Analyst Coverage Networks and Corporate Financial Policies*

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Abstract

Sell-side analysts help propagate corporate capital structure choices across firms. Using exogenous characteristics of analyst network peers as well as the "friends-of-friends" approach, we find that changes to financial policies of firms covered by an analyst lead other firms covered by the same analyst to implement similar policy choices. Consistent with analysts playing an important role in transmitting information about financial policies across firms, these analyst network peer effects are more pronounced among peers connected by analysts that are more experienced and from more influential brokerage houses, and weaken following the curbs on selective disclosure imposed by Regulation FD.

Keywords: Analyst network; Friends of friends; Peer effects; Equity shock; Capital structure

JEL classification: G12;G24;G30;G32;

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1 Introduction

A growing literature documents the importance of peer effects in corporate policies.[1] Yet, the mechanisms through which firms learn about, and are influenced by, the choices of their peers are still not fully understood. In this paper, we study the role of security analysts in transmitting financial policy-relevant information across firms.

Sell-side analysts are important players in financial markets. Their role in acquiring, analyzing, and disseminating information for investors has been much studied.[2] In their role as information intermediaries, analysts not only learn about firm performance and prospects from company disclosures and conversations with managers, but may also communicate their assessment of market conditions and preferred firm policies to management during meeting with managers, conference calls and through their research reports. Since analysts typically cover a portfolio of firms, the two-way communication between an analyst and management can also result in the propagation of financial policies across the firms in an analyst's portfolio. Our objective is to identify the propagation of financial policies through analyst networks.[3]

Apart from regularly communicating with the firms, analysts also employ common models to value the firms and benchmark them with one another. During the course of their communication and valuation, analysts obtain information that can be transferred to other firms. Such information can be about the state of financial markets, growth opportunities, a particular financial policy etc., and may originate either from a particular portfolio firm or from the analyst.[4] If analysts communicate such intelligence to other portfolio firm managers and if such firms act on this information, then we expect financial policies to propagate from

[1] Examples include Matvos and Ostrovsky (2010); Shue (2013); Leary and Roberts (2014); Kaustia and Rantala (2015); Fracassi (2016).

[2] See, for example, Frankel et al. (2006), Kadan et al. (2012); Muslu et al. (2014); Chang et al. (2006); Piotroski and Roulstone (2004)and Piotroski and Roulstone (2004)

[3] We note that recent research has shown that analysts can influence firm policies either directly by exerting influence (Degeorge et al. (2013); Becher et al. (2015)) or indirectly, if managers alter firm policies to meet analyst forecasts, (Bhojraj et al. (2009); Gunny (2010); Hribar et al. (2006)). We differ from this earlier work in that we study the information flow from one firm to another in an analyst network.

[4] As we explain below, our tests will help isolate the effect of information that originates from a portfolio firm.

one firm to another within the analyst's portfolio. We use the latest identification techniques from the social networks literature to document the causal effect of analyst peer firm financial policies on a firm's financial policy. Note that although the policies of peer firms may be public knowledge, we believe analysts may play an important role in communicating the nuances of the policy to other firms and enable management to better assess the suitability of the policy for the firm.

We focus on financial policies such as leverage, debt issuance, and equity issuance. We classify all firms that share a common analyst with a firm as its "analyst peers" and relate the firm's financial policy to the weighted average financial policy of its analyst peers. We use the number of common analysts between the firm and its peer firms as the weights. This methodology gives rise to a network, which we refer to as the analyst coverage network – i.e., the graph where the firms are the nodes and the weighted edges between two firms are the number of common analysts between the firms.

We begin by documenting a positive association between a firm's financial policy and that of its analyst peers. The association holds for leverage in levels and changes as well as debt and equity issuance decisions, and is robust to controlling for firm characteristics, analyst peer characteristics, the average policies of industry peers and industry peer characteristics. When we differentiate between within industry analyst peers and outside industry analyst peers we find that the association extends to both sets of peers.

