm's information environment is endogenously shaped by the interplay of its own mandatory and voluntary disclosures, the mandatory and voluntary disclosures of its peers, external information production by information intermediaries such as sellside analysts, and investor demand for information. This means that we require an exogenous shock to a peer's disclosures to make progress. Even then, the channels through which the focal firm might be affected are not only many, they are potentially inter-related. Suppose a firm is mandated to release a non-marginal amount of material information. What might happen next? Its peers might respond by increasing or reducing voluntary disclosure, depending on whether disclosures are strategic complements or substitutes. Analysts might respond by increasing or reducing information production about one or both firms, depending on whether increased disclosure crowds in or crowds out information production within and across firms. And investor demand for information might change.

We propose a shock to a firm's information environment emanating from a peer becoming subject to existing mandatory disclosure requirements for the first time. The shock takes the form of the filing of an S-1 in connection with a top 5 peer firm's decision to go public. The logic of the experiment is very simple.

[1] See Beyer et al. (2010) and Leuz and Wysocki (2016) for recent reviews.

SEC rules mandate that firms wishing to go public in the U.S. must disclose what amounts to a treasure trove of information in their S-1 filings. These filings routinely run to hundreds of pages. Given the near absence of disclosure requirements for privately held firms in the U.S., an S-1 filing marks the transition from an almost entirely opaque firm to one that is subject to one of the most demanding disclosure regimes in the world.[2] We exploit this shock using a matched-firm difference-in-differences (DD) design and identify peer firms using Hoberg and Phillips' (2010) product similarity scores.

Underlying our research design is the assumption that a peer's S-1 filing contains information that investors consider relevant to their understanding of an already-listed firm. We validate this assumption using the search histories of each IP address accessing the SEC's database of EDGAR filings (Lee, Ma, and Wang 2015). Of those users who search EDGAR for an already-listed firm's filings, on average 4.7% also search the peer firm's S-1 filing on the S-1 filing day, rising to 25.9% over the first week from filing and 57.7% over the first month. In other words, lifting the veil on a previously private peer results in a substantial amount of interest in the peer's S-1 filing among users of the already-listed firm's information.

Our main empirical finding is that a top 5 peer firm's S-1 filing leads to a significant improvement in the already-listed firm's trading liquidity. The treatment effect is consistent across four standard measures of liquidity (such as bid-ask spreads), economically large (measuring around 3% relative to the pre-treatment mean), and heterogeneous (larger the worse the initial level of liquidity). It is larger the more novel the information contained in the peer's S-1 filing. It is short-lived, reverting after one quarter, suggesting that the S-1 filing gives rise to a larger information spillover than the peer firm's subsequent disclosures once listed. The intensity of treatment abates with repeated treatments, consistent with diminishing marginal spillover effects as more peers have gone public.

Our empirical design appears well-identified, in the sense that we find no evidence of diverging pre-trends in liquidity between treated firms and their matched controls that would lead us to question the

[2] We thus exploit a shock that is non-marginal, in contrast to the often quite subtle changes in mandatory disclosure rules studied in prior work. Methodologically, S-1 filings by top peers represent shocks that are staggered across time in ways that facilitate identification, in contrast to changes in disclosure rules that typically apply to all firms at the same time and whose effects are therefore difficult to disentangle from unobserved contemporaneous events affecting all firms.

parallel-trends assumption required for identification in a DD setting. Moreover, the treatment effect is entirely absent in a placebo sample constructed such that the S-1 filer is informationally unrelated to the already-listed firm. Still, we acknowledge that a peer's decision to go public is not random and thus not exogenous in some universal sense.[3] Clearly, though, the peer's decision is one-removed from the focal firm. Indeed, that is what is meant by disclosure involving externalities: when choosing to disclose information in connection with its IPO, the peer firm does not fully internalize the effects its disclosure will have on already-listed firms. Consistent with some degree of internalization, we find attenuated liquidity effects among already-listed firms that are themselves strategically important to the S-1 filers.

The one-removed nature of the decision-maker means that our research design is relatively immune to standard identification concerns. Nonetheless, we take seriously the possibility that liquidity might improve for non-information reasons but find no evidence that it does. Specifically, the timeline of our empirical design (as well as a placebo test) rule out the possibility that liquidity improves because the peer's arrival in the stock market helps traders diversify, hedge, or arbitrage their positions in an already-listed firm's stock. We can also rule out that S-1 filings coincide with industry-wide improvements in standard drivers of liquidity, such as adverse selection risk and inventory costs. While S-1 filings do coincide with better industry-wide investment opportunities, it is not the case that already-listed firms respond by raising external funding (which would require additional disclosure and so could improve liquidity independently).

Having established that IPOs plausibly create information externalities, we consider potential channels through which one firm's disclosure affects another firm's liquidity. Standard microstructure models of liquidity such as Kyle (1985) and Glosten and Milgrom (1985) provide a direct channel: mandatory disclosure reduces information asymmetries among investors and thereby reduces the risk of relatively less well informed market participants unwittingly trading against better informed investors. The reduction in information asymmetries in turn increases liquidity. Our findings are consistent with this channel.

In addition, we consider three indirect channels, involving changes in firms' voluntary disclosure

[3] For example, it may involve strategic considerations: the peer may already compete with the focal firm in the product market, and both its decision to go public and what it discloses may be strategic with a view to influencing product-market competition.

choices, in analysts' information-production decisions, and in investor demand. We show that already-listed firms increase their earnings guidance in response to a top 5 peer firm's S-1 filing, shift from providing qualitative guidance to relatively more informative quantitative guidance, furnish investors with more current-event updates (i.e., 8-Ks), and increase the granularity of their financial-statement disclosures. Unlike the temporary improvement in liquidity, these changes in voluntary disclosure are persistent. They are absent in our placebo sample of informationally unrelated peers, suggesting that firms alter their voluntary disclosure policies only in response to disclosures by informationally related peers. They are stronger when the S-1 filer and the already-listed firm are mutually important to each other ("reciprocity").

These patterns are consistent with firms acting *strategically* when setting their voluntary disclosure policies. The direction of responses is consistent with disclosures being strategic complements: firms disclose more information the more information is available about their peers. Given that our S-1 filing experiment involves a large dose of mandatory disclosure by the peer, the crowding in of voluntary disclosure is consistent with a key justification regulators invoke for mandating disclosure in the first place.

The second indirect channel, involving sellside analysts, is also at play in our setting. In response to the peer's S-1 filing, analyst coverage of the already-listed firm increases significantly (especially among firms with low pre-treatment coverage) and the informativeness of analysts' earnings forecasts improves.

Finally, we use EDGAR searches around key information releases (i.e., earnings announcements or the filing of a 10-Q or 10-K) to proxy for investor demand for information. We find that EDGAR searches for already-listed firms' EDGAR filings increase in intensity after a top 5 peer files an S-1. This finding is consistent with increased disclosure at one firm increasing investor demand for information at another.

Taken together, we interpret this rich tapestry of findings as follows. Information production by analysts is a function of the voluntary and mandatory disclosures of both the covered firm and its peers. The information contained in a peer firm's S-1 filing and in its future disclosures reduce information-production costs, leading to expanded coverage, and improves the informativeness of analyst forecasts. In other words, there is cross-firm complementarity between one firm's disclosures and another firm's analyst information production. At the same time, already-listed firms increase their voluntary disclosures strategically, which could give rise to within-firm complementarity between voluntary disclosure and analyst information production. Finally, investors' information demand increases, either because the S-1 filing increases the already-listed firm's salience to investors or in response to either increased voluntary disclosure by the firm or increased information production by analysts covering the firm (or both).

Our paper contributes to the literatures on mandatory disclosure specifically and the determinants of corporate information environments generally. First, we use staggered non-marginal increases in disclosure at peer firms to show that mandatory disclosure affects other firms' information environments, overcoming the limitations of prior cross-sectional studies. Unlike prior work that tends to code all firms in an industry as peers, we exploit rich variation in the bilateral importance of any two firms to identify both asymmetric and reciprocal peers and firms that are informationally unrelated. We do so in a unified setting in which all firms are subject to mandatory disclosure regulations, avoiding potential apples-to-oranges problems often encountered in settings that study spillovers between regulated and unregulated firms.

Second, we shed light on the channels through which peer disclosures affect focal firms. The theory literature is divided on whether mandatory disclosure crowds voluntary disclosure *out* (Verrecchia 1990, Admati and Pfleiderer 2000) or *in* (Dye 1990, Darrough 1993, Dye and Sridhar 1995). Our findings suggest a crowding-in effect, implying that mandatory disclosure can improve the market-wide information environment consistent with regulators' intentions. How mandatory disclosure affects analysts' information production is similarly an open question. In Goldstein and Yang's (2017) model, peers' mandatory disclosures reduce analysts' information production for focal firms. Our findings instead point to cross-firm complementarity between disclosure and analysts' information production. Finally, our findings suggest that one firm's disclosures increase investor demand for information about its peers. This contrasts with arguments in the literature that firms disclose too much information (from a welfare perspective) in the hope of attracting investor attention at the expense of their peers (Fishman and Hagerty 1989).

I. Empirical strategy and data

A. Identification strategy

To tease apart the interplay of mandatory disclosure, voluntary disclosure, external information production, and investor information demand in a multiple-firm setting, we analyze how the filing of an S-1 by an already-listed firm's top 5 product-market peer affects the already-listed firm's information environment. We identify peers using the product similarity scores from which Hoberg and Phillips' (2010) text-based network industry classifications (TNIC) are derived. The scores are based on a textual comparison of the ways listed firms describe their products or services in their annual 10-K filings.

Our identification strategy exploits the dramatic increase in publicly available information that occurs when a private firm files for an IPO. As a rule, private firms in the U.S. are not required to publicly disclose much (if any) information, and certainly not the kind of detailed and standardized information listed firms are mandated to share with investors and the public. Private U.S. firms thus tend to be opaque. Going public in the U.S. dramatically changes the amount of publicly available information about private firms. When going public, firms are mandated to disclose in their so called S-1 filing an abundance of information about their financials, strategies, operations, major markets and customers, risks, and recent material changes. Filings are reviewed by both the SEC (to ensure compliance with mandatory disclosure requirements) and the exchange on which the firm seeks to list (to ensure compliance with listing rules) and are subject to SEC sanctions and the threat of class-action lawsuits in case of incomplete, materially false, or misleading statements.

By virtue of the IPO firm being a top 5 product-market peer, the information it discloses in its S-1 filing is likely to be materially relevant to investors' understanding of the already-listed firm's future prospects. (We will test this assumption shortly.) An S-1 filing by a top 5 peer should therefore enrich the already-listed firm's information environment in measurable ways.

To illustrate our empirical strategy, consider the example of Facebook's 2012 IPO. On February 1, 2012, Facebook filed a 150-page S-1 (not counting financial statements and other appendices), in which it disclosed publicly for the first time financial and other details of the online advertising model that is at the heart of its business.[4] We conjecture that Facebook's S-1 was highly relevant to investors' understanding of Google, the already-listed market leader in online advertising. Indeed, according to TNIC, in 2012,

[4] The word root "advertis-" appears 268 times in Facebook's S-1.

Facebook was Google's number one product-market peer, while Google was Facebook's number two peer (LinkedIn being Facebook's number one peer in 2012).[5] Our tests aim to estimate the effect of Facebook's disclosures on Google's information environment, beginning with Facebook's S-1 filing and as shaped by Google's own voluntary disclosure choices, the actions of external information intermediaries such as sell-side analysts, and investor information demand.[6]

Our identification strategy uses a standard difference-in-differences (DD) design, comparing a set of firms that are treated in the sense that one of their top 5 product-market peers files for an IPO, to a set of matched control firms with similar characteristics whose top 5 peers do not file for an IPO. Specifically, we estimate DD regressions of the following general form:

$$outcome_{it} = \alpha + \beta_1 \mathit{peer's\ S\text{-}1\ filing}_{it} + \beta_2 \mathit{next\ four\ quarters}_{it} + \gamma \mathbf{X}_{it-1} + c_i + c_q + c_{if} + \varepsilon_{it}, \quad (1)$$

where $outcome_{it}$ is measured for firm i in fiscal quarter t; β_1 estimates the treatment effect in the quarter in which the top 5 peer files its S-1; β_2 estimates the average treatment effect over the next four quarters; $\mathbf{X}_{it-1}$ is a vector of control variables; and c_i, c_q, and c_{if} are firm, time, and fiscal-quarter fixed effects, respectively. Standard errors are clustered at the firm level, given that we exploit a firm-level shock and the time dimension of our panel is substantially smaller than the firm dimension (Petersen (2009), Section 3).[7]

B. Treated and control firms

We focus on U.S. stock market listed firms with ordinary common shares traded on the NYSE, NASDAQ, or AMEX between 1996 and 2017.[8] We construct our samples of treated and control firms as

[5] IPO firms join the TNIC matrix at the end of the year in which they go public. We thus assume that a firm that files to go public in, say, February and that Hoberg and Phillips (2010) score as being similar to an already-listed firm as of December that year was already informationally relevant for the already-listed firm at the time of its February S-1 filing.
[6] A given IPO can affect more than one already-listed firm. For example, we view Twitter's S-1 filing on March 10, 2013 as a material shock to the information environments of LinkedIn, Facebook, and Google (for all of which Twitter was the number 1 peer in 2013), and we view Virgin America's S-1 filing on July 28, 2014 as a material shock to the information environments of Alaska Air Group, Allegiant Travel, Delta Air Lines, JetBlue Airways, Spirit Airways, Southwest Airlines, and United Airlines (for all seven of which Virgin was a top 5 peer in 2014).
[7] Alternatively, we could cluster at the level of the S-1 filer. Our results are never statistically weaker and occasionally statistically stronger using that clustering level. Our results are also robust to double clustering by firm and fiscal quarter, consistent with Petersen's (2009, p. 460) conclusion that when the time dimension is substantially smaller than the firm dimension, "clustering by the more frequent cluster yields results that are almost identical to clustering by both firm and time."
[8] The sample period is dictated by the years for which Hoberg and Phillips' (2010) TNIC scores are available.

follows. First, we assemble a comprehensive sample of 4,467 S-1 filers over the period 1996 to 2017 using data from Thomson SDC. After filtering out filers on exchanges other than the NYSE, NASDAQ, or AMEX, those with CRSP share codes greater than 11 (foreign issuers, real estate trusts, and the like), those withdrawing their IPO, and those that are already or have previously been public filers (for example, because they have outstanding public bonds or a large number of shareholders), we are left with a set of 3,656 IPOs. (See Appendix A for details of our filters.)

To focus on those IPO firms that are informationally relevant (as we define it) to already-listed firms, we restrict the set of S-1 filers to those that are a top 5 peer of one or more already-listed firms. To identify peers, we use Hoberg and Phillips' (2010) TNIC matrix, which for every pair of Compustat firms provides a similarity score based on the words they use to describe their products or services. The matrix is updated annually using 10-K filings and thus is time-varying. We reverse-sort pairs of firms by their similarity scores, which results in an asymmetric ranking (i.e., firm B can be a top 5 peer of firm A without firm A necessarily being a top 5 peer of firm B).[9] It is important to note that Hoberg and Phillips' approach measures how closely firms are located to each other in product space, not how large they are relative to each other. For example, in fiscal year 1996, Dollar General Corp's top peer in terms of product similarity is Family Dollar Stores, Inc., while its largest competitor by market share is Walmart Inc. (which in turn ranks 41st among Dollar General Corp's peers by product similarity).

Of the 13,777 firms in the TNIC matrix that satisfy our filters, 6,308 are treated at least once, in the sense that they experience one of their top 5 peers filing an S-1 between 1996 and 2017. Firms are considered treated in the fiscal quarter of the S-1 filing.[10] The average treated firm is shocked 1.9 times over our sample period, for a total of 11,759 treated firm-quarters. We follow each treated firm for nine fiscal quarters centered on the treatment quarter. For a treated firm-quarter to be included in the treatment sample, we require the treated firm not to have experienced a previous S-1 shock in the four quarters

[9] We exploit this feature of the data to help disentangle the potential mechanisms through which S-1 filers' disclosures affect already-listed firms.

[10] Following the enactment of the JOBS Act on April 5, 2012, firms that satisfy the criteria for so called "emerging growth companies" are eligible to request a non-public review of their S-1 filing. In these cases, the quarter of S-1 filing is the quarter in which the S-1 filing becomes publicly available on EDGAR, rather than the quarter of (confidential) filing.

leading up to the focal S-1 filing (which removes 69 serially shocked firms) and not itself to have gone public during the previous four quarters (which removes 257 recent IPOs). This leaves us with a sample of 11,433 treated firm-quarters, though some of these will drop out of the sample in the next step because there exist no suitable control firms that are sufficiently observably similar.