As discussed by Manski (1993), a positive association between a firm's policy and that of its peers can arise from multiple sources. First, there can be one or more unobserved common characteristic between the firm and its peers which makes them follow similar policies. This is what Manski (1993) calls "correlated effects". For example, firms in the same analyst network may operate in similar product markets or be of similar size. This is especially likely given that analysts cover firms with common underlying economic features. Firms with common analysts may also follow similar policies due to the preferences of their common analysts (Degeorge et al. (2013)). These common characteristics can result in the

firms choosing similar financial policies for reasons unrelated to analyst peer effects. We conduct several empirical tests to provide evidence that analyst peer effects are distinct from such correlated effects.

To start, we control for correlated effects following the procedure of Leary and Roberts (2014). Specifically, we use idiosyncratic equity return shocks as an exogenous source of variation in peer firm financial policy (and possibly characteristics) and relate it to a firm's financial policy. A large prior literature in finance shows that firms change their leverage, debt and equity issuance decision in response to changes to their stock price (Marsh (1982); Baker and Wurgler (2002)), which support the relevance of our instrument. To the extent we are able to isolate idiosyncratic shocks to peer firm's equity value, the shocks are unlikely to be correlated with the characteristics of the firm in question and thus any peer effects we document are unlikely to include correlated effects. In constructing the idiosyncratic equity shock, we estimate an augmented market model controlling for the average returns of analyst peers.

We estimate reduced-form regressions that establish a robust association between a firm's financial policy and the idiosyncratic return shocks of its analyst network peers. We find that this association is robust to controlling for the financial policies, characteristics, and return shocks of the firm's industry peers, suggesting that the analyst network effect is distinct from an industry effect.[5] The positive association exists for leverage, changes in leverage, equity issues and share repurchases. We also use the idiosyncratic shock to peer firms' stock prices as an instrument for peer firm financial policies in a two-stage least squares (2SLS) specification and document a positive association between a firm's financial policy and analyst peer policies that is distinct from correlated effects. We refer to this as "social effects".

[5]We conduct our tests using traditional industry classification measures based on three-digit SIC codes, and also alternative industry classifications such as the Fama-French industry clasifications, the Hoberg-Phillips industry peers (Hoberg and Phillips (2010)) and S&P GICS codes to allow for the possibility that alternative industry grouping better capture economic commonalities across firms. Our results on the analysts' peer effect are robust across these various industry definitions.

Idiosyncratic changes to peer firms' stock price can influence a firm's policies either because the return shocks affect the peers' financial policies or because the return shocks reflect changes to one or more of the peers' characteristics.[6] Firms may change their financial policy in response to changes in peer firm characteristics, especially if there are underlying economic linkages between firms in an analyst network. For example, if a peer firm gets a new investment opportunity, a firm may respond by possibly changing its investment and financial policy. This is what Manski (1993) calls "exogenous peer effects", since it is the change in an "exogenous" characteristic of the peer that drives the change in financial policy. Alternatively, firms may respond specifically to analyst peers' financial policy choices (what Manski (1993) refers to as "endogenous peer effect"). Distinguishing between exogenous and endogenous effects is relevant since, for example, there are policy interventions such as targeted industry tax subsidies for debt financing, which may influence the financial policy of peers while leaving their fundamentals unchanged. These policies may generate multiplier effects through endogenous peer effects (Glaeser et al. (2003)).

To distinguish endogenous peer effects from exogenous peer effects, we exploit the fact that we can observe intransitive triads in the analyst network. That is, we can observe firm triads i, j and k, such that firms i & j and firms j & k have common analysts while firms i & k do not have any.[7] As shown by Bramoullé et al. (2009) and Goldsmith-Pinkham and Imbens (2013), this is a key property of the analyst coverage network that allows for identification of peer effects by exploiting the "friends of friends" approach. Note that this methodology can identify endogenous peer effect - a firm changing its financial policy in response to peer firm financial policy – even if the analyst network is endogenous because analysts choose firms with common (unobserved) economic linkages to cover.

We use the exogenous characteristic of firm k, namely idiosyncratic equity shock, as an

[6] Or perhaps both. For example, a shock to a peer firm's investment opportunities that generates a positive return shock may affect the peer's investment behavior and also elicit an equity issuance to fund the investment.