Control firms are used to establish the counterfactual, that is, how treated firms would have fared but for the treatment. To provide a plausible counterfactual, control firms need to be selected such that they are observably similar to treated firms along the dimension(s) of interest, not themselves shocked while serving as controls, and not likely to be affected by the treated firm's response to treatment (the stable unit treatment value assumption, or SUTVA).

We select control firms based on their similarity in trading liquidity, our main outcome variable of interest. Specifically, we use a nearest-neighbor propensity-score method to match treated and controls on bid-ask spread and Amihud's (2002) illiquidity measure in the two quarters leading up to treatment, blocking on fiscal year-end. To ensure control firms are not themselves shocked while serving as controls (which could lead to biases in staggered DD approaches with time-varying treatments and treatment effect heterogeneity, as Baker, Larcker, and Wang 2021 note), we limit the set of potential controls to firms that have not themselves experienced a top 5 peer filing an S-1 in the nine quarters centered on the treated firm-quarter. To minimize potential violations of SUTVA, we exclude firms that are top 5 peers of the treated firm in the year of treatment.[11] Following standard practice, only matches in the common support are considered valid, using a 0.01 caliper. This limits our estimation sample to a total of 6,649 treated firm-quarters (representing 4,586 unique firms) and 6,649 controls. The sample contains a total of 2,081 unique S-1 filings, meaning that the average S-1 filer is a top 5 peer of 3.2 already-listed firms (=6,649/2,081).

C. Validating the information-relevance assumption

At the heart of our research design is the assumption that at least part of the information a top 5 peer

[11] In practice, this filter is much more conservative than it might sound. Only 20 control firms have *any* TNIC link to treated firms and the average TNIC rank of these 20 control firms is 162. In other words, treated firms and their matched controls have no meaningful product-market links in our sample, at least according to Hoberg and Phillips' (2010) product similarity measure. The same is true of control firms and the S-1 filers in our sample: only 95 control firms have *any* TNIC link to our S-1 filers, and the average TNIC rank of these 95 control firms is 190.

discloses in its S-1 filing is "informationally relevant" to an already-listed firm. We validate this assumption using Lee, Ma, and Wang's (2015) "co-search" approach. If it is true that the S-1 filing of firm A contains information that is relevant to investors' understanding of already-listed firm B, we expect investors (and others) who show interest in firm B (by searching its filings in the SEC's EDGAR database) to be more likely to also search firm A's S-1 filing, compared to investors who search the filings of unrelated control firm C.

We test this prediction using the SEC's EDGAR server logs, which are available for the period February 2003 to June 2017. The server logs contain the search histories of each IP address accessing the EDGAR database. Using these histories, we compute, for each treated firm and its matched control, the probability that an EDGAR user who searches the already-listed firm's EDGAR filings also searches the IPO firm's S-1 filing on the same day. We compute this conditional probability over three time windows: on the day the S-1 is filed, over the course of the week beginning with the S-1 filing, and over the course of the month from the S-1 filing date.

Table 1 reports the results. We find strong evidence consistent with the assumption that investors view the S-1 filings of top 5 peer firms as informationally relevant. Of those users who search EDGAR for a treated already-listed firm's filings, an average of 4.7% also search the IPO firm's S-1 filing on the S-1 filing day, rising to 25.9% over the first week from filing and 57.7% over the first month. These conditional probabilities are economically and statistically significantly higher than for control firms. Of those users who search a control firm's EDGAR filings, only 1.8% also search the IPO firm's S-1 filing on the S-1 filing day, rising to a more modest 7.3% over the first week and 12.4% over the first month. Figure 1 illustrates these patterns.

To further validate the information-relevance assumption, Table 1 uses a more demanding co-search measure, "toggling." Toggling occurs if an EDGAR user goes back and forth between the filings of two firms, in the pattern A→B→A or B→A→B. Our toggling results support the information-relevance assumption. Of those who search EDGAR for a treated already-listed firm's filings, 0.12% toggle between its filings and the IPO firm's S-1 filing on the S-1 filing day, rising to 0.6% over the first week and 1.17%

over the first month. Among control firms, we essentially never see any toggling involving the S-1 filing.

D. Outcome variables

We study the interplay of mandatory disclosure, voluntary disclosure, external information production, and investor demand for information in a multiple-firm setting by focusing on four groups of outcome variables: trading liquidity, voluntary disclosure, sellside analyst behavior, and information demand. Trading liquidity is a summary measure of the net effect of changes in a firm's information environment. In standard microstructure models such as Kyle (1985) and Glosten and Milgrom (1985), reductions in information asymmetries among investors lead to improvements in liquidity. Voluntary disclosure is a key way in which already-listed firms can, if they so wish, respond to investors gaining access to the previously private information of one of their top 5 peers. Analysts process new information – whether coming from an S-1 filing or an already-listed firm's response to it – and thereby help shape the firm's external information environment. Investor demand for information, in turn, may influence both firms' voluntary guidance choices and information production by analysts.

We measure trading liquidity in four ways: using bid-ask spreads, Amihud's (2002) illiquidity measure (known as AIM), Lesmond, Ogden, and Trzcinka's (1999) fraction of trading days with zero or missing returns, and Goyenko, Holden, and Trzcinka's (2009) effective tick measure. (Variable definitions and details of their construction can be found in Appendix B.)

Our voluntary-disclosure measures focus on firms voluntarily disclosing information in four separate ways: through earnings guidance, through 8-K current reports, through the provision of additional detail in their financial statements, and through information accompanying their earnings announcements. We measure both whether a firm provides earnings guidance and if so, whether the guidance is quantitative rather than qualitative (see Balakrishnan et al. 2014). Using Form 8-K filings, we count the number of current reports a firm issues each fiscal quarter. We use the disclosure quality (DQ) measure of Chen, Miao, and Shevlin (2015) to capture the level of disaggregation in financial-statement data.[12] Finally, we

[12] Chen, Miao, and Shevlin (2015) construct their DQ measure at an annual frequency. We adapt their measure to the quarterly frequency used in our empirical design. Note that our inclusion of fiscal-quarter fixed effects in equation (1) controls for potential seasonalities in disclosure quality over the course of the fiscal year.

investigate the market's reaction to information released in connection with earnings announcements.

We study analyst behavior using the number of analysts who cover a firm (capturing the extensive treatment margin), the informativeness of their forecasts (measured as the price impact that can be attributed to forecast revisions, following Lehavy, Li, and Merkley 2011 and Merkley, Michaely, and Pacelli 2017), and the dispersion in their forecasts.

Finally, in the spirit of Bauguess, Cooney, and Hanley (2018), we measure investors' information demand each fiscal quarter as the number of EDGAR searches for the already-listed firm's EDGAR filings on two alternative days: the day the firm announces its quarterly or annual earnings and the day the firm files its 10-Q or 10-K. In the former case, we count the total number of EDGAR searches of the 10-Qs, 10-Ks, and 8-Ks the firm filed in the previous four quarters (given that firms announce earnings some time before filing the corresponding 10-Q or 10-K). In the latter case, we count the total number of EDGAR searches of the newly filed 10-Q or 10-K.

As the summary statistics in Table 2 show, treated and control firms generally have very similar levels of liquidity, voluntary disclosure, analyst behavior, and investor information demand in the fiscal quarter before treatment. For example, 23.1% of treated firms and 23.0% of controls are earnings guiders in the quarter before treatment. More importantly for identification purposes, we generally find no significant differences in pre-treatment changes in our outcome variables between treated firms and their matched controls, suggesting there is generally no significant divergence in pre-trends.

There are two notable – and economically interesting – exceptions to the general absence of diverging pre-trends: in the quarter before treatment (and relative to control firms), significantly more treated firms become guiders and analyst coverage of treated firms increases significantly. This suggests that both firms and analysts respond to a top 5 peer's imminent IPO *before* the S-1 filing actually releases information of relevance to investors.[13] Treated firms may be pre-positioning themselves to preemptively manage

[13] Notable IPOs – as those we use as information shocks are most likely to be – are typically widely anticipated in the financial media. For example, three months before Facebook's S-1 filing, the Wall Street Journal ran an article on Facebook's dual-class share structure, noting "the social-network company is expected to file for a 2012 IPO." ("One share, one vote?", Wall Street Journal, Oct. 28, 2011.)

expectations (Ajinkya and Gift 1984), knowing that new information will soon become available to investors. Analysts may be pre-positioning themselves for three reasons. Coverage may increase as the information-acquisition and information-processing costs of analyzing an already-listed firm fall, thanks to either the top 5 peer's expected S-1 filing or the already-listed firm's increase in earnings guidance. We label these two forms of potential supply complementarities "cross-firm complementarity" (between one firm's disclosure and analysts' information production about a related firm) and "within-firm complementarity" (between a firm's voluntary disclosure and analysts' information production about it). Additionally (or alternatively), coverage may increase because the top 5 peer's imminent IPO increases investor interest in the already-listed firm, which we call the investor-demand channel.[14]

E. Control variables

As Table 2 shows, our sample is well balanced on nearly all outcome variables, obviating the need to include an extensive set of control variables. In addition to including fiscal-quarter fixed effects to remove the effects of accounting seasonalities in the DD regression (1), we follow standard practice and control for log equity market capitalization to hold firm size constant.

II. Empirical results

A. Effects of S-1 filings on focal firms' trading liquidity

Our first set of DD estimates focuses on the effect of a top 5 peer firm's S-1 filing on an already-listed firm's trading liquidity. Table 3 reports the results. For all four of our liquidity measures, we find that liquidity improves significantly in the quarter in which a top 5 peer files its S-1. The treatment effects are economically sizeable. To illustrate, relative to control firms, bid-ask spreads in column 1 tighten by 3% from their pre-treatment mean in Table 2 (p=0.001), Amihud's (2002) illiquidity measure in column 2 improves by 3.2% on average (p=0.023), the fraction of firms with zero or missing returns in column 3 drops from 8.7% to 8.5% (p=0.009), and effective tick in column 4 falls by 2.6% (p=0.023), all else equal.

The improvement in liquidity dissipates after one quarter and so is short-lived: averaged over the four

[14] It is also possible that analysts increase coverage of the already-listed firm in the hope of better understanding the IPO firm. We investigate this possibility in Section II.G.

quarters following the S-1 filing, liquidity is not significantly different than before the top 5 peer's S-1 filing, on average, with the exception of a marginally significant drop in the fraction of firms with zero or missing returns (p=0.085). This timing pattern suggests that the peer's S-1 filing gives rise to a disproportionately large information spillover whereas the peer's subsequent ongoing disclosures (once it is listed) do not generate significant spillover effects.

The average treatment effects in Table 3 hide some interesting cross-sectional heterogeneity. Figure 2 graphs estimates from quantile DD regressions (Koenker and Bassett 1978) for our four liquidity measures. In all four graphs, we see a negative slope, meaning the improvement in liquidity in the quarter of a top 5 peer's S-1 filing is larger the worse the initial level of liquidity. The slope is steep, implying that the variation in the magnitude of the effects across deciles is large.

The internal validity of our DD analysis requires that treated and control firms would have experienced similar trends in liquidity but for the S-1 treatment. A standard way to gauge the plausibility of the parallel-trends assumption is to check for the absence of diverging trends before treatment. Figure 3 plots dynamic DD estimates of the effects of S-1 filings on liquidity over our nine-quarter window, along with 95% confidence intervals. The figure confirms the absence of diverging pre-trends for all four measures: liquidity is statistically similar among treated and control firms in the quarters before an S-1 filing and then improves significantly among treated firms in the quarter a top 5 peer files its S-1. Over the next four quarters, liquidity returns to its pre-treatment level. Using formal Wald tests, we cannot reject the null hypothesis of no diverging pre-trends. (The p-values are 0.416, 0.289, 0.102, and 0.691 for spreads, AIM, return fraction, and effective tick, respectively.)

The absence of diverging pre-trends supports a causal interpretation of the patterns in Table 3 and Figure 3: the trading liquidity of already-listed firms temporarily improves when a top 5 peer files an S-1. This establishes our main empirical result: a firm's decision to go public has a positive externality effect on its listed peers' trading liquidity.

B. Potential information channels

Why does liquidity improve? In the remainder of Section II, we investigate various direct and indirect information channels. We consider potential non-information channels in Section III (with particular focus on the endogeneity of a top 5 peer's decision whether and when to go public), but find no evidence to suggest that non-information channels can explain why already-listed firms' liquidity improves when a top 5 peer files an S-1.

Canonical microstructure models of liquidity stress the importance of information asymmetries and adverse selection as drivers of liquidity (Kyle 1985, Glosten and Milgrom 1985). As we have seen, users of the already-listed firm's EDGAR filings show significant interest in its top 5 peer's S-1 filing, consistent with our assumption that investors view the S-1 filing as informationally relevant to their understanding of the already-listed firm. It is not too great a leap from this observation to the conjecture that the S-1 filing directly improves the already-listed firm's information environment in such a way that investors perceive a reduced adverse selection risk. In other words, mandatory disclosures may spill over to related firms, reducing their adverse selection risk and thereby improving their liquidity.[15]

To shed further light on the information-spillover channel, we test if liquidity improves by more when the S-1 contains a greater amount of information that is novel to investors. To measure information novelty, we follow Hanley and Hoberg (2010), who use word content analysis to decompose the information content of an S-1 into standard and informative components. The decomposition builds on a comparison of the S-1's "Management Discussion & Analysis" (MD&A) section to the MD&A sections of recent related S-1s. The lower is the overlap between the focal S-1 and recent S-1s, the more novel the focal S-1's information content (see Appendix B for further details). Columns 5 through 8 of Table 3 report the results of continuous-treatment DD models relating liquidity to information novelty. The estimates confirm that the already-listed firm's liquidity improves by significantly more the more novel is the information its top 5 peer discloses in its S-1.[16] This pattern is consistent with an information-spillover channel.

[15] A direct way to test if a top 5 peer's S-1 reduces investors' perceptions of adverse selection risk in the already-listed stock is to test for reductions in the probability of informed trading (PIN). Using Stephen Brown's estimates of Venter and DeJong's (2006) PIN, which are available for the period 1993 to 2010 at https://terpconnect.umd.edu/~stephenb/, Table IA.1 in the Internet Appendix reports a significant decrease in adverse selection risk starting in the fiscal quarter a top 5 peer files an S-1. (Unfortunately, we lack access to intra-day TAQ data and so cannot update PIN through 2017.)
[16] PIN too improves by significantly more the more novel the information in the S-1. See Table IA.1, column 2.

In addition to directly enriching the already-listed firm's information environment, the top 5 peer's S-1 filing could give rise to indirect effects. First, if firms make voluntary disclosure decisions strategically, in the sense that they condition their disclosure choices on their peers' disclosures, a peer's S-1 filing (and the prospect of the peer's future ongoing disclosures once listed) could trigger disclosure changes at the already-listed firm. The already-listed firm's strategic response could then contribute to the observed improvement in its information environment.[17]

Second, sellside analysts help shape a firm's external information environment, not least by producing reports that contain analyses of the firm and its industry, earnings forecasts, share price targets, and buy/sell recommendations which they disseminate in written form and in meetings with investors. A key input into analysts' information production is mandatory and voluntary disclosures, not just by the focal firm but also by its peers (Hinson and Piao 2019, De George, Phan, and Stoumbos 2019, and Brown et al. 2020). A top 5 peer's S-1 filing (followed by its ongoing disclosures) could thus affect analysts' information sets in ways that enable them to produce more informative research about an already-listed firm at a lower cost.

Third, a top 5 peer's S-1 filing could increase investor demand for information about the already-listed firm, either directly (perhaps because the S-1 filing increases the already-listed firm's salience to investors) or indirectly (in response either to any voluntary-disclosure actions the already-listed firm may take or to increased information production about the already-listed firm by analysts).

In what follows, we investigate how one firm's disclosure (the S-1 filing) affects its peers' voluntary disclosure choices, the behavior of analysts, and investor demand for information.

C. Focal firms' responses: Voluntary disclosure

How do already-listed firms respond when one of their top 5 peers files an S-1? Table 4 reports DD estimates for our voluntary-disclosure measures. Column 1 shows that an S-1 filing significantly increases the likelihood that already-listed firms provide earnings guidance (relative to matched controls), by 1.6 percentage points in the quarter of the S-1 filing ($p<0.001$) and by 2.9 over the next four quarters

[17] The theory literature is divided on whether firms' disclosure choices are strategic complements or strategic substitutes, and we keep an open mind. Models that predict strategic complementarity include Dye (1990), Darrough (1993), and Dye and Sridhar (1995). Models that predict strategic substitutability include Verrecchia (1990) and Admati and Pfleiderer (2000).