[7] Note that this is in contrast to, for example, peer effects arising due to industry membership. If firms i & j and j & k belong to the same industry, then i & k must also belong to the same industry.

instrument for the financial policy of firm j to document its influence on i's financial policy. We refer to firm k as an indirect peer of i. The exclusion restriction for this approach is that firm k's equity shock should influence firm i's financial policy only through its influence on firm j's financial policy and not otherwise. One necessary condition is that firm i does not respond directly to firm k's financial policies. This is reasonable given that the set of firms two analyst connections away is large and heterogeneous, consisting of firms that not only have no common analysts, but are also mostly in different industries.[8]

Identification also requires that firm k's equity shock should not be correlated with firm j's and firm i's characteristics. To the extent we are able to isolate "idiosyncratic shocks" to equity values of firm k, it is reasonable to assume that it is uncorrelated with firm j's characteristics. To the extent firm k and firm i do not even have common analysts, it is much more reasonable to expect idiosyncratic shocks to firm k's equity to be uncorrelated with firm i's characteristics. One potential threat to the former is if firm j is a supplier or customer to firm k, in which case economic shocks may have spillover effects. However, a major advantage of using shocks to firms outside of firm i's analyst network as instruments is that we can control for the stock returns of the firms within the analyst network. In that case, any identification threat would have to come from a shock to firm j that is a) significant enough to solicit a response from firm i, but b) not reflected in firm j's stock return, a scenario we consider unlikely.

We find robust evidence for endogenous peer effects using the friends of friend approach. The effects we document are economically significant. A one standard deviation increase in peer firm average leverage is associated with a 0.39 standard deviation increase in a firm's leverage. Peer effects are also present in a firm's decision to issue equity. A one standard deviation increase in net (gross) equity issuance likelihood by peers leads to a 0.33 (0.6) standard deviation increase in net (gross) equity issuance likelihood. Overall, after controlling for the endogeneity in the network formation we find that peer firms in the same

[8]In additional robustness test, we repeat our estimates after excluding all indirect peers in the same industry as firm i.

analyst coverage network affect each other. Note that the presence of endogenous peer effects is consistent with information originating in a portfolio firm being transmitted by the analyst to other firms in the network.

Our results clearly establish that firm financial policy responds to firms with common analysts. This can happen either if firms within the analyst network share economic linkages and react to each other's financial policies independent of the analyst, or if the analyst has a role in the propagation of the financial policy. We follow a two-pronged strategy to show evidence for the latter mechanism.

We first do a battery of tests to ensure that our results are not a result of common industry linkages. First, as mentioned before, in all our tests, we control for industry average policies, either directly or through industry average return shocks. Second, we find similar results when we focus on the firms in the analyst network that are not from the same industry as the firm in question. Third, we estimate a placebo test in which we define pseudo peer groups as firms in the same industry as a firm's direct analyst peers but that do not have a common analyst with the firm in question. We find no evidence of peer effects in this sample. These results are robust across various industry definitions such as Hoberg-Phillips industry peers and GICS code.

We next document cross-sectional variation in our estimated social effects that are unique to information transmission through the analyst network. First, we test to see if analysts that are expected to be more influential are more effective at transmitting information across firms. Consistent with this idea, we find stronger peer effects among firms connected by analysts from brokerage houses with more "all-star" rated analysts and by more experienced analysts. Second, we exploit the passage of Regulation Fair Disclosure (Reg FD), which curtailed the practice of selective disclosure of material information from management to analysts and institutional investors, and arguably reduced the informativeness and influence of analysts on corporate officers. We show that after Reg FD, direct peers connected by common analysts are significantly less important in influencing firm financial policies than

before, highlighting the unique importance of the analyst channel.

We make a number of important contributions. First, we document the important role that analysts play in propagating financial policies across firms. While previous studies document peer effects in firm financial policies, our paper identifies an important channel through which such peer effects may arise. An important question that we do not answer is whether such propagation is efficient or inefficient. Future research should explore this important question. Our second contribution is methodological to the finance literature, by employing the "friends of friends" approach to document the existence of endogenous peer effects. This approach can be productively used to document endogenous peer effects in other networks that partially overlap such as board networks and supply chain networks.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 discusses our data and empirical methodology. Section 4 discusses the empirical evidence and section 6 concludes.