(p<0.001). The observed increase is consistent with disclosures being strategic complements: when one firm discloses more, its peers respond by disclosing more too. To the extent that much of an S-1 represents mandatory (rather than voluntary) disclosure, it is also consistent with mandatory disclosure at one firm crowding in voluntary disclosure at peer firms. As noted in the introduction, such positive externalities of mandatory disclosure are a prominent justification regulators use for mandating disclosure in the first place.

Figure 4 plots dynamic DD estimates of the effects of S-1 filings on earnings guidance over our nine-quarter window. In contrast to the dynamic DD estimates for liquidity shown in Figure 3, we do find evidence of significantly diverging pre-trends in guidance: treated firms become significantly more likely to provide earnings guidance one quarter before the S-1 filing (consistent with the univariate evidence reported in Table 2). In our setting, we view diverging pre-trends as a feature, not a bug. They suggest that already-listed firms respond to an imminent S-1 filing by providing earnings guidance *in anticipation of* a top 5 peer disclosing information that investors (based on their EDGAR search behavior in Table 1) tend to view as relevant to their understanding of the already-listed firms. Such anticipatory behavior is consistent with firms ramping up guidance in order to bridge an "expectations gap" (Ajinkya and Gift 1984) and is what we would expect if firms act *strategically* when choosing their level of voluntary disclosure.[18]

Column 2 focuses on a specific aspect of guidance: the provision of quantitative guidance (in the form of a point estimate or a range of estimates firms disclose for their next-quarter earnings), as opposed to qualitative guidance (in the form of statements such as "earnings are predicted to recover"). Restricting the sample to firms that guide to isolate this intensive margin, column 2 shows that firms respond to a top 5 peer's S-1 filing by switching from providing qualitative to providing quantitative guidance: over the four quarters following the S-1 filing, the share of quantitative guiders rises by an economically and statistically significant 1.7 percentage points (p=0.042), from 43.7% to 45.4%.[19] Insofar as quantitative guidance helps resolve more uncertainty than qualitative guidance, we interpret this finding as consistent with corporate

[18] From an identification perspective, Figure 4 suggests that the treatment quarter – as far as the voluntary guidance response is concerned – is the quarter before the peer's S-1 filing (i.e., the quarter when the peer announces its intention to soon go public). With this in mind, our research design nonetheless permits causal inference.
[19] According to Table 2, 23.1% of treated firms provide some form of guidance in the quarter before treatment, and 10.1% of treated firms provide quantitative guidance. Hence, $\frac{0.101}{0.231} = 43.7\%$ of treated guiders provide quantitative guidance pre-treatment.

disclosures being strategic complements. Finally, guidance is not the only dimension of disclosure firms ramp up: they also respond by issuing significantly more 8-Ks (column 3) and providing more detailed and disaggregated financial statements (column 4).[20]

This increase in voluntary disclosure is sustained, in the sense that it persists beyond the S-1 filing quarter. By the next quarter, the typical S-1 filer would have completed its IPO, becoming a public filer of standard mandatory disclosures (such as 10-Ks, 10-Qs, and 8-Ks) that typically provide less incremental information than the S-1. The fact that already-listed firms change their voluntary disclosure behavior in a sustained manner suggests that they are responding not just to the sudden release of a large quantum of information (the S-1) but also to the emergence of a peer whose continued incremental disclosures shape their own external information environments. In that sense, their response differs from that of investors, whose liquidity-improving behavior reverts back to normal after the filing quarter as the initial large quantum of information contained in the S-1 is incorporated in trading decisions and prices and the peer firm transitions to being a public filer of regular (and more incremental) information updates.

The remainder of Table 4 focuses on the information content of earnings announcements. Column 5 shows that already-listed firms' earnings announcements move prices by significantly more (in absolute terms) in the four quarters after a top 5 peer files an S-1 than before (p=0.005). This is apparently *not* because the level of the announced earnings catches investors off-guard: standardized unexpected earnings (measured using either a seasonal random walk or analyst consensus forecasts to established expected earnings) are virtually unchanged, economically or statistically, around S-1 filings (columns 6 and 7). If it is not earnings news that accounts for the increased price impact on earnings days, there are two alternative information channels. First, firms may have increased their disclosure of share-price-relevant information, either in their earnings releases or during the earnings calls (typically held the same day). Second, conditioning information contained in a top 5 peer's S-1 and its subsequent filings may help investors to better interpret information released in the already-listed firm's earnings release or earnings call: something

[20] Table IA.2 in the Internet Appendix presents continuous-treatment versions of these four binary-treatment DD models, showing that already-listed firms increase voluntary guidance by more the more novel the information contained in the peer's S-1. This reinforces our interpretation that IPOs create information spillovers rather than affecting already-listed firms in some other way.

no-one would otherwise have picked up on may become interesting new information against the background of the peer firm's disclosures. Either way, Table 4 suggests that earnings days become more significant information events in the wake of a top 5 peer's IPO.[21]

D. Sellside analyst responses

How do sellside analysts respond when a top 5 peer of an already-listed firm files an S-1? We study changes in analyst behavior on both the extensive and the intensive treatment margin. On the extensive margin, we investigate changes in coverage, measured as the number of analysts who cover the already-listed firm. Coverage could increase or decrease as a result of treatment. Cross-firm complementarity between mandatory disclosure and external information production by analysts implies an increase in coverage, all else equal: access to previously private information, thanks to the peer firm's S-1 filing, lowers the information acquisition and processing costs of covering the already-listed firm, leading to coverage initiations (i.e., "entry") by analysts who did not previously cover the firm. Similarly, within-firm complementarity between voluntary disclosure and external information production by analysts also implies more coverage: the increase in the already-listed firm's voluntary disclosure triggered by its peer's S-1 filing lowers the information acquisition and processing costs of covering the already-listed firm, leading to an increase in the number of analysts covering the stock.

In addition to these supply-complementarity channels, there is a potential investor-demand channel that could lead to more coverage: if the top 5 peer's IPO or the already-listed firm's increased voluntary disclosure increases investor interest in the already-listed firm, more analysts might begin covering the firm. We consider changes in information demand in the next section.

The main reason to expect a fall in coverage is substitution resulting from production constraints: time-constrained analysts might switch from covering the already-listed firm to covering its top 5 peer instead.

On the intensive margin, we investigate the informativeness of analysts' earnings forecasts, measured

[21] Importantly, firms do not change their earnings management practices in response to a top 5 peer's S-1 filing. As Table IA.3 in the Internet Appendix shows, neither the use of discretionary accruals nor firms' tendency to manage reported earnings to narrowly meet-or-beat analyst consensus forecasts changes significantly (economically or statistically) in the wake of a top 5 peer's S-1 filing. This suggests that earnings management is driven by factors unrelated to peer firms' disclosure decisions in our setting. Our findings contrast with those of Billett, Ma, and Yu (2021) who report that the already-listed firms in their (differently constructed) sample manage their earnings down in an effort to harm their peers' IPO valuations.

as the price impact that can be attributed to forecast revisions (Lehavy, Li, and Merkley 2011, Merkley, Michaely, and Pacelli 2017). Assuming that analysts either find the information released by the top 5 peer informationally relevant or that they find the already-listed firm's increased voluntary disclosure helpful, we expect the informativeness of analyst forecasts for the already-listed firm to increase.

The second intensive-margin measure we investigate is dispersion in analysts' earnings forecasts, measured as the standard deviation of forecasts (Lehavy, Li, and Merkley 2011). Dispersion could rise or fall. It would rise if only some, but not all, analysts covering the already-listed firm made use of the peer's S-1 disclosure, or if coverage increased in a way that introduces new opinions. It would fall if the peer's S-1 disclosure or the already-listed firm's increased voluntary disclosure resolved substantial points of disagreement among analysts covering the already-listed firm.

Table 5 reports the binary-treatment DD estimates. Column 1 shows that an S-1 filing significantly increases coverage: the number of analysts covering the already-listed firm increases from the pre-treatment mean of 4.7 to 4.8 in the quarter of the S-1 filing (p<0.001) and further to 4.95 over the next four quarters (p<0.001), relative to matched controls. Put differently, in the year after a peer's S-1 filing, one in four firms sees coverage increase by one analyst on average. For the average (moderately covered) firm in our sample, this is an economically sizeable increase: Kelly and Ljungqvist (2012) estimate that exogenously increasing coverage by one analyst increases the firm's share price by 1% on average. Reinforcing this point, the quantile DD estimates in Figure 5 show that coverage increases the most for companies with the lowest pre-treatment coverage.[22]

The dynamics of analyst coverage mirror those of firms' voluntary disclosure discussed earlier. Like the sustained increase in voluntary disclosure in Table 4, the increase in analyst coverage persists beyond the S-1 filing. And as was the case for guidance in Figure 4, the coverage increase precedes the S-1 filing: Figure 6 shows that coverage increases significantly one quarter before the S-1 filing (consistent with the univariate evidence reported in Table 2). As before, we view diverging pre-trends in this particular context

[22] In the top decile of most covered stocks, we see a significant *reduction* in coverage, suggesting that some analysts in heavily-covered stocks find it harder to add value on the margin as more information becomes available to investors.

as a feature, not a bug. They suggest that analysts pre-position themselves *in anticipation of* a top 5 peer's expected S-1 filing, consistent with the top 5 peer's pending IPO increasing analysts' interest in covering the already-listed firm.[23]

One interpretation of the positive effects on coverage in Table 5 is that one firm's mandatory disclosure crowds in another firm's external information production and so helps shape the other firm's information environment, consistent with cross-firm complementarity. Consistent with this interpretation, Table IA.2 in the Internet Appendix shows that coverage increases by more the more novel the information contained in the peer's S-1. Another (not mutually exclusive) interpretation is that the already-listed firm's increased disclosure crowds in external information production, consistent with within-firm complementarity between voluntary disclosure and external information production. A third possibility, which we investigate in the next section, is that investor demand for information changes in ways that increase the return to covering the already-listed firm.

Our two intensive-margin DD tests, reported in Table 5, columns 2 and 3, support the presence of information spillovers. A top 5 peer's S-1 filing leads to a large increase in the informativeness of analysts' forecasts for the already-listed firm, significantly so over the following four quarters when average informativeness increases by 3.2% relative to the pre-treatment mean (p=0.001). Increased informativeness is consistent with information spillovers, be they from the peer's initial and on-going disclosures or the already-listed firm's increased voluntary disclosure. Forecast dispersion too increases significantly, both in the filing quarter (p=0.087) and (twice as strongly) over the next year (p=0.026). This suggests that on net, the richer information environment that results from a top 5 peer's IPO increases disagreement more than it resolves uncertainty among analysts. Finally, Table IA.2 in the Internet Appendix shows that both informativeness and dispersion increase by more the more novel the information contained in the peer's S-1, which once more reinforces our conclusion that IPOs create information spillovers rather than affecting already-listed firms in some other way.

[23] As noted earlier, from an identification perspective, Figure 6 suggests that the treatment quarter – as far as analyst coverage is concerned – is the quarter before the S-1 filing. The research design nonetheless permits causal inference, suitably caveated.

E. Changes in investor demand for information

Table 6 shows that investor demand for information about the already-listed firm, measured as EDGAR searches for its filings, changes after a top 5 peer files its S-1. Specifically, the number of EDGAR searches for the already-listed firm's most recent EDGAR filings increases significantly on the day it announces its earnings via a press release, both in the S-1 filing quarter and over the next year, relative to control firms (p=0.003 and p<0.001 in column 1, respectively). Similarly, the number of EDGAR searches on the day the already-listed firm files a 10-Q or 10-K is higher in the four quarters after the top 5 peer's S-1 filing than before (p=0.006 in column 2). Economically, search volume increases by around 2% relative to the pre-treatment mean for each measure.

F. Testing for Strategic S-1 Disclosures

We next exploit the richness of our research design to investigate the concern that S-1 filings are "endogenous" in the sense that the IPO firm internalizes part of the expected effect on the already-listed firm's information environment, for example by disclosing less non-mandated information in its S-1 filing. Such internalization would lead to smaller information spillovers, implying that our empirical estimates are smaller than they would be absent "endogeneity" of this kind. We expect internalization, if it occurs, to be more prevalent when the already-listed firm is relatively more strategically important to the S-1 filer.

The richness we exploit is the potential asymmetry in the strategic importance of the two firms (the S-1 filer and the already-listed firm) to each other, measured using the Hoberg-Phillips scores. By construction, every S-1 filer in our baseline sample is a top 5 peer of one or more already-listed sample firms, but there is a great deal of heterogeneity in the importance of the already-listed firm(s) to the S-1 filer. For example, while Facebook was a top 5 peer of already-listed AOL and Marchex, Inc. when Facebook filed its S-1 in February 2012, these two firms were in turn relatively unimportant to Facebook: AOL ranked in 12th place and Marchex in 31st place. We exploit this asymmetry to test whether Facebook's S-1 filing (to stick with the example) has a larger effect on the information environments of AOL and Marchex than on that of Google, whose no. 2 ranking among Facebook's peers may have influenced what non-mandated Google-related information Facebook chose to disclose in its S-1.

Table 7 divides already-listed firms into two groups: those that (like Google) are themselves top 5 peers of the S-1 filer ("reciprocal peers") and those (like AOL and Marchex) that are not. Rather than reporting the full suite of all 14 outcome variables, we focus on one liquidity measure (bid-ask spreads), one voluntary-disclosure measure (earnings guidance), two analyst measures (coverage and informativeness), and one information-demand measure (EDGAR searches at earnings release).

The results are consistent with some degree of endogenous attenuation in the effect of a top 5 peer's S-1 filing on an already-listed firm's trading liquidity when the two firms are mutually strategically important to each other. Specifically, the significant short-term improvement in the already-listed firm's liquidity is marginally significantly smaller (p=0.057) when the already-listed firm is itself a top 5 peer of the S-1 filer. This suggests that for reciprocal peers, the S-1 filer may indeed draft its S-1 in such a way that the effect of its disclosures on its already-listed top 5 peer's liquidity is dampened.[24]

For voluntary guidance and analyst coverage, we find the opposite of attenuation. The increase in the probability of guiding is on average three times as large in the filing quarter (p=0.002) and twice as large over the next year (p=0.012) when the already-listed firm is itself a top 5 peer of the S-1 filer. Reciprocity of this form suggests that the strategic complementarity in firms' disclosure choices found in Section II.C is even stronger when the firms are mutually (rather than asymmetrically) important to each other.

We find similarly strong evidence of reciprocity in analyst coverage decisions: the increase in analyst coverage is substantially larger (significantly so in the four quarters following the S-1 filing) when the already-listed firm is itself a top 5 peer of the S-1 filer. Reciprocity of this form is consistent both with supply complementarities that work through the cost of information acquisition and information processing and with investor-demand effects. Informativeness, on the other hand, shows no sign of reciprocity: the informativeness of analyst forecasts for the already-listed firm increases following a top 5 peer's S-1 filing regardless of whether the already-listed firm is itself a top 5 peer of the S-1 filer.

[24] Alternative explanations are certainly possible. For example, interpreted through the lens of adverse selection based microstructure models, the already-listed firm may be at greater risk of attracting informed traders the more it itself is informationally related to the IPO firm. In other words, adverse selection risk may be greater in pairs of stocks that are mutually informationally related. We are unaware of microstructure models exploring this possibility.

Finally, investor demand for information shows no sign of attenuation either: EDGAR searches of the already-listed firm's filings increase following a top 5 peer's S-1 filing whether or not the already-listed firm is itself a top 5 peer of the S-1 filer.

G. Placebo tests

Table 8 reports placebo tests constructed such that the S-1 filer is unlikely to be informationally relevant to the already-listed firm, whereas the already-listed firm is likely to be informationally relevant to the S-1 filer. Specifically, we create a sample of matched treated and control firms such that treated firms rank among the S-1 filer's top 5 peers and the S-1 filer ranks among treated firms' *bottom* 5 peers.[25] Given this setup, we expect:

- no information spillovers from S-1 filers to treated firms;
- no strategic complementarity that would give rise to a change in voluntary disclosure at treated firms;
- no change in analyst forecast informativeness for treated firms; and
- no change in investor information demand at treated firms.

Coverage could go either way. We expect an increase in coverage to the extent that analysts benefit from supply complementarities, in the sense that covering the treated firm helps them better understand the S-1 filer. We expect no change in coverage if coverage decisions mainly reflect investor demand.

The results support our predictions. Liquidity as measured by bid-ask spreads is unchanged when a lowly ranked peer files an S-1, suggesting that its disclosure is largely informationally irrelevant to investors' understanding of the already-listed firm. This placebo result supports our interpretation of the baseline results in Table 3 that an informationally relevant peer's mandatory disclosure spills over to improve the focal firm's liquidity. Earnings guidance is similarly unaffected by the placebo treatment (suggesting that strategic complementarity in voluntary disclosure decisions arises only when the peer firm is informationally relevant to the focal firm), as is information demand.

Analyst coverage, on the other hand, increases significantly when a bottom 5 peer files an S-1

[25] Table IA.4 in the Internet Appendix reports summary statistics for this sample.

(p=0.002) and persists at a significantly higher level over the next four quarters (p=0.031).[26] Since the S-1 filer is, by construction, unlikely to be informationally relevant (an assumption that is validated by the lack of liquidity response), it is presumably not the case that analysts show greater interest in the already-listed firm *because* one of its unimportant peers has filed to go public – a firm whose S-1 filing empirically neither generates information spillovers nor affects investor demand for coverage of the already-listed firm. Given that by construction, the already-listed firm is highly informationally relevant to the S-1 filer, we favor the (to us) more plausible explanation that more analysts choose to cover the already-listed firm in an effort to better understand the S-1 filer. In other words, coverage decisions are in part driven by supply complementarities, even absent investor demand effects.

Finally, the informativeness of analysts' forecasts for the already-listed firm is unaffected by a bottom 5 peer's S-1 filing, as expected, even though analyst coverage increases. This suggests that informativeness is a function not of analyst coverage per se but of changes in the availability of information – which are unlikely to occur in the placebo sample considered here.

H. Intensity of treatment

We conclude our empirical investigation of information channels by considering variation in the intensity of treatment. We expect a diminishing marginal effect of S-1 filings on already-listed firms' liquidity, voluntary disclosure choices, analyst coverage, and investor information demand the richer their pre-treatment information environments. To test these predictions, we exploit the fact that many sample firms are subject to multiple treatments. For example, Google is first treated by Facebook's February 2012 S-1 filing and then again by Twitter's March 2013 S-1 filing. We expect the earlier filing to have a larger effect on Google's information environment than the later one, all else equal.

Table 9 returns to our main estimation sample and interacts the short-term and long-term treatment indicators with two indicators capturing whether it is the second or third time the already-listed firm experiences a top 5 peer filing for an IPO. (The uninteracted coefficients capture the effects of a first-time

[26] In contrast to the main sample, we find no evidence of diverging pre-trends in the placebo sample (p=0.182). This makes good economic sense: when the S-1 filer is informationally irrelevant, analysts do not pre-position themselves by increasing coverage of the already-listed firm.

S-1 filing.) At the bottom of the table, we report Wald tests of the null hypothesis that second-time or third-time S-1 filings have no effect on already-listed firms. By way of preview, we find strong evidence of diminishing marginal effects in all dimensions we consider.

The estimates in column 1 show that already-listed firms experience a significant short-term improvement in liquidity the first time a top 5 peer files an S-1 (p<0.001), an economically smaller and only marginally significant improvement the second time (p=0.056), and no improvement either statistically or economically the third time (p=0.116). Column 2 shows a large and sustained increase in the probability of providing earnings guidance the first time, an economically smaller increase the second time, and no increase the third time a top 5 peer files an S-1. Column 3 reports similar evidence for analyst coverage: coverage increases significantly and persistently after the first S-1 filing, by significantly less after the second S-1 filing, and not at all statistically or economically after the third S-1 filing. Finally, column 4 shows that the informativeness of analyst forecasts improves significantly only after a first S-1 filing, while column 5 shows that investor demand for information increases significantly the first and second times a top 5 peer files an S-1, but not the third time.

Compared to the corresponding baseline estimates reported in Tables 3 through 6, which represent an average of first-, second-, and third-time treatment effects, the economic magnitudes of the first-time treatment effects reported in Table 9 are considerably larger, consistent with the predicted diminishing marginal effects of information spillovers. In other words, the positive information externalities firms impose on their peers when deciding to go public diminish the more peers have gone public before them.

III. Potential non-information channels

While the results reported in Section II are consistent with information spillovers among listed firms, we take seriously the possibility that liquidity might improve for non-information reasons (as well or, potentially, instead). In this section, we consider four key non-information channels. The first three involve various aspects of the fact that a top 5 peer's S-1 filing is not exogenous. The fourth deals with the fact that an IPO may change the competitive landscape in an already-listed firm's industry. Our tests suggest that none of these can explain why already-listed firms' liquidity improves when a top 5 peer files an S-1.

The first potential non-information channel is that liquidity improves not because of an information spillover from the peer's S-1 filing but because the peer's arrival in the stock market helps liquidity providers or traders diversify, hedge, or arbitrage their positions in an already-listed firm's stock in ways that improve its liquidity. However, the timeline of our empirical design is inconsistent with this type of channel. S-1 filings are, on average, filed 87 days (one quarter) before the stock starts trading. Alternative channels that require the peer's stock to be physically available to traders (say, for hedging purposes) thus cannot explain the significant improvement in an already-listed firm's liquidity in the quarter of *filing*. Moreover, as Table 3 shows, most of the liquidity improvement is short-lived, having dissipated by the time the S-1 filer's stock starts trading. This suggests that liquidity improves in response to the filing, not in response to the start of trading (and thus physical availability) of the peer's stock. This conclusion is supported by a placebo test. Table IA.5 in the Internet Appendix uses the start of trading instead of the S-1 filing as the shock. We find no significant changes, economically or statistically, in already-listed firms' liquidity in response to a top 5 peer's shares starting to trade. Thus, the baseline results in Table 3 are more consistent with information externalities than with trading-related externalities.

The second potential non-information channel allows for the endogenous timing of a peer's S-1 filing. According to standard microstructure models (Ho and Stoll 1981, Kyle 1985, Glosten and Milgrom 1985), liquidity is a decreasing function of the adverse selection risk traders face and of the inventory risk liquidity providers face. Suppose there is a common industry component to these sources of risk and that S-1 filings are timed to coincide with periods of "cheap" liquidity but do not themselves have a direct effect on the already-listed firm's information environment. The observed liquidity improvement in Table 3 may then be spurious. Table IA.6 shows that this is not the case. Using PIN (the probability of informed trading) and return volatility in the already-listed firm's TNIC industry as standard proxies for industry-wide adverse selection risk and industry-wide inventory risk, respectively, we find that S-1 filings do not coincide with periods of low adverse selection risk or low inventory risk in the already-listed firm's TNIC industry.

The third potential non-information channel considers a different timing-related confound. It is likely that firms file to go public when their investment opportunities improve, and investment opportunities likely have a common industry component. Indeed, Table IA.6, column 3 shows that S-1 filings coincide with periods of significantly higher Tobin's Q in the filer's industry. On their own, improved investment opportunities should not lead to improved liquidity (at least not in any microstructure model we are aware of), but there is a potential indirect mechanism: already-listed firms might respond to better investment opportunities in their industry by raising external funding, and external fund-raising requires disclosure which could independently improve their liquidity (by reducing adverse selection risk). However, as Table IA.7 in the Internet Appendix shows, we find no evidence that already-listed firms fund-raise coincident with or in the wake of a top 5 peer's S-1 filing. Specifically, their net issuance of both equity and long-term debt is unchanged, as is their short-term leverage, long-term leverage, and total leverage.

The final potential non-information channel concerns product-market interactions: some TNIC peers are not only linked informationally, they also interact strategically with each other in the product market. Perhaps, then, the IPO strengthens the IPO firm's competitive position (by virtue of the capital it raises in the IPO) in a way that improves the already-listed firm's liquidity (though how exactly is unclear: we are not aware of any theoretical model that links product-market competition to liquidity). Empirically, we find no support for such a channel.

First, we ask whether IPOs in fact affect the competitive landscape in our setting. If they did, we would expect a top 5 peer's S-1 filing to be "bad news" for already-listed firms. However, we find no evidence of significant market reactions around S-1 filings: cumulative abnormal returns in the [-1, 1] trading-day window average a mere -2 basis points using the market model (p=0.799) and an equally tiny -7 basis points using the Fama-French three-factor model (p=0.440). In other words, investors do not view a top 5 peer's S-1 filing as affecting already-listed firms' expected future cash flows.

This non-result is consistent with a feature of Hoberg and Phillips' (2010) approach discussed in Section I.B: an S-1 filer in our sample is a top 5 peer of an already-listed firm based on the similarity of their products *but regardless of the scale of its sales*. We exploit this distinction in a second test. Table IA.8 in the Internet Appendix allows the effect of an S-1 filing on the already-listed firm's liquidity to vary with the filer's market share rank among the already-listed firm's peers. This reveals that a top 5 peer's S-1 filing improves the already-listed firm's liquidity regardless of the filer's competitive position in the product market. This suggests that it is the information content of the S-1 filing, rather than the peer's importance as a competitor, that accounts for the liquidity improvement in Table 3.[27]

In summary, we find no evidence to suggest that already-listed firms' liquidity improves for non-information reasons. This leads us to conclude that what investors primarily respond to, when faced with a top 5 peer's S-1 filing, is likely an improvement in the focal firm's external information environment.

IV. Concluding thoughts

We quantify the presence of information externalities across firms listed on U.S. stock exchanges using staggered non-marginal increases in disclosure at peer firms unaccompanied by changes in mandatory disclosure at focal firms. Our empirical design exploits the dramatic increase in available peer information when an already-listed firm's top 5 peer files to go public.

Our findings show that a peer firm's mandatory disclosure improves the focal firm's trading liquidity directly by reducing adverse selection risk and indirectly through the subtle interplay of mandatory disclosure, voluntary disclosure, external information production, and investor information demand: the peer firm's mandatory disclosure crowds in both voluntary disclosure and analyst information production at the focal firm as investor demand for information increases. Positive information externalities, and the complementarities they operate through, support regulators' use of mandatory disclosure to improve the market-wide information environment.

Beyond the implications of our findings for the debate on the optimal level of mandatory disclosure and our understanding of the determinants of corporate information environments, the finding that going public involves positive information externalities for already-listed firms has implications for the debate on the shrinking of the public markets (Doidge, Karolyi, and Stulz 2017, Eckbo and Lithell 2020). Ever fewer firms are traded on stock markets. The U.S. is a prominent example. Over the past 25 years, the U.S. stock

[27] This conclusion is supported by two auxiliary tests reported in Section IA.2 in the Internet Appendix. The first exploits the fact that not every firm that goes public raises capital; the second exploits the fact that not every firm that files for an IPO also completes the IPO. These tests show that liquidity improves even if the top 5 peer raises no capital in the IPO and whether or not the peer completes or abandons its IPO.

market has halved in size (though not in value). Using data going back to 1790, Figure 7 shows that the number of stock market listed firms in the U.S. peaked at more than 7,500 in 1997 and has since declined almost monotonically. By December 2019, the number stood at 3,643 – less than half the 1997 count. Doidge, Karolyi, and Stulz attribute about half of the decline since 1997 to a historically high number of delistings (as companies have merged or been taken private by private equity firms) and half to an unusually low level of IPO activity (as fewer and fewer privately held firms see value in going public).

Our findings suggest that by not going public, privately held firms deprive the stock market of the benefit of positive information spillovers, resulting in a sub-optimally small stock market, all else equal.

References

Admati, A.R., and P. Pfleiderer. 2000. Forcing firms to talk: Financial disclosure regulation and externalities. *Review of Financial Studies* 13:479-519.

Ajinkya, B.B., and M.J. Gift. 1984. Corporate managers' earnings forecasts and symmetrical adjustments of market expectations. *Journal of Accounting Research* 22:425-444.

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

Asker, J., J. Farre-Mensa, and A. Ljungqvist. 2015. Corporate investment and stock market listing: A puzzle? *Review of Financial Studies* 28:342-90.

Baker, A.C., D.F. Larcker, and C.C.Y. Wang. 2021. How much should we trust staggered difference-in-differences estimates? Working paper, Stanford University.

Balakrishnan, K., M.B. Billings, B. Kelly, and A. Ljungqvist. 2014. Shaping liquidity: On the causal effects of voluntary disclosure. *Journal of Finance* 69:2237-2278.

Bauguess, S.W., J.W. Cooney, and K.W. Hanley. 2018. Investor demand for information in newly issued securities. Working paper.

Bernard, V.L., and J.K. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13:305-340.

Beyer, A., D.A. Cohen, T.Z. Lys, and B.R. Walther. 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics* 50:296-343.

Billett, M.T., M. Ma, and X. Yu. 2021. Torpedo your competition: Strategic reporting and peer firm IPO. Working paper.

Brown, A.B., D. Byard, M.N. Darrough, and J. Suh. 2020. Do M&A delistings impact U.S. capital markets? Evidence of negative information externalities for industry peer firms. Working paper.

Brown, J. R., S. M. Fazzari, and B. C. Petersen. 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D Boom. *Journal of Finance* 64:151-185.

Chen, S., B. Miao, and T. Shevlin. 2015. A new measure of disclosure quality: The level of disaggregation of accounting data in annual reports. *Journal of Accounting Research* 53:1017-1054.

Darrough, M.N. 1993. Disclosure policy and competition: Cournot vs. Bertrand. *Accounting Review* 68:432-561.

Dechow, P.M., R.G. Sloan, and A.P. Sweeney. 1995. Detecting earnings management. *Accounting Review* 70:193-225.

De George, E.T., M. Phan, and R.C. Stoumbos. 2019. Negative externalities of financial reporting frequency: Peer reporting choice and the loss of investor attention. Working paper.

Doidge, C., A. Karolyi, and R. Stulz. 2017. The U.S. listing gap. *Journal of Financial Economics* 123:464-487.

Dye, R.A. 1990. Mandatory versus voluntary disclosures: The cases of financial and real externalities. *Accounting Review* 65:1-24.

Dye, R.A., and S.S. Sridhar. 1995. Industry-wide disclosure dynamics. *Journal of Accounting Research* 33, 157-174.

Easley, D., N.M. Kiefer, M. O'Hara, and J.B. Paperman. 1996. Liquidity, information, and infrequently traded stocks. *Journal of Finance* 51:1405-1436.

Easterbrook, F., and D. Fischel. 1991. The Economic Structure of Corporate Law. Harvard University Press, Cambridge, MA.

Eckbo, B.E., and M. Lithell. 2020. Follow the assets: Is the U.S. listing gap "real"? Working paper.

Fishman, M.J., and K.M. Hagerty. 1989. Disclosure decisions by firms and the competition for price efficiency. *Journal of Finance* 44:633-646.

Glosten, L., and P. Milgrom. 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed agents. *Journal of Financial Economics* 14:71-100.

Goldstein, I., and L. Yang. 2017. Information disclosure in financial markets. *Annual Review of Financial Economics* 9:101-125.

Goyenki, R. Y., C. W. Holden, and C.A. Trzcinka. 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92:153-181.

Hanley, K.W., and G. Hoberg. 2010. The information content of IPO prospectuses. *Review of Financial Studies* 23:2821-2864.

Heflin, F., K.R. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *Accounting Review* 78:1-37.

Hinson, L., and J. Piao. 2019. Disclosure spillover: Evidence from going-private activity. Working paper.

Ho, T., and H. Stoll. 1981. Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics* 9:47-73.

Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23:3773-3811.

Hughes, J.S., J.L. Kao, and M. Williams. 2002. Public disclosure of forward contracts and revelation of proprietary information. *Review of Accounting Studies* 7:459-478.

Kanodia, C., A. Mukherji, H. Sapra, and R. Venugopalan. 2000. Hedge disclosures, future prices, and production distortions. *Journal of Accounting Research* 38:53-82.

Kelly, B., and A. Ljungqvist. 2012. Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25:1366-1413.

Koenker, R., and G. Bassett. 1978. Regression quantiles. *Econometrica* 46:33-50.

Kothari, S.P., A.J. Leone, and C.E. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39:163-197.

Kothari, S.P., E. So, and R. Verdi. 2016. Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics* 60:245-284.

Kyle, A. 1985. Continuous auctions and insider trading. *Econometrica* 53:1315-1335.

Lee, C.M.C., P. Ma, and C.C.Y. Wang. 2015. Search-based peer firms: Aggregating investors' perceptions through internet co-searches. *Journal of Financial Economics* 116:410-431.

Lehavy, R., F. Li, and K. Merkley. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *Accounting Review* 86:1087-1115.

Lesmond, D. A., J.P. Ogden, and C.A. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12:1113-1141.

Leuz, C., and P.D. Wysocki. 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research* 54:525-622.

Lin, Y., Y. Mao, and Z. Wang. 2018. Institutional ownership, peer pressure, and voluntary disclosures. *Accounting Review* 93:283-308.

Malmendier, U., and G. Tate. 2009. Superstar CEOs. *Quarterly Journal of Economics* 124:1593-1638.