2 Related Literature

Our paper is related to three main streams of literature. The first is the literature on the role of analysts in financial markets, the second is the vast literature on capital structure, the third is the one that explores the effect of social networks in corporate finance. Our paper's main contribution to these is to show that analysts play an important role in facilitating peer effects in capital structure policies and that analyst networks influence the way firms interact with one another.

A large literature studies the role of analysts as information intermediaries between firms and outside investors. Prior studies indicate that analysts acquire, analyze, and disseminate useful information to investors. Examples include Womack (1996); Piotroski and Roulstone (2004); Frankel et al. (2006); Kadan et al. (2012); Muslu et al. (2014), among others. Evi-

dence from Kelly and Ljungqvist (2012) suggests that the information produced by analysts is effective in reducing information asymmetry in financial markets. Additionally, a number of recent studies have shown evidence that analysts can impact the decisions of the firms they follow. For example, Chen et al. (2015) show that the monitoring activities of analysts help align managerial behavior with investor interests. Other studies show that analysts' information production impacts firms' cost of capital (Derrien and Kecskés (2013);Fracassi et al. (2014)), security issuance decisions (Chang et al. (2006)) and merger completion probability (Becher et al. (2015)). Degeorge et al. (2013) show evidence consistent with analysts having preferred financial policies, which their portfolio firms tend to adopt. Relative to these earlier studies, our study highlights a previously unexplored role of analysts in transmitting information across their portfolio firms resulting in peer effects in firm financial policies.

There is also a recent literature focused on understanding the role of analysts in transmitting information across firms. Specifically, Muslu et al. (2014) and Israelsen (2014) document stock return comovement between pairs of firms connected by common analysts. They argue that analysts provide common and useful information for connected firms. Petzev (2016) and Hilary and Shen (2013) also study how analysts facilitate information diffusion through connected firms. Finally, Brochet et al. (2016) examine information transfer during conference calls and show that the information discussed by analysts regarding one firm also affects the returns of firms connected by common coverage after the conference calls. We add to this literature by showing that analysts play an important role in propagating financial policies across connected firms.

The literature on firm capital structure is vast.[9] Among the papers in this literature, our paper is most closely related to Leary and Roberts (2014), which demonstrates the existence of peer effects in financing decisions among industry peers. Our analysis builds on their paper to show the important role analysts play in driving peer effects in leverage. We find that controlling for analyst peers reduces the magnitude of industry peer effects by half. We

[9]See survey papers by Frank and Goyal (2008a), Parsons and Titman (2008) and Graham and Leary (2011).

also borrow from and add to the identification technique used in Leary and Roberts (2014). While the Leary and Roberts (2014) approach helps identify social effects from correlated effects, the friends-of-friends approach helps distinguish endogenous from exogenous peer effects.

The last stream of literature our paper is related to explores how peer effects, or the interaction among agents, can affect outcomes. Most of this literature either provides evidence for information transmission through the networks or of correlated behavior by members of the network – which potentially could arise from information transmission. Evidence of network effects in corporate policies is shown by Shue (2013) and Fracassi (2016), while Matvos and Ostrovsky (2010) and Pool et al. (2015) document peer effects among mutual fund managers.

Our paper differs from these earlier ones in our focus on the role of analyst networks as a mechanism behind corporate peer effects. Kaustia and Rantala (2013, 2015) also examine peer effects within the context of analyst coverage networks. However, their focus is on stock split decisions and they use analyst networks to identify groups of related firms rather than study the role of analysts in transmitting information from one firm to another.

Our paper also differs methodologically from earlier studies of peer effects in corporate finance. As mentioned before, we are the first to use the friends-of-friends approach to differentiate endogenous peer effects from exogenous effects. Our main model is an extended version of the Manski-type linear-in-means model similar to those studied in Goldsmith-Pinkham and Imbens (2013) and Bramoullé et al. (2009) (see also the survey by Blume et al. (2010)).

3 Data and Empirical Methodology

3.1 Sample selection

We obtain our data from standard sources: financial information from Compustat, stock price information from CRSP, and analyst coverage information from IBES. From the overall CRSP-Compustat merged dataset, we exclude financial firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900 and 4949) and government companies (SIC codes greater than or equal to 9000). We then match the CRSP-Compustat sample to IBES and identify all firms that are connected to at least one other firm in the sample through a common analyst. We identify an analyst as following a firm in a fiscal year if she makes at least one earnings forecast during the year and the forecast is made at most six months before and three months after the end of the fiscal period. We also require the analyst to follow the pair of firms for at least two years in the entire sample for us to consider them to be connected through the analyst. Our sample spans the period 1993-2013 and includes 37,960 firm-year observations.