Matsumoto, D.A., and S. Shaikh. 2017. Discussion of 'When does peer information environment matter? *Journal of Accounting and Economics* 64:215-220.

Merkley, K., R. Michaely, and J. Pacelli. 2017. Does the scope of the sell-side analyst industry matter? An examination of bias, accuracy, and information content of analyst reports. *Journal of Finance* 72:1285-1334.

Minnis, M., and N. Shroff. 2017. Why regulate private firm disclosure and auditing? *Accounting and Business Research* 47:473-502.

Petersen, M.A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22:435-480.

Venter, J.H., and D.C.J. DeJongh. 2006. Extending the EKOP model to estimate the probability of informed trading. *Studies in Economics and Econometrics* 30:25-39.

Verrecchia, R.E. 1990. Information quality and discretionary disclosure. *Journal of Accounting and Economics* 12:365-380.

Vives, X. 1984. Duopoly information equilibrium: Cournot and Bertrand. *Journal of Economic Theory* 34:71-94.

Appendix A. Construction of treatment sample.

Sampling step			No. of obs.
No. of IPOs in Thomson SDC, 1996-2017			4,467
less: share code > 11, exchange code >3	-	491	
less: withdrawn IPO, already EDGAR filer, previously listed ("repeat IPO")	-	320	
No. of filtered IPOs in Thomson SDC, 1996-2017			3,656
No. of firms in TNIC, 1996-2017			13,808
less: share code > 11, exchange code > 3	-	31	
less: never shocked by a top 5 peer's IPO filing	-	7,469	
No. of firms with one or more IPO filing shocks			6,308
No. of firm-quarters with one or more IPO filing shocks			11,759
less: already shocked in previous four quarters	-	69	
less: itself a recent IPO	-	257	
less: no match in common support (0.01 caliper)	-	4,784	
No. of treated firm-quarters after matching			6,649
Treatment sample			
No. of treated firm-quarters			6,649
No. of unique treated firms (by Compustat gvkey)			4,586
No. of unique S-1 filers (by Compustat gvkey)			2,081

Appendix B. Variable definitions.

Co-search

Co-search is the number of unique EDGAR users (i.e., IP addresses) who search the already-listed firm's 10-K, 10-Q, or 8-K filings and who also search the IPO firm's S-1 filing in a given day (regardless of the search order). Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day. We obtain data on EDGAR search traffic from the SEC's Division of Economic and Risk Analysis (DERA) database. See Lee, Ma, and Wang for further details.

Toggle-search is the number of co-searches involving a unique EDGAR user (i.e., IP address) going back and forth between the filings of firms A and B on the same day, in the pattern A→B→A or B→A→B. Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day. We obtain data on EDGAR search traffic from the SEC's Division of Economic and Risk Analysis (DERA) database. See Lee, Ma, and Wang for further details.

Conditional co-search probability is measured as the ratio of the number of co-searches involving an already-listed firm and the total number of searches involving the already-listed firm in a given time interval (a day, a week, or a month). Co-searches are as defined above. The total number of searches is defined as the count of unique Edgar users (i.e., IP addresses) who search the already-listed firm's 10-K, 10-Q, or 8-K filings in a given day. Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day.

Conditional toggled-search probability is measured as the ratio of the number of toggle-searches involving an already-listed firm and the total number of searches involving the already-listed firm. Toggle-searches are as defined above. The total number of searches is defined as the count of unique Edgar users (i.e., IP addresses) who search the already-listed firm's 10-K, 10-Q, or 8-K filings in a given day. Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day.

Liquidity

Bid-ask spread is the quarterly average of a firm's daily bid-ask spread. We use daily closing bid and ask data from CRSP (variables ask and bid) to calculate $100 \times (ask - bid)/[(ask + bid)/2]$. Both bid and ask are measured in dollars. We then average these daily bid-ask spreads over the fiscal quarter. Observations with crossed quotes (negative spreads) are excluded.

Log AIM is the natural log of one plus Amihud's (2002) illiquidity measure. We use daily CRSP data to calculate the ratio of absolute return to dollar volume, $1{,}000{,}000 \times |ret|/(|prc| \times vol)$, for each trading day in a fiscal quarter. We then average over the quarter and take logs. Trading volume on Nasdaq is adjusted using the Gao and Ritter (2010) procedure.

Fraction zero-return is a firm's fraction of trading days with zero or missing returns in a fiscal quarter, expressed in percent. See Lesmond, Ogden, and Trzcinka (1999) and Goyenko, Holden, and Trzcinka (2009) for further details.

Effective tick is a firm's quarterly average of Goyenko, Holden, and Trzcinka's (2009) effective tick measure. Using daily CRSP data (CRSP variables prc and vol) and based on end-of-day price clustering, we calculate an average effective spread over the quarter as the probability-weighted average of each effective spread size deflated by the stock price.

Adverse selection risk: Probability of informed trading

PIN is measured using Venter and DeJongh's (2006) version of Easley et al.'s (1996) probability of informed trading (PIN) measure. The Venter-DeJongh approach improves on Easley et al.'s PIN measure by allowing for the strong positive correlation observed between the number of buy orders and the number of sell orders. The PIN data are obtained from https://terpconnect.umd.edu/~stephenb/ and available through fiscal year 2010 only.

Information novelty

Information novelty captures the extent to which information disclosed in a top 5 peer's S-1 filing is unique compared with the content of recent S-1s (filed in the preceding 90 days) and of related past S-1s by firms in the same Fama-French 48 industry code (filed between 91 and 365 days earlier). The coding follows Hanley and Hoberg (2010). We first extract each S-1's "management's discussion & analysis" (MD&A) section and purge attachments and exhibits. We exclude common words and articles and keep only alphabetic characters. We lemmatize the entire MD&A using natural language toolkits programmed in Python to find word roots. We drop word roots that are not included in dictionaries of American, British, Canadian, and Australian dialects. Using these word roots, we create a normalized word vector for each S-1 filer i, $norm_{tot,i}$. We then estimate the regression, $norm_{tot,i} = a_{rec,i}norm_{rec,i} + a_{ind,i}norm_{ind,i} + \varepsilon$ for each S-1 filer i, where $norm_{rec,i}$ is the average normalized word vector of recent S-1s and $norm_{ind,i}$ is the average normalized word vector of past S-1s in the same Fama-French industry. Information novelty is defined as the sum of the absolute value of the residuals. See Hanley and Hoberg (2010) for further details.

Industry conditions

Industry PIN is the quarterly market-value-weighted average PIN of all firms in a given TNIC industry (Hoberg and Phillips 2010). PIN is measured using Venter and DeJongh's (2006) version of Easley et al.'s (1996) probability of informed trading (PIN) measure. The Venter-DeJongh approach improves on Easley et al.'s PIN measure by allowing for the strong positive correlation observed between the number of buy orders and the number of sell orders. The PIN data are obtained from https://terpconnect.umd.edu/~stephenb/ and available through fiscal year 2010 only.

Industry volatility is the quarterly market-value-weighted average stock return volatility in a given TNIC industry (Hoberg and Phillips 2010).

Industry Tobin's Q is the quarterly market-value-weighted average Tobin's Q in a given TNIC industry (Hoberg and Phillips 2010). Tobin's Q is defined as the market value of assets (Compustat variables $atq - ceqq + cshoq * prccq$) in the current fiscal quarter over the book value of assets (Compustat variable atq) in the previous fiscal quarter.

Fund-raising

Net issuance of common and preferred stock is the net cash raised through new stock issues in fiscal quarter t, scaled by the book value of total assets (Compustat variable atq) in fiscal quarter $t - 1$. The net cash raised through new stock issues is defined as the sale of common and preferred stock (Compustat variable $sstky$) minus the purchase of common and preferred stock (Compustat variable $prstkcy$). See Brown, Fazzari, and Petersen (2009) for further details.

Net issuance of long-term debt is net new long-term debt in fiscal quarter t, scaled by the book value of total assets (Compustat variable atq) in fiscal quarter $t - 1$. Net new long-term debt is defined as long-term debt issued (Compustat variable $dltisy$) minus long-term debt reduction (Compustat variable $dltry$). See Brown, Fazzari, and Petersen (2009) for further details.

Short-term leverage is the short-term leverage ratio, which is measured as short-term debt (Compustat variable $dlcq$) in fiscal quarter t scaled by the book value of total assets (Compustat variable atq) in fiscal quarter $t - 1$.

Long-term leverage is the long-term leverage ratio, which is measured as long-term debt (Compustat variable $dlttq$) in fiscal quarter t scaled by the book value of total assets (Compustat variable atq) in fiscal quarter $t - 1$.

Total leverage is the total leverage ratio, which is measured as the sum of long-term debt (Compustat variable $dlttq$) and short-term debt (Compustat variable $dlcq$) in fiscal quarter t scaled by the book value of total assets (Compustat variable atq) in fiscal quarter $t - 1$.

Disclosure

Guider is an indicator variable that equals one if a firm's management supplies earnings guidance in a given fiscal quarter, and zero otherwise. Following Balakrishnan et al. (2014), we measure earnings guidance using quarterly management forecasts and pre-announcements of earnings per share obtained from the Company Issued Guidance (CIG) file, accessed via the First Call Historical Database (FCHD). For fiscal years 2009 through 2017, we augment the CIG file with the Thomson Reuters IBES guidance dataset.

Quantitative guidance is an indicator variable that equals one if a firm's management supplies quantitative earnings guidance in the form of either a point forecast or a range forecast. We use quarterly management forecasts and pre-announcements of earnings per share obtained from the Company Issued Guidance (CIG) file, accessed via the First Call Historical Database (FCHD). For fiscal years 2009 through 2017, we augment the CIG file with the Thomson Reuters IBES guidance dataset.

Log no. of 8-Ks is the natural log of one plus the total number of a firm's 8-K filings in a given fiscal quarter.

DQ is a firm's quarterly "disclosure quality" score. It captures the level of disaggregation in its financial reporting by counting the number of non-missing Compustat line items. The score ranges from 0 to 1, where 0 (1) equals the lowest (highest) disclosure quality. It is computed separately for the income statement and the balance sheet and averaged to the firm level. See Chen, Miao, and Shevlin (2015) for further details.

Price convergence is the absolute cumulative abnormal return around a firm's quarterly earnings announcement date (Compustat variable rdq). Following Heflin, Subramanyam, and Zhang (2003), we compute $\left|\prod_{d=-1}^{2}\left(1 + AR_{i,q,d}\right) - 1\right|$ for each firm i and fiscal quarter t, from the day before the earnings announcement to two days after. Daily abnormal returns are adjusted for market movements using the CRSP value-weighted index.

$\boldsymbol{SUE}$ is standardized unexpected earnings. We code earnings surprises using either a seasonal random walk or analyst consensus to estimate expected earnings. The former follows Bernard and Thomas (1990). SUE for firm i in fiscal quarter t announced in fiscal quarter $t + 1$ is defined as the difference between I/B/E/S reported earnings per share (I/B/E/S detail history variable $value$) and expected earnings, scaled by the standard deviation of that difference, where expected earnings equal the firm's realized earnings four quarters previously plus a time trend. The latter follows Barron, Byard, and Yu (2008). SUE for firm i in fiscal quarter t announced in fiscal quarter $t + 1$ is defined as the absolute difference between I/B/E/S reported earnings per share (I/B/E/S detail history variable $value$) and the median outstanding analyst earnings forecast made for quarter t earnings, scaled by the firm's quarter $t - 1$ quarter-end share price. Analyst earnings forecasts are taken from the I/B/E/S unadjusted detail history file. Share prices are taken from the CRSP monthly file (variable prc).

<u>Analyst response</u>

No. of analysts is the number of analysts who issue earnings-per-share forecasts for a firm in a fiscal quarter. We count unique I/B/E/S analyst identifiers (I/B/E/S unadjusted detail file variable *analys*) to compute this variable.

Informativeness is the fraction of cumulative daily absolute abnormal returns that can be attributed to analyst forecasts in a fiscal quarter, expressed in percent. Following Lehavy, Li, and Merkley (2011) and Merkley, Michaely, and Pacelli (2017), the measure is defined as $\sum_{d=1}^{NREVS} |R_{id} = Dec\ ret_{id}| / \sum_{d=1}^{D} |R_{id} - Dec\ ret_{id}|$, where *NREVS* is the number of trading days for which there is at least one analyst forecast in the I/B/E/S details history file; *D* is the number of trading days in a quarter; R_{id} is the daily return of firm *i* on day *d* (CRSP variable *ret*); and $Dec\ ret_{id}$ is the CRSP size-decile portfolio return (variable *decret*).

Dispersion is the standard deviation of analysts' earnings forecasts made in fiscal quarter *t* (I/B/E/S variable *stdev*), scaled by the end-of-quarter stock price (CRSP variable *prc*) and expressed in percent. I/B/E/S data are obtained from the unadjusted summary history files. Dispersion is based on forecasts made for the current fiscal year ($fpi = 1$). See Lehavy, Li, and Merkley (2011) for further details.

<u>Investors' information demand</u>

EDGAR searches on the day earnings are announced equals the log of one plus the total number of searches in EDGAR of the 10-Ks, 10-Qs, and 8-Ks the firm filed in the previous four quarters, measured on the day the firm announces its quarterly earnings (Compustat variable rdq). We measure EDGAR searches of a firm's past filings because firms announce earnings before they file the corresponding 10-Q or 10-K. Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day. We obtain data on EDGAR search traffic from the SEC's Division of Economic and Risk Analysis (DERA) database.

EDGAR searches on the day a 10-Q/K is filed equals the log of one plus the total number of searches in EDGAR of the firm's newly filed 10-Q or 10-K measured on the filing day. Most firms file one 10-Q or 10-K per fiscal quarter. In the rare event that a firm files more than one 10-Q or 10-K in a given fiscal quarter (for example, due to a late filing), we average the number of searches on the filing dates in that fiscal quarter. Following Lee, Ma, and Wang (2015), we limit analysis to human users ($code$ < "300" and $crawler$ = "0") and drop IP addresses that search for more than 50 unique firms' filings in a day. We obtain data on EDGAR search traffic from the SEC's Division of Economic and Risk Analysis (DERA) database.

Earnings management

Disc. accruals (Kothari) is performance-matched discretionary accruals in a fiscal quarter, defined following Kothari, Leone, and Wasley (2005) as a firm's discretionary accruals from a modified Jones model minus the discretionary accruals of a matched firm in the same Fama-French 48 industry with the closest return on assets.

Disc. accruals (Jones) is firm *i*'s discretionary accruals in fiscal quarter *t* obtained from a modified Jones model following Dechow, Sloan, and Sweeney (1995). The modified Jones model is specified as $TA_{iq}/ASSET_{iq-1} = \beta_0 + \beta_1(1/ASSET_{iq-1}) + \beta_2(\Delta REV_{iq}/ASSET_{iq-1}) + \beta_3(PPE_{iq}/ASSET_{iq-1}) + \varepsilon_{iq}$, where TA_{iq} is total accruals, defined as earnings before extraordinary items and discontinued operations (Compustat variable *ibq*) minus operating cash flows (Compustat variable *oancfy*); $ASSET_{iq-1}$ is lagged total assets (Compustat variable *atq*); ΔREV_{iq} is the change in quarterly revenue (Compustat variable *saleq*); and PPE_{iq} is gross property, plant, and equipment (Compustat variable *ppegtq*). Jones discretionary accruals is defined as $DA_{iq} = TA_{iq}/ASSET_{iq-1} - NA_{iq}$, where $NA_{iq} = \widehat{\beta_0} + \widehat{\beta_1}(1/ASSET_{iq-1}) + \widehat{\beta_2}(\Delta REV_{iq} - \Delta AR_{iq})/ASSET_{iq-1} + \widehat{\beta_3}(PPE_{iq}/ASSET_{iq-1})$ and AR_{iq} is accounts receivable (Compustat variable *rectq*).

Meet-or-beat (median) is an indicator variable that equals one if a firm's *EPS* is both greater than and within one cent of the median analyst's outstanding earnings forecast, and zero otherwise.

Meet-or-beat (mean) is an indicator variable that equals one if a firm's *EPS* is both greater than and within one cent of the mean analyst's outstanding earnings forecast, and zero otherwise.