3.2 Empirical methodology

We begin by documenting the extent to which financial policies of analyst peers are associated with a firm's financial policy. We do that by estimating the following regression:

$$y_{ijt} = \alpha + \beta_1 y_{-it}^{ACN} + \beta_2 y_{-ijt}^{IND} + \gamma_1^{'} X_{-it-1}^{ACN} + \gamma_2^{'} X_{-ijt-1}^{IND} + \gamma_3^{'} X_{ijt-1} + \delta^{'} u_i + \phi^{'} v_t + \epsilon_{ijt} \quad (1)$$

where the indices i, j and t refer to firm, industry and year respectively. The dependent variables that we model are, *Leverage*, Δ *Leverage*, *Net Debt, Net Equity* and *Gross Equity*. All variables we use in our analysis are defined in Appendix A. *Net Debt*, *Net Equity* and *Gross Equity* are dummy variables that identify debt and equity issuances. These take a

value one if the firm issues debt (equity) in excess of 1% of total assets, and zero otherwise.[10] X_{ijt-1} is the set of firm-specific controls. Following Leary and Roberts (2014), we include lagged (one period) values of *Log(Sales)*, *Market to book*, *Tangibility* and *Profitability* as our controls. y_{-it}^{ACN} represents the weighted average value of the outcome variable for all the firms that are connected to firm i through common analysts (analyst network from now). The weights for each firm l in the analyst network equals the number of common analysts between firm l and firm i. Specifically:

$$y_{-it}^{ACN} = \frac{\sum_{i \neq l}^{I} n_{ilt} y_{lt}}{\sum_{i \neq l}^{I} n_{ilt}} \tag{2}$$

where n_{ilt} represents the number of common analysts between firm i and firm l. Note that in calculating y_{-it}^{ACN} we use the financial policies of peer firms in the current year along with the current network structure. We use a weighted average instead of a simple average to give more weight to peer firms with more common analysts. Such peers may have a stronger influence on a firm's financial policy because there is a greater likelihood that one or more analyst will transmit information across the firms. Our coefficient of interest is β_1. We also include a set of weighted average peer firm characteristics (X_{-it-1}^{ACN}) as controls. These are the same set of characteristics as included in X_{ijt-1} and discussed above. To calculate X_{-it-1}^{ACN}, we use the current network structure and lagged peer firm characteristics.

To distinguish the effect of analyst network peers from that of industry peers (Leary and Roberts (2014)), we also control for the average value of the outcome variable for all other firms in the same industry (based on three-digit SIC code), y_{-ijt}^{IND} (excluding the firm i) and their average characteristics, X_{-ijt-1}^{IND}, as additional controls.[11] In all the regressions, except for those with changes in *Leverage* as the outcome variable, we include firm- and year-fixed effects. For the regressions with change in leverage as the outcome variable, we include

[10] In all the regressions we use the 1% threshold for the gross and net equity (debt) issuances to define the indicator variable. We explicitly identify the cases in which we use a different threshold.

[11] We also create an alternative measure of industry average outcomes that includes only firms that are in the same industry as firm i, but are not in the same analyst network as firm i. In other words, we exclude the set of firms that overlap across the analyst coverage network and industry of firm i.

industry- and year-fixed effects. We also include the independent variables in first difference form in this specification. The standard errors we estimate are robust to heteroskedasticity and clustered at the firm-level.