Figure 1. Validating the Information-Relevance Assumption: Co- and Toggled Searches Around a Top 5 Peer's S-1 Filing.
This figure graphs the conditional co-search and toggled-search probabilities reported in Table 1. Our identification strategy assumes that at least part of the information a top 5 peer discloses in its S-1 filing is "informationally relevant" to the already-listed firms it is linked to. We validate this assumption using Lee, Ma, and Wang's (2015) "co-search" approach. Using the EDGAR server logs, we construct two measures. First, we compute, for each treated firm and its matched control, the probability that an EDGAR user who searches the already-listed firm's EDGAR filings also searches the top 5 peer's S-1 filing on the same day. We compute this conditional "co-search" probability over three time windows: on the day the S-1 is filed, over the course of the week beginning with the S-1 filing, and over the course of the month from the S-1 filing date. Second, we restrict co-searches to those involving an EDGAR user going back and forth between the filings of the two firms, in the pattern A→B→A or B→A→B ("toggled search"). Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and Amihud's (2002) illiquidity measure) and fiscal quarter using a 0.01 caliper.

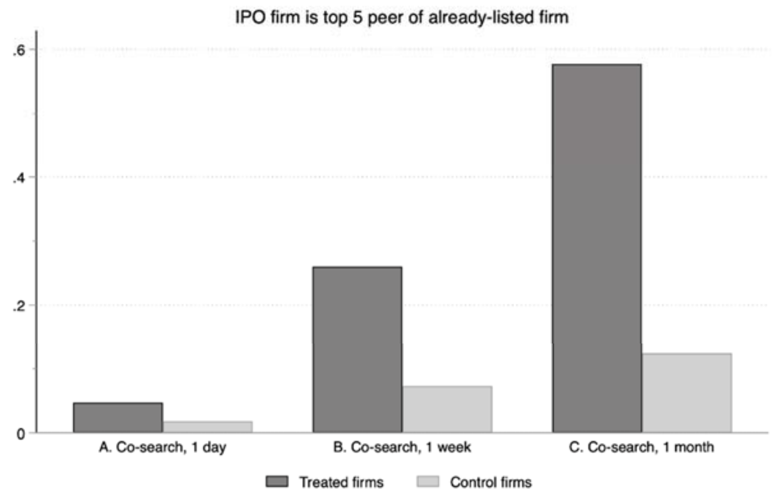

Fig. 1(a). Co-search.

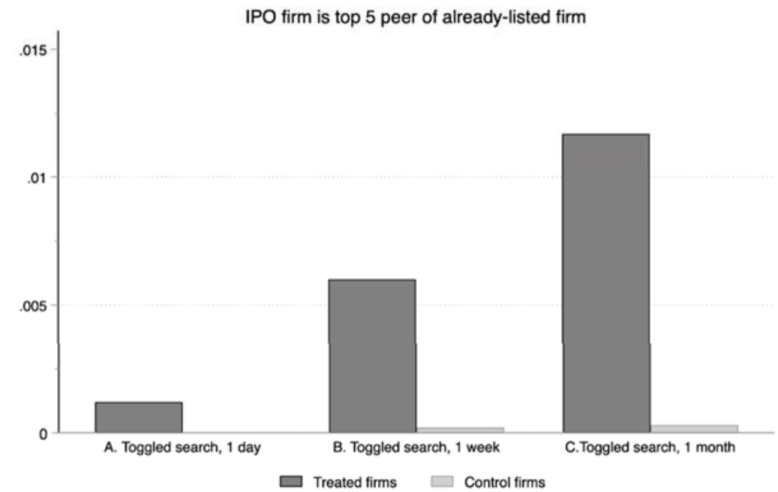

Fig. 1(b). Toggled search.

Figure 2. Quantile Regressions: Liquidity.

The figure graphs quantile-regression DD estimates of the effect of a top 5 peer filing an S-1 on an already-listed firm's liquidity in the S-1 filing quarter. All specifications are estimated using quantile regressions (Koenker and Bassett 1978) and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). The dashed lines indicate 95% bootstrapped confidence intervals. For variable definitions and details of their construction see Appendix A.

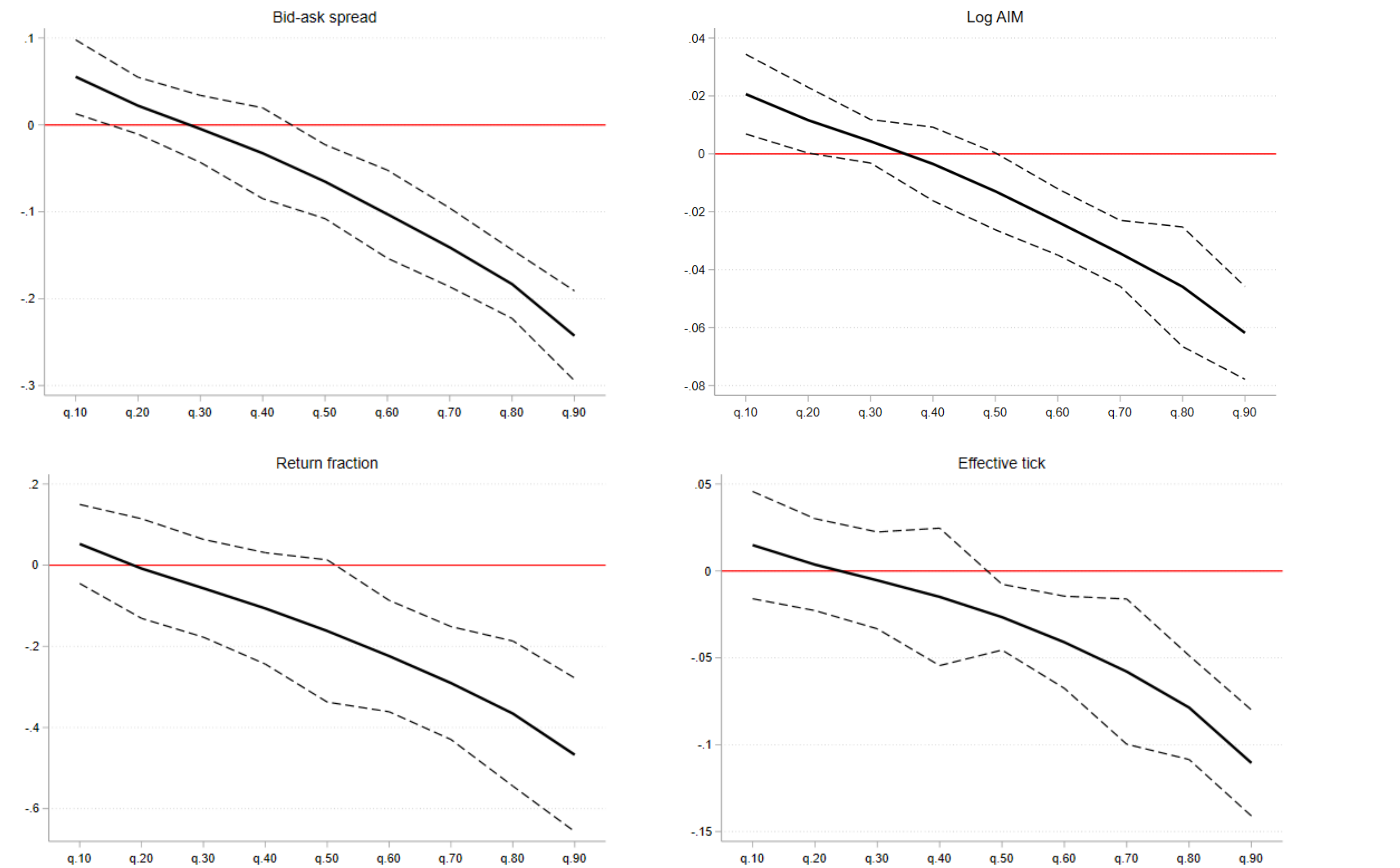

Figure 3. Testing for Diverging Pre-trends: Liquidity.
The figure graphs difference-in-differences estimates of the effect of a top 5 peer filing an S-1 on an already-listed firm's liquidity. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). The vertical lines capture 95% confidence intervals. For variable definitions and details of their construction see Appendix B.

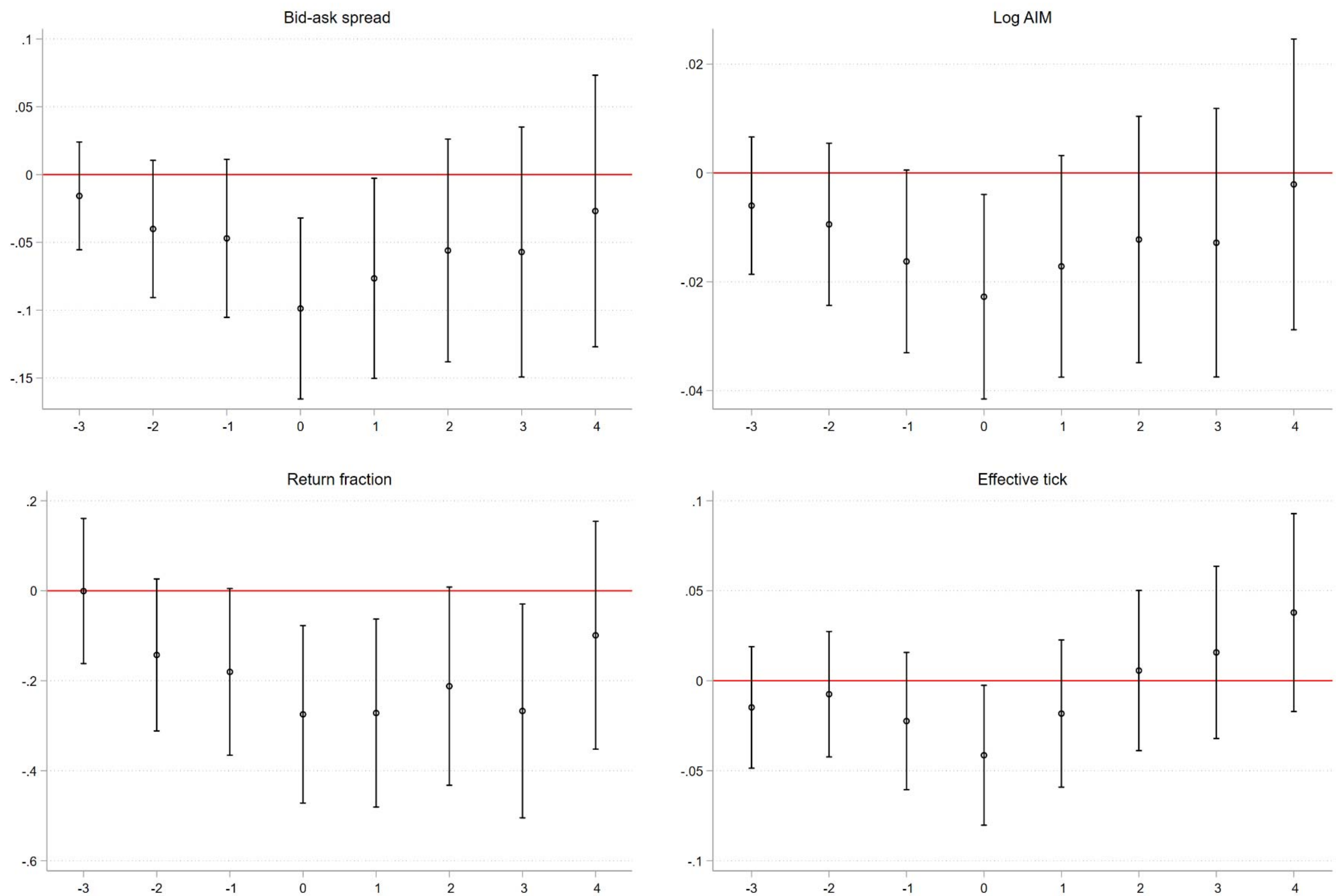

Figure 4. Testing for Diverging Pre-trends: Earnings Guidance.

The figure graphs difference-in-differences estimates of the effect of a top 5 peer filing an S-1 on an already-listed firm's choice to provide earnings guidance. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B.

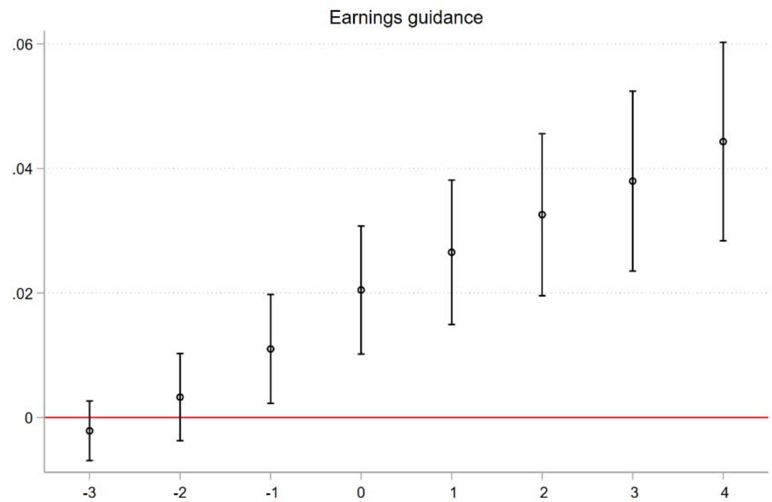

Figure 5. Quantile Regressions: Analyst Coverage.

The figure graphs quantile-regression DD estimates of the effect of a top 5 peer filing an S-1 on an already-listed firm's analyst coverage in the S-1 filing quarter, measured as the number of analysts providing earnings forecasts for the firm. All specifications are estimated using quantile regressions (Koenker and Bassett 1978) and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). The dashed lines indicate 95% bootstrapped confidence intervals. For variable definitions and details of their construction see Appendix A.

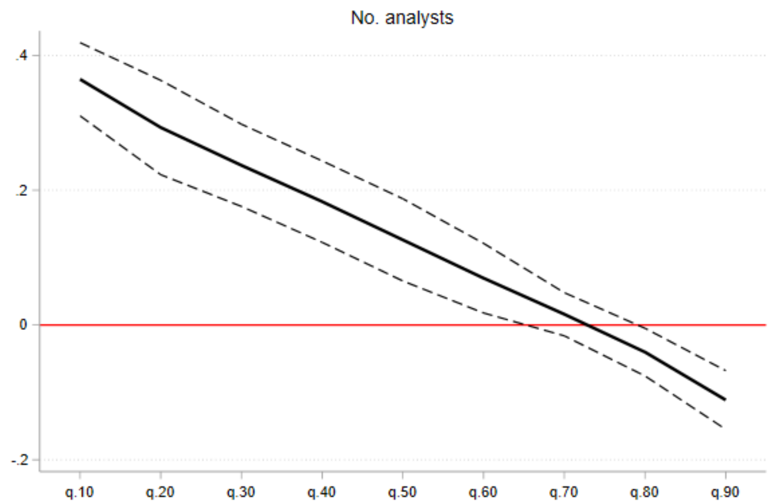

Figure 6. Testing for Diverging Pre-trends: Analyst Coverage.

The figure graphs difference-in-differences estimates of the effect of a top 5 peer filing an S-1 on an already-listed firm's analyst coverage as measured by the number of analysts providing earnings forecasts for the firm. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B.

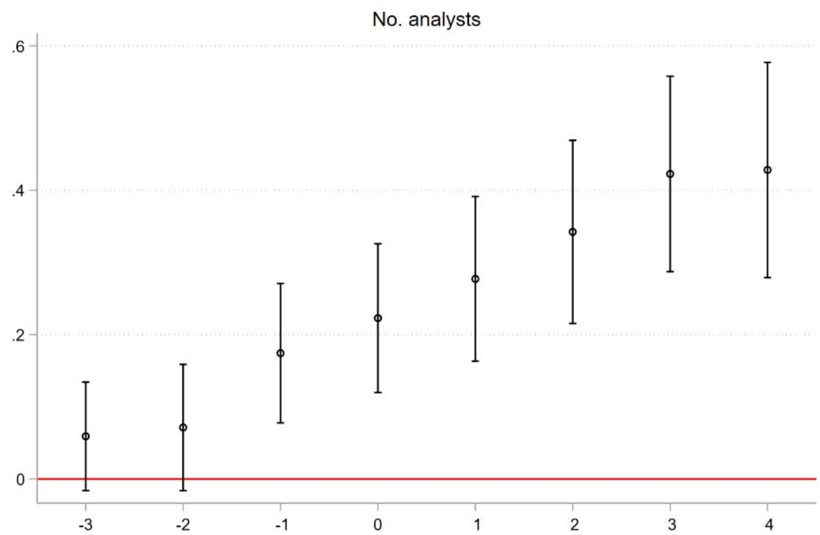

Figure 7. The Number of Listed Firms in the U.S., 1790-2019.

The figure shows the number of U.S. companies with common stock listed on the NYSE, AMEX, and NASDAQ each December, extracted from the Global Financial Database (GFD). Until 1953, AMEX was known as the New York Curb Exchange. NYSE Euronext acquired AMEX in October 2008 re-branded it first as NYSE Alternext US and later as NYSE MKT.