As shown in Manski (1993), a significant β_1 can arise from one of three sources. First, it can reflect the fact that there are some unobserved similarities among firms in the same analyst network (correlated effects). These similarities may result in the firms choosing similar financial policies. Alternatively it can arise from firms responding to either the behavior (endogenous peer effects) or characteristics (exogenous peer effects) of the peer firms. To control for correlated effects, following Leary and Roberts (2014), we use idiosyncratic shocks to the value of the peer firm's equity as an instrument for their financial policy (or characteristic). We define expected returns based on a one-factor market model augmented to include the excess return on the analyst network portfolio. We use the equally-weighted portfolio returns of all firms that share a common analyst with a firm to calculate the excess returns. While the excess return on the analyst network firms does not necessarily represent a priced risk factor, we include it to absorb any common shocks that may affect firms in the same analyst network.[12] For example, Muslu et al. (2014) and Israelsen (2014) show that shared coverage explains comovement and excess comovement between pairs of stocks with common analysts. Thus, we model the firm's stock return as:

$$r_{it} = \alpha_{it} + \beta_{it}^{M}(rm_t - rf_t) + \beta_{it}^{ACN}(\bar{r}_{-it}^{ACN} - rf_t) + \eta_{it}$$

where the subscript t refers to time in months, rm_t and rf_t are the monthly return on the market and risk free asset respectively, $\bar{r}_{-it}^{ACN}$ is the equally weighted average return of all firms in the analyst network of firm i. We estimate this regression individually for each firm-year using a five year rolling window.[13] We then calculate *Equity shock* for firm i in year t as

[12] Leary and Roberts (2014) show evidence that this strategy produces idiosyncratic return estimates that are uncorrelated, both serially and cross-sectionally, within networks.

[13] In each year we calculate monthly peer returns using the firm's analyst network in that year. In order to calculate $\bar{r}_{it}^{ACN}$, we require that a firm has at least one peer firm with valid returns during the time period in which we estimate the loadings.

the difference between the return on the firm's stock in year t and the predicted return based on the market and peer portfolio excess returns during the year and the loadings estimated using the data from the prior five years. We require firms to have at least 24 months of historical data to estimate the above model. *Equity shock* represents the idiosyncratic shock to a firm's stock return. We then calculate the weighted average equity shock for the analyst network, *Equity shock*$_{-it}^{ACN}$, using the number of common analysts as the weights and the industry average equity shock, *Equity shock*$_{-ijt}^{IND}$, as the simple average equity shock for all firms in the same industry as firm i.

We use *Equity shock*$_{-it}^{ACN}$ as an instrument for y_{-it}^{ACN} and employ a reduced form model and 2SLS to estimate its effect on firm i's financial policy after controlling for industry corporate policy and industry characteristics. To the extent that *Equity shock*$_{-it}^{ACN}$ captures idiosyncratic shocks to the stock price and consequently leverage of analyst peer firms, it is unlikely to be correlated with firm i's characteristics. To this extent the reduced form model and the 2SLS will isolate the social effects and exclude correlated effects. The specific identifying assumptions that we make for this are the following. First, for instrument relevance we assume that *Equity shock*$_{-it}^{ACN}$ is correlated with the peer firm's financial policy either directly or indirectly through one or more characteristic. A large prior literature documents the important effect stock prices can have on firm financial policies (Marsh (1982); Baker and Wurgler (2002), among others) and stock price changes often reflect changes in firm characteristics such as investment opportunities, expected profitability or risk, which in turn have been shown to be important determinants of firm financial policies. This suggests the relevance assumption will be satisfied in our setting, which is further supported by strong first-stage results below. The second assumption we make to isolate social effects is that *Equity shock*$_{-it}^{ACN}$ is uncorrelated with firm i's characteristics. To the extent our procedure for defining *Equity shock*$_{-it}^{ACN}$ isolates truly idiosyncratic shocks, this assumption is likely to be valid. Leary and Roberts (2014) explore the properties of this instrument in depth and demonstrate its suitability in this context.

Note that our tests employing *Equity shock*$^{ACN}_{-it}$ as an instrument will not be able to isolate endogenous peer effects from exogenous peer effects because the idiosyncratic shock to equity values can change, or reflect changes in, some (possibly unobserved) peer firm characteristic and firms may respond to the changes to peer firm characteristic as opposed to the changes in peer firm behavior.