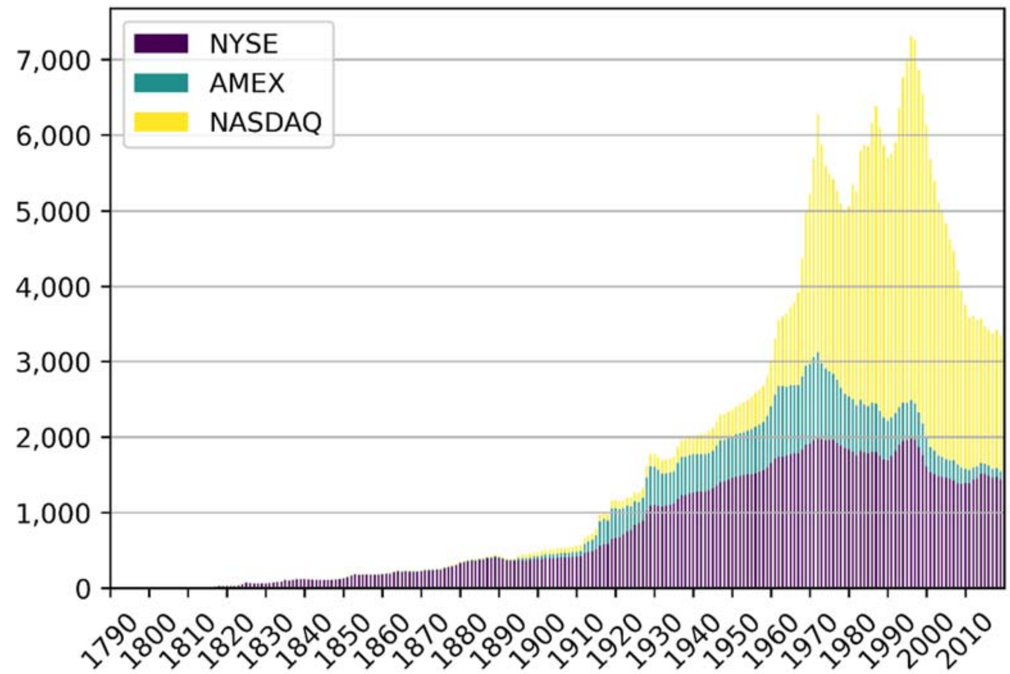

Table 1. Validating the Information-Relevance Assumption: Co- and Toggled Searches Around a Top 5 Peer's S-1 Filing.
Our identification strategy assumes that at least part of the information a top 5 peer discloses in its S-1 filing is "informationally relevant" to the already-listed firms it is linked to. We validate this assumption using Lee, Ma, and Wang's (2015) "co-search" approach. Using the EDGAR server logs, we construct two measures. First, we compute, for each treated firm and its matched control, the probability that an EDGAR user who searches the already-listed firm's EDGAR filings also searches the top 5 peer's S-1 filing on the same day. We compute this conditional "co-search" probability over three time windows: on the day the S-1 is filed, over the course of the week beginning with the S-1 filing, and over the course of the month from the S-1 filing date. Second, we restrict co-searches to those involving an EDGAR user going back and forth between the filings of the two firms, in the pattern A→B→A or B→A→B ("toggled search"). Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and Amihud's (2002) illiquidity measure) and fiscal quarter using a 0.01 caliper.

	IPO firm is top 5 peer of already-listed firm			
	No. firms	Treated	Control	*t*-test (*p*)
Prob(co-search S-1 | searching already-listed firm's filings)				
Day of S-1 filing	2,714	0.047	0.018	0.000
Week beginning with S-1 filing	2,714	0.259	0.073	0.000
Month beginning with S-1 filing	2,714	0.577	0.124	0.000
Prob(toggle-search already-listed firm's filings | searching S-1)				
Day of S-1 filing	2,714	0.0012	0.0000	0.000
Week beginning with S-1 filing	2,714	0.0060	0.0002	0.000
Month beginning with S-1 filing	2,714	0.0117	0.0002	0.000

Table 2. Summary Statistics.

The table reports summary statistics for the outcome variables used in our analysis, separately for treated and control firms measured in levels and changes in the quarter before treatment. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and Amihud's (2002) illiquidity measure) and fiscal quarter using a 0.01 caliper. For variable definitions and details of their construction see Appendix B. The final two columns test whether the difference in pre-treatment changes between treated firms and their matched controls is statistically significant.

	Pre-treatment levels (quarter *t*-1)						**Pre-treatment changes (from quarter *t*-2 to quarter *t*-1)**							
	Treated firm-quarters			Control firm-quarters			Treated firm-quarters			Control firm-quarters			Treated - controls	
	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	Differ-ence	*t*-stat
Liquidity:														
Bid-ask spread	6,649	2.401	3.626	6,649	2.753	4.627	6,649	-0.107	1.531	6,649	-0.100	1.744	-0.007	-0.259
Log AIM	6,601	0.441	0.901	6,477	0.552	1.026	6,564	-0.035	0.415	6,419	-0.030	0.478	-0.005	-0.617
Fraction zero-return (%)	6,649	8.7	9.3	6,649	9.7	10.0	6,649	-0.370	5.875	6,649	-0.216	6.217	-0.154	-1.467
Effective tick	6,649	1.208	2.263	6,649	1.298	2.689	6,649	-0.060	1.623	6,649	-0.011	1.795	-0.049	-1.656
Voluntary disclosure:														
Guider	6,649	0.231	0.421	6,649	0.230	0.421	6,649	0.013	0.167	6,649	0.006	0.148	0.008	2.801
Quantitative guidance	6,649	0.101	0.301	6,649	0.093	0.291	6,649	0.010	0.250	6,649	0.003	0.245	0.007	1.611
Press releases (8-K)	5,770	0.839	0.694	5,841	0.807	0.686	5,503	0.037	0.517	5,555	0.028	0.505	0.009	0.957
DQ	6,643	0.743	0.145	6,643	0.715	0.170	6,642	0.005	0.060	6,643	0.003	0.066	0.002	1.994
Price convergence (%)	6,304	7.5	8.1	6,187	6.6	7.9	6,083	-0.074	10.755	5,958	-0.083	10.351	0.009	0.048
SUE (random walk)	5,845	0.042	0.437	5,543	0.039	0.221	5,615	-0.004	0.470	5,323	0.002	0.216	-0.006	-0.868
SUE (consensus)	3,910	0.318	18.284	3,182	0.026	0.115	3,551	0.320	19.186	2,901	-0.002	0.084	0.322	0.904
Analyst response:														
No. of analysts	6,649	4.7	6.3	6,649	4.1	6.0	6,649	0.113	2.080	6,649	-0.014	1.943	0.128	3.654
Informativeness (%)	4,847	11.6	10.7	4,361	11.5	10.6	4,522	0.308	8.991	4,038	0.066	8.615	0.242	1.269
Dispersion (%)	4,467	1.1	6.4	3,972	0.9	3.7	4,337	-0.006	7.783	3,881	0.100	2.916	-0.105	-0.794
Information demand:														
Earnings release day	3,191	24.8	53.2	3,191	26.2	56.1	3,181	2.010	33.980	3,175	1.261	33.508	0.750	0.885
10-Q or10-K filing day	3,191	13.0	22.1	3,190	14.4	23.2	3,174	0.351	22.831	3,168	-0.389	38.519	0.740	0.931

Table 3. Information Externalities on Focal Firms' Trading Liquidity.

The table reports difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on four standard measures of the already-listed firm's trading liquidity: bid-ask spreads, Amihud's (2002) illiquidity measure (AIM), Lesmond, Ogden, and Trzcinka's (1999) fraction of trading days with zero or missing returns, and Goyenko, Holden, and Trzcinka's (2009) effective tick measure. Treatment in columns 1 through 4 is the filing of an S-1 by an already-listed firm's top 5 peer, captured using binary treatment indicators. Treatment in columns 5 through 8 is the novelty of the information content of the S-1 filed by the already-listed firm's top 5 peer (coded following the approach of Hanley and Hoberg 2010), captured using continuous treatment variables. In either case, the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. The numbers of observations in columns 5 through 8 are lower than in columns 1 through 4 due to some S-1s not being machine-readable. The estimation panel includes data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Binary treatment				Continuous treatment			
	Bid-ask spread	log AIM	Return fraction	Effective tick	Bid-ask spread	log AIM	Return fraction	Effective tick
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quarter of top 5 peer filing its S-1	-0.071***	-0.014**	-0.183***	-0.031**	-0.089***	-0.018**	-0.245***	-0.030*
	0.021	*0.006*	*0.070*	*0.014*	*0.025*	*0.007*	*0.085*	*0.017*
Next four quarters	-0.027	-0.003	-0.122*	0.017	-0.052	-0.006	-0.179**	0.011
	0.030	*0.008*	*0.071*	*0.016*	*0.035*	*0.009*	*0.084*	*0.020*
Firm FE?	Y	Y	Y	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.874	0.855	0.804	0.769	0.875	0.850	0.796	0.757
# treated and control firm-quarters	13,298	13,199	13,298	13,298	11,689	11,619	11,689	11,689
# observations	114,230	112,254	114,230	114,302	100,914	99,398	100,914	100,983

Table 4. Focal Firms' Voluntary Disclosure Responses and Earnings Announcements.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on four standard measures of the already-listed firm's voluntary disclosure choices: whether to provide earnings guidance and if so, whether to provide quantitative earnings guidance, the number of 8-Ks, and Chen, Miao, and Shevlin's (2015) disclosure quality (DQ) measure, which captures the level of disaggregation of financial-statement data. To measure information released in connection with earnings announcements, we compute share price changes around earnings-announcement dates (price convergence) and construct two measures of standardized unexpected earnings (SUE). Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Voluntary disclosure				Earnings announcements		
	Guider (1)	Quantitative guidance (2)	Log no. of 8-Ks (3)	DQ (4)	Price convergence (5)	SUE (random walk) (6)	SUE (consensus) (7)
Quarter of top 5 peer filing its S-1	0.016***	0.007	0.010*	0.002***	0.080	0.000	0.001
	0.003	*0.009*	*0.006*	*0.001*	*0.108*	*0.001*	*0.001*
Next four quarters	0.029***	0.017**	0.022***	0.002**	0.255***	0.001	0.001
	0.005	*0.009*	*0.006*	*0.001*	*0.090*	*0.001*	*0.001*
Firm FE?	Y	Y	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y	Y	Y
R-squared	0.829	0.541	0.752	0.930	0.287	0.447	0.567
# treated and control firm-quarters	13,298	4,339	13,231	13,294	13,039	12,095	8,316
# observations	114,355	37,765	105,837	114,213	107,923	98,835	60,398

Table 5. Analyst Coverage, Informativeness, and Dispersion at Focal Firms.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on three standard measures of sellside analyst behavior: the number of analysts who cover the firm (capturing the extensive treatment margin), the informativeness of their forecasts (measured as the price impact that can be attributed to forecast revisions, following Lehavy, Li, and Merkley 2011 and Merkley, Michaely, and Pacelli 2017), and the dispersion in their forecasts. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	No. of analysts (1)	Informative-ness (2)	Forecast dispersion (3)
Quarter of top 5 peer filing its S-1	0.125***	0.115	0.048*
	0.027	*0.121*	*0.028*
Next four quarters	0.250***	0.376***	0.095**
	0.032	*0.112*	*0.042*
Firm FE?	Y	Y	Y
Time FE?	Y	Y	Y
Controls?	Y	Y	Y
R-squared	0.934	0.676	0.516
# treated and control firm-quarters	13,298	10,378	9,248
# observations	114,355	78,755	72,644

Table 6. Changes in Investors' Information Demand at Focal Firms.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on investor demand for information about the already-listed firm, measured as EDGAR searches of the already-listed firm's filings on two alternative days each fiscal quarter: the day the firm announces its quarterly or annual earnings (in column 1) and the day the firm files its 10-Q or 10-K (in column 2). In the former case, we count the total number of human searches of the 10-Qs, 10-Ks, and 8-Ks the firm filed in the previous four quarters (given that firms announce earnings some time before filing the corresponding 10-Q or 10-K). In the latter case, we count the total number of human searches of the newly filed 10-Q or 10-K. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. EDGAR search data are only available for the period February 2003 to June 2017. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	EDGAR searches on the day…	
	earnings are announced (1)	a 10-Q/K is filed (2)
Quarter of top 5 peer filing its S-1	0.041***	0.015
	0.014	*0.015*
Next four quarters	0.049***	0.038***
	0.013	*0.014*
Firm FE?	Y	Y
Time FE?	Y	Y
Controls?	Y	Y
R-squared	0.823	0.722
# treated and control firm-quarters	6,651	6,602
# observations	55,377	55,136

Table 7. Testing for Strategic S-1 Disclosures.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on bid-ask spreads, earnings guidance, analyst coverage, the informativeness of analyst forecasts, and investor demand for information. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We interact treatment with an indicator capturing whether the already-listed firm in turn is a top 5 peer of the IPO firm ("reciprocity"). We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	Guider (2)	No. of analysts (3)	Informative-ness (4)	EDGAR searches on earnings release days (5)
Quarter of top 5 peer filing its S-1	-0.099***	0.009**	0.095***	0.208	0.025
	0.028	*0.004*	*0.032*	*0.157*	*0.017*
x is top 5 peer of IPO firm	0.071*	0.017***	0.079	-0.211	0.043
	0.038	*0.006*	*0.056*	*0.229*	*0.026*
Next four quarters	-0.049	0.021***	0.146***	0.313**	0.041***
	0.037	*0.005*	*0.036*	*0.131*	*0.015*
x is top 5 peer of IPO firm	0.056	0.019**	0.267***	0.145	0.022
	0.046	*0.008*	*0.058*	*0.178*	*0.020*
Firm FE?	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y
R-squared	0.874	0.829	0.934	0.676	0.823
# treated and control firm-quarters	13,298	13,298	13,298	10,378	6,651
# observations	114,230	114,355	114,355	78,755	55,377

Table 8. Placebo Tests.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's peer filing an S-1 on bid-ask spreads, earnings guidance, analyst coverage, the informativeness of analyst forecasts, and investor demand for information. Unlike in previous tables, treatment is the filing of an S-1 by an already-listed firm's *bottom 5* peer in cases where the already-listed firm is a top 5 peer of the S-1 filer. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	Guider (2)	No. of analysts (3)	Informative-ness (4)	EDGAR searches on earnings release days (5)
Quarter of bottom 5 peer filing its S-1	-0.089	0.002	0.320***	0.294	0.018
	0.125	*0.013*	*0.107*	*0.531*	*0.055*
Next four quarters	-0.066	0.018	0.257**	0.239	-0.034
	0.163	*0.021*	*0.120*	*0.484*	*0.056*
Firm FE?	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y
R-squared	0.842	0.821	0.935	0.658	0.863
# treated and control firm-quarters	728	728	728	539	332
# observations	6,293	6,300	6,300	4,134	2,851

Table 9. Intensity of Treatment.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on bid-ask spreads, earnings guidance, analyst coverage, the informativeness of analyst forecasts, and investor demand for information. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We interact treatment with an indicator capturing whether it is the second or third time an already-listed firm experiences a top 5 peer filing for an IPO ("wave 2" or "wave 3", respectively). We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	Guider (2)	No. of analysts (3)	Informative-ness (4)	EDGAR searches on earnings release days (5)
Quarter of top 5 peer filing its S-1	-0.114***	0.025***	0.179***	0.358**	0.063***
	0.031	*0.004*	*0.035*	*0.154*	*0.022*
x wave 2	0.046	-0.014**	-0.082	-0.491*	-0.009
	0.046	*0.007*	*0.064*	*0.278*	*0.033*
x wave 3	0.153***	-0.029***	-0.150**	-0.473	-0.052*
	0.038	*0.007*	*0.070*	*0.309*	*0.030*
Next four quarters	-0.078*	0.043***	0.403***	0.788***	0.078***
	0.042	*0.006*	*0.041*	*0.135*	*0.019*
x wave 2	0.094*	-0.021**	-0.269***	-0.893***	-0.024
	0.055	*0.010*	*0.068*	*0.220*	*0.026*
x wave 3	0.129***	-0.043***	-0.417***	-0.784***	-0.060***
	0.044	*0.009*	*0.075*	*0.234*	*0.023*
Firm FE?	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y
R-squared	0.874	0.829	0.934	0.677	0.823
Wald tests (*p*-value):					
wave 2=0, shock quarter	0.056	0.061	0.070	0.576	0.036
wave 3=0, shock quarter	0.116	0.569	0.625	0.675	0.600
wave 2=0, next 4 quarters	0.716	0.008	0.020	0.586	0.007
wave 3=0, next 4 quarters	0.091	0.983	0.833	0.986	0.289
# treated and control firm-quarters	13,298	13,298	13,298	10,378	6,651
# observations	114,230	114,355	114,355	78,755	55,377

INTERNET APPENDIX

for

Information Externalities Among Listed Firms [†]

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Table IA.1. Adverse Selection Risk.