To help isolate the endogenous peer effects from exogenous peer effects, we exploit the fact that analyst networks partially overlap with each other, and we can find intransitive triads in the analyst network. Bramoullé et al. (2009) show that one can identify peer effects when there are intransitive triads, even when the analyst network is endogenous, say because analysts choose to cover firms with common (unobserved) features. In other words, in our network there are triads i, j and k, such that firms i & j and firms j & k have common analysts while firms i & k do not have any common analyst. Following the "friends-of-friends" approach outlined in Bramoullé et al. (2009), we use the characteristic of firm k (namely *Equity shock*) as an instrument for the financial policy of firm j to identify its influence on firm i's financial policy. In our subsequent discussion we refer to firm k as an indirect peer of firm i. Note that we use a slightly modified and in some senses a stricter version of the friends-of-friends approach proposed by Bramoullé et al. (2009). To identify endogenous peer effects, they only require that some of the indirect peers not be direct peers of the firm in question. If that is true then one can use the characteristics of *all* the indirect peers as instruments for peer firm behavior. In our tests we use the *Equity shock* of only the indirect peers that are not direct peers of the firm in question to instrument for peer firm behavior. By construction, there are no analysts in common between firms i and its indirect peers. Therefore, the specific instrument we employ is the simple average *Equity shock* of the indirect peers.

The identifying assumptions necessary for us to isolate the endogenous peer effects are as follows. First, we require that the *Equity shock* of firm k be correlated with the behavior of firm j. This will happen as long as there are some social effects in analyst networks, which

our earlier results confirm. Our second assumption has two parts to it. First, we require firm k's equity shock to not be correlated with firm j's characteristic. Note that this is exactly the same as the exclusion restriction in our IV estimate and is also similar to the assumption in Leary and Roberts (2014). The second part of our assumption is that firm k's equity shock not be correlated with firm i's characteristic. Note that this assumption is more easily satisfied than the previous assumption as in addition to our instrument being idiosyncratic, firm i and firm k do not have any common analysts and they are often not even from the same industry.

Additionally, since firm k is in a different analyst network than firm i, we can control for the average equity return of firm i's analyst network in this specification, which further rules out any confounding influence from common shocks to fundamentals that are not captured by the asset pricing model or spillovers from firm k to firm j, and allows for identification even when the analyst network is endogenous. For example, if firm j is a supplier to firm k then a shock to firm k may impact firm j's characteristics. This raises the possibility that we could still be picking up a contextual effect (i.e., firm i responding to firm j's characteristic) in the friends-of-friends approach. However, because we can partial out the return shocks of the direct peers, such a spillover would have to be significant enough to impact firm i's financial policy, yet not be captured by firm j's stock return. Finally, if firm i responds directly to firm k's financial policy or characteristics, then we may not capture peer effects operating through analyst networks with this approach. However, we argue this is unlikely, given that the indirect peers consist of firms that do not share any common analysts with firm i and (in some specifications) are also in different industries.[14] Thus, any social interaction effects should be much stronger among direct peers than between indirect peers. Further, we perform cross-sectional tests below to demonstrate the relevance of analyst connections in transmitting policy choices across firms.

[14]On average, only 7% of indirect peers are in the same industry (three-digit SIC code) as firm i.

3.3 Summary Statistics

Panel A of Table 1 provides descriptive statistics for the analyst networks. On average, a firm is connected to 41.5 other firms through common analysts. Interestingly, only 10.41 (28%) of these connections are from the same three digit-SIC code industry. The low percentage of within industry connections helps us independently estimate peer effects arising from both industry and analyst networks. Even with alternate definitions of industry (Fama-French and GICS codes) we find that the percentage of within industry analyst peers is uniformly less than 50%. We find that on average, two connected firms in our sample have 1.88 analysts in common. Surprisingly, this number does not vary much in the sample. The 25th percentile of the number of common analysts is 1.1 while the 75th percentile is 2.33. We find that firms within an industry are likely to have more common analysts as compared to firms across industries. Two firms within the same industry have on average 3.11 common analysts whereas this number is only 1.54 for two firms from different industries.

Note that we exclude from our analysis firms that are not connected to any other firm through common analysts. The variable *Connected Firms* identifies the percentage of firms that are connected to at least one other firm each year in the overall CRSP-Compustat-IBES sample. We find that about 94% of the firms in the overall sample are connected to at least one other firm. Thus the unconnected firms, which we exclude, constitute only 6% of the CRSP-Compustat-IBES merged sample.