The table reports difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on a measure of adverse selection risk: Venter and DeJongh's (2006) version of Easley et al.'s (1996) probability of informed trading (PIN) measure. Note that PIN data are available only through fiscal year 2010. Treatment in column 1 is the filing of an S-1 by an already-listed firm's top 5 peer, captured using binary treatment indicators. Treatment in column 2 is the novelty of the information content of the S-1 filed by the already-listed firm's top 5 peer (coded following the approach of Hanley and Hoberg 2010), captured using continuous treatment variables. In either case, the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. The number of observations in column 2 is lower than in column 1 due to some S-1s not being machine-readable. The estimation panel includes data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Binary treatment	Continuous treatment
	PIN	PIN
	(1)	(2)
Quarter of top 5 peer filing its S-1	-0.475***	-0.435***
	0.149	*0.173*
Next four quarters	-0.411***	-0.316*
	0.159	*0.177*
Firm FE?	Y	Y
Time FE?	Y	Y
Controls?	Y	Y
R-squared	0.648	0.669
# treated and control firm-quarters	10,726	9,125
# observations	88,837	75,690

Table IA.2. Continuous Treatments: Voluntary Disclosure and Analyst response.

The table reports continuous-treatment difference-in-differences estimates of the effects of the novelty of the information contained in an a top 5 peer's S-1 filing on the voluntary disclosure measures used in Table 4 and the analyst response measures used in Table 5. The novelty of the information content of the S-1 filed by the already-listed firm's top 5 peer is coded following the approach of Hanley and Hoberg (2010). The already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. The numbers of observations are somewhat lower than in the corresponding binary-treatment models in Tables 3 through 5 due to some S-1s not being machine-readable. The estimation panel includes data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Voluntary disclosure				Analyst response		
	Guider (1)	Quantitative guidance (2)	Log no. of 8-Ks (3)	DQ (4)	No. of analysts (5)	Informativeness (5)	Forecast dispersion (5)
Continuous treatment							
Quarter of top 5 peer filing its S-1	0.014***	0.002	0.012*	0.002**	0.147***	0.165	0.054
	0.004	*0.010*	*0.007*	*0.001*	*0.033*	*0.144*	*0.033*
Next four quarters	0.025***	0.022**	0.023***	0.002**	0.267***	0.344**	0.107**
	0.006	*0.010*	*0.007*	*0.001*	*0.038*	*0.134*	*0.052*
Firm FE?	Y	Y	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y	Y	Y
R-squared	0.836	0.551	0.749	0.933	0.937	0.677	0.512
# treated and control firm-quarters	11,689	4,018	11,655	11,685	11,689	9,239	8,257
# observations	101,017	35,042	96,713	100,905	101,017	70,849	65,343

Table IA.3. Focal Firms' Earnings Management Responses.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on four standard measures of the already-listed firm's earnings management choices: discretionary accruals (either measured using Kothari, Leone, and Wasley's (2005) performance-matched discretionary accruals or obtained from Dechow, Sloan, and Sweeney's (1995) modified Jones model) and the tendency for a firm's reported earnings to narrowly meet-or-beat analyst consensus forecasts, with consensus measured either as the mean or the median of outstanding forecasts. (Malmendier and Tate (2009) show that the pressure to avoid missing consensus can induce CEOs to manage earnings to at least meet consensus. This shows up in the empirical distribution of earnings surprises as bunching in the interval from a zero to one cent difference between reported earnings and consensus.) Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Discretionary accruals (Kothari) (1)	Discretionary accruals (Jones) (2)	Meet-or-beat (median) (3)	Meet-or-beat (mean) (4)
Quarter of top 5 peer filing its S-1	0.000	0.000	-0.007	-0.009
	0.001	*0.001*	*0.007*	*0.006*
Next four quarters	0.000	-0.001	-0.004	-0.006
	0.001	*0.001*	*0.006*	*0.005*
Firm FE?	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y
Controls?	Y	Y	Y	Y
R-squared	0.107	0.192	0.239	0.226
# treated and control firm-quarters	12,965	13,016	9,740	9,740
# observations	105,543	110,442	70,850	70,850

Table IA.4. Summary Statistics, Placebo Sample.

The table reports summary statistics for the placebo sample used in Table 8 in the main text, separately for treated and control firms measured in levels and changes in the quarter before treatment. Unlike in previous tables, treatment is the filing of an S-1 by an already-listed firm's *bottom 5* peer in cases where the already-listed firm is a top 5 peer of the S-1 filer. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. For variable definitions and details of their construction see Appendix B in the main text. The final two columns test whether the difference in pre-treatment changes between treated firms and their matched controls is statistically significant.

	Pre-treatment levels (quarter *t*-1)						**Pre-treatment changes (from quarter *t*-2 to quarter *t*-1)**							
	Treated firm-quarters			Control firm-quarters			Treated firm-quarters			Control firm-quarters			Treated - controls	
	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	# obs.	Mean	Std. dev.	Differ-ence	*t*-stat
Liquidity:														
Bid-ask spread	364	2.933	4.110	364	3.554	8.441	364	-0.183	1.761	364	-0.096	2.700	-0.087	-0.515
Log AIM	359	0.553	1.015	352	0.578	1.003	359	-0.042	0.412	350	-0.007	0.409	-0.036	-1.154
Fraction zero-return (%)	364	10.7	10.3	364	10.8	10.5	364	-0.384	6.245	364	-0.674	6.265	0.290	0.626
Effective tick	364	1.317	2.099	364	1.462	2.687	364	-0.018	1.166	364	-0.075	2.187	0.057	0.437
Voluntary disclosure:														
Guider	364	0.228	0.420	364	0.212	0.409	364	0.005	0.166	364	0.014	0.189	-0.008	-0.626
Quantitative guidance	364	0.080	0.271	364	0.074	0.262	364	-0.003	0.262	364	0.003	0.283	-0.005	-0.272
Press releases (8-K)	325	0.812	0.693	327	0.778	0.725	300	0.051	0.494	307	0.077	0.467	-0.026	-0.673
DQ	364	0.756	0.116	364	0.728	0.154	364	-0.002	0.061	364	0.008	0.065	-0.011	-2.314
Price convergence (%)	345	7.3	7.6	336	7.5	8.4	330	-0.323	10.154	320	0.829	10.251	-1.152	-1.439
SUE (random walk)	314	0.030	0.084	303	0.044	0.167	300	-0.012	0.187	286	-0.114	2.027	0.102	0.867
SUE (consensus)	183	0.024	0.115	167	0.017	0.031	162	-0.014	0.133	156	-0.003	0.030	-0.011	-1.016
Analyst response:														
No. of analysts	364	3.8	5.3	364	3.9	5.8	364	-0.022	2.105	364	0.088	1.620	-0.110	-0.789
Informativeness (%)	242	11.1	9.4	232	11.1	10.1	226	0.106	8.908	211	0.499	8.413	-0.392	-0.473
Dispersion (%)	226	0.4	0.8	210	0.8	1.4	219	-0.080	1.265	205	0.148	0.901	-0.229	-2.129
Information demand:														
Earnings release day	164	31.8	50.2	164	24.4	44.8	163	3.816	22.703	164	2.110	27.393	1.706	0.613
10-Q or10-K filing day	136	15.9	19.7	119	17.7	19.1	118	-2.780	21.999	108	-0.912	20.692	-1.868	-0.656

Table IA.5. Placebo Test: Trading Externalities on Focal Firms' Liquidity.

The table reports difference-in-differences estimates of the effects of an already-listed firm's top 5 peer's stock starting to trade on four standard measures of the already-listed firm's trading liquidity: bid-ask spreads, Amihud's (2002) illiquidity measure (AIM), Lesmond, Ogden, and Trzcinka's (1999) fraction of trading days with zero or missing returns, and Goyenko, Holden, and Trzcinka's (2009) effective tick measure. As in the baseline sample, control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. The estimation panel includes data from a nine-fiscal quarter window centered on the fiscal quarter in which the top 5 peer's stock starts to trade. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	log AIM (2)	Return fraction (3)	Effective tick (4)
Quarter of top 5 peer's stock starting to trade	-0.025	-0.007	-0.067	-0.012
	0.020	*0.005*	*0.059*	*0.013*
Next four quarters	0.022	0.010	0.060	0.042***
	0.027	*0.007*	*0.062*	*0.015*
Firm FE?	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y
Controls?	Y	Y	Y	Y
R-squared	0.868	0.862	0.806	0.765
# treated and control firm-quarters	16,698	16,570	16,698	16,698
# observations	143,847	141,202	143,846	143,938

Table IA.6. Industry Conditions Around S-1 Filings: PIN, Volatility, and Tobin's Q.

The table reports difference-in-differences estimates of changes in three measures of industry conditions around an already-listed firm's top 5 peer filing an S-1: PIN, share return volatility, and Tobin's Q. For each of these measures, we use the market-value-weighted average in the already-listed firm's TNIC industry. Note that PIN data are available only through fiscal year 2010. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use *** and ** to denote significance at the 1% and 5%, respectively.

	Industry PIN (1)	Industry volatility (2)	Industry Tobin's Q (3)
Quarter of top 5 peer filing its S-1	0.000	0.041***	0.237***
	0.001	*0.013*	*0.077*
Next four quarters	0.001	0.048***	0.202***
	0.001	*0.015*	*0.049*
Firm FE?	Y	Y	Y
Time FE?	Y	Y	Y
Controls?	Y	Y	Y
R-squared	0.742	0.760	0.612
# treated and control firm-quarters	10,542	13,082	13,081
# observations	85,620	109,557	109,517

Table IA.7. Focal Firms' Fund-Raising Around S-1 Filings.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on five measures of fund-raising: net issuance of equity or long-term debt and short-term, long-term, and total leverage. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use *** and ** to denote significance at the 1% and 5%, respectively.

	Net issuance of common and preferred stock (1)	Net issuance of long-term debt (2)	Short-term leverage (3)	Long-term leverage (4)	Total leverage (5)
Quarter of top 5 peer filing its S-1	-0.003	0.003	-0.002	0.002	0.002
	0.004	*0.003*	*0.002*	*0.002*	*0.002*
Next four quarters	-0.004	0.006	-0.001	0.002	0.001
	0.004	*0.004*	*0.002*	*0.002*	*0.003*
Firm FE?	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y
R-squared	0.696	0.684	0.668	0.777	0.773
# treated and control firm-quarters	13,298	13,298	13,298	13,298	13,298
# observations	114,355	114,355	114,355	114,355	114,355

Table IA.8. Disentangling Information Effects from Competitive Effects.

The table reports difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on four standard measures of the already-listed firm's trading liquidity: bid-ask spreads, Amihud's (2002) illiquidity measure (AIM), Lesmond, Ogden, and Trzcinka's (1999) fraction of trading days with zero or missing returns, and Goyenko, Holden, and Trzcinka's (2009) effective tick measure. We interact treatment with an indicator set equal to one if the S-1 filer ranks among the already-listed firm's top 5 product-market competitors by market share. (Results are robust to alternative cutoffs and to using all market share ranks as a continuous variable.) The estimation panel includes data from a nine-fiscal quarter window centered on the fiscal quarter in which the top 5 peer's stock starts to trade. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	log AIM (2)	Return fraction (3)	Effective tick (4)
Quarter of top 5 peer's S-1 filing	-0.069***	-0.014**	-0.194***	-0.029**
	0.022	*0.006*	*0.073*	*0.014*
x S-1 filer is top 5 competitor of IPO firm	-0.014	-0.003	0.098	-0.021
	0.070	*0.020*	*0.229*	*0.048*
Next four quarters	-0.024	-0.003	-0.117	0.020
	0.030	*0.008*	*0.072*	*0.016*
x S-1 filer is top 5 competitor of IPO firm	-0.031	0.003	-0.043	-0.027
	0.087	*0.021*	*0.190*	*0.050*
Firm FE?	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y
Controls?	Y	Y	Y	Y
R-squared	0.874	0.855	0.804	0.769
# treated and control firm-quarters	13,298	13,199	13,298	13,298
# observations	114,230	112,254	114,230	114,302

IA.2. Auxiliary product-market channel tests

In this section, we report two auxiliary tests that help disentangle the information effects of a peer's S-1 filing from potential competition-related effects. The first test exploits the fact that not every firm that goes public raises capital. The second exploits the fact that not every firm that files for an IPO also completes the IPO.

Columns 1 through 4 of Table IA.9 interact our two treatment indicators with an indicator for secondary-only IPOs.[28] The interaction effects are not statistically significant for any of our four liquidity measures, indicating that the filing of a top 5 peer's S-1 has the same effect on an already-listed firm's liquidity whether or not the peer raises fresh capital in its IPO.

Columns 5 through 8 of Table IA.9 add to our baseline estimation sample a sample of already-listed firms that are treated by a top 5 peer's S-1 filing that does not result in a stock market listing (along with their matched controls). Withdrawn IPOs involve the same extensive S-1 disclosures as completed IPOs, but leave the peer without fresh capital. Here too the interaction effects are not statistically significant for any of our four liquidity measures, indicating that the filing of a top 5 peer's S-1 has the same effect on an already-listed firm's liquidity whether or not the peer completes or abandons its IPO.

[28] Going public without raising capital for the firm involves selling only secondary shares (i.e., shares belonging to existing pre-IPO shareholders). We identify secondary-only IPOs using the algorithm outlined in Asker, Farre-Mensa, and Ljungqvist (2015).

Table IA.9. Auxiliary Tests of Product-Market Channels.

The table reports binary-treatment difference-in-differences estimates of the effects of an already-listed firm's top 5 peer filing an S-1 on four standard measures of the already-listed firm's trading liquidity: bid-ask spreads, Amihud's (2002) illiquidity measure (AIM), Lesmond, Ogden, and Trzcinka's (1999) fraction of trading days with zero or missing returns, and Goyenko, Holden, and Trzcinka's (2009) effective tick measure. Treatment is the filing of an S-1 by an already-listed firm's top 5 peer; the already-listed firm is the treated firm. Control firms are nearest-neighbor propensity-score matched on pre-treatment liquidity (using bid-ask spread and AIM) and fiscal quarter using a 0.01 caliper. Columns 1 through 4 interact the treatment indicators with an indicator set equal to one for IPOs by top 5 peers that raise no new capital for the firm ("secondary-only IPOs"). Columns 5 through 8 include a second set of treated and control firms, constructed using S-1 filings associated with subsequently withdrawn IPOs. We include data from a nine-fiscal quarter window centered on the fiscal quarter in which the S-1 is filed. All specifications are estimated using OLS and include controls (the one-quarter lag of log market cap as well as fixed effects for calendar-quarter, fiscal-quarter, and firm). For variable definitions and details of their construction see Appendix B. Heteroskedasticity consistent standard errors clustered at the firm level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

	Bid-ask spread (1)	log AIM (2)	Return fraction (3)	Effective tick (4)	Bid-ask spread (5)	log AIM (6)	Return fraction (7)	Effective tick (8)
Quarter of top 5 peer filing its S-1	-0.072***	-0.015**	-0.187***	-0.032**	-0.065***	-0.013**	-0.174**	-0.027*
	0.021	*0.006*	*0.070*	*0.014*	*0.021*	*0.006*	*0.070*	*0.014*
x secondary-only IPO	0.077	0.097	0.527	0.060				
	0.212	*0.065*	*0.704*	*0.098*				
x IPO subsequently withdrawn					0.005	0.012	-0.379	-0.051
					0.077	*0.023*	*0.256*	*0.053*
Next four quarters	-0.030	-0.004	-0.126*	0.016	-0.023	-0.001	-0.116*	0.022
	0.030	*0.008*	*0.071*	*0.016*	*0.030*	*0.008*	*0.071*	*0.016*
x secondary-only IPO	0.360	0.121	0.639	0.178				
	0.349	*0.078*	*0.617*	*0.177*				
x IPO subsequently withdrawn					-0.076	-0.005	-0.056	-0.076
					0.092	*0.025*	*0.204*	*0.058*
Firm FE?	Y	Y	Y	Y	Y	Y	Y	Y
Time FE?	Y	Y	Y	Y	Y	Y	Y	Y
Controls?	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.874	0.855	0.804	0.769	0.873	0.855	0.802	0.765
# treated and control firm-quarters	13,298	13,199	13,298	13,298	13,920	13,816	13,920	13,920
# observations	114,230	112,254	114,230	114,302	119,576	117,517	119,576	119,656