The average (median) number of indirect connections – defined as the pairs i & k, such that firms i & j and firms j & k have common analysts while firms i & k do not have any– are 411.64 (379) and the 25th percentile of the number of indirect connections is 221 while the 75th percentile is 570. Most of the indirect connections are to firms in different three-digit-SIC code industries. The mean (median) number of across industry indirect connections is 391.56 (357).

Panel B reports the average value of the outcome variables we use in our analysis. We find that the average *Leverage* (change in *Leverage*) for the firms in our sample is 21% (1%).

When we identify debt issuances as instances when there is a more than 1% increase in the book value of total debt relative to the book value of total assets, we find that firms issue debt during 36% of the firm-years in our sample period. We use two variables to identify equity issuances. Our first variable defines equity issuances as instances when the difference between cash flow from equity issues less cash flow from equity repurchases is greater than 1% of the book value of total assets, *Net equity*. Based on this definition, firms issue equity in 23% of firm-year. When we define gross equity issuances as years when the cash flow from equity issues is more than 1% of the book value of total assets, *Gross equity*, we find that equity issuances occur 36% of the firm-years.

In Panel C we provide the summary information for *Equity shock*. While the average value of the own firm's equity shock (Equity shock^{OWN}) in our sample is close to zero at -.03, it has sufficient dispersion with a standard deviation of 0.50. As expected, the dispersion declines when is averaged over either the industry or analyst peer firms.

Finally in panel D we provide the summary information for all the control variables in our sample. The summary values are similar to those for the full CRSP-Compustat-IBES merged sample. We winsorize all our variables of interest at the 1st and 99th percentiles.

4 Empirical Results

In this section we discuss our empirical results. The discussion is divided into four parts. First, we document a positive association between a firm's financial policy and that of its analyst peers. We then employ *Equity shock* as an exogenous peer firm characteristic to establish the existence of social effects distinct from correlated effects. We also provide a series of robustness and placebo tests to distinguish peer effects operating through analyst networks from those operating within industries. We further perform several cross-sectional tests that provide a richer picture of the mechanism underlying the peer effects. In our final

set of tests, we employ the friends-of-friends approach to isolate endogenous peer effects from exogenous peer effects.

4.1 Baseline Regressions

We provide the results of estimating equation (1) in our full sample in Table 2. The outcome variable in columns (1) and (3) is *Leverage* in first difference and level, respectively. The positive and significant coefficient on *Industry average* highlights the positive association between a firm's leverage and average leverage of other firms in its industry (Welch (2004), Frank and Goyal (2008b)). Coefficients on the firm-specific control variables are consistent with prior studies (e.g., Rajan and Zingales (1995)). From the coefficients on the industry average characteristics we find that only industry average *Profitability* is consistently related to firm leverage. Consistent with the findings in Leary and Roberts (2014), firms from more profitable industries have higher leverage.

In columns (2) and (4) we augment the model with *Peer average*, the weighted average leverage (in first difference and level) of all firms in the analyst network. We also include the weighted average characteristics of the analyst peer firms in the regressions. We find that the coefficient on *Peer average* is positive and significant. The coefficient on *Peer average* is significantly larger than that on *Industry average* and inclusion of *Peer average* reduces the size of the coefficient on *Industry average* in first difference (level) from .491 (.412) to .271 (.286). This is consistent with analyst peer firm leverage having a large effect on a firm's leverage. Focusing on the peer firm characteristics, we find that only the coefficients on peer firm average *Log(Sales)* and *Market to book* are significant in both columns.

In columns (5)-(6) we repeat our tests with *Net debt* as the dependent variable and from column (6) we find that there is a positive association between the probability of debt issuances by a firm in a year and debt issuances of analyst-connected peer firms. Here again we find that the coefficient on *Peer average* is larger than that on *Industry average*.

Interestingly we find that none of the industry or analyst peer characteristics are significantly related to a firm's decision to issue debt. In columns (7) - (10) we focus on equity issuances and irrespective of our measure of equity issuance, we find that there is a positive association between equity issuances by a firm and equity issuances by analyst peer firms in the same year. The coefficients on both *Peer average* and *Industry average* are of similar magnitude. Overall our results in Table 2 show that firm financial policies are positively related to the financial policies of firms that are connected through common analysts. The magnitude of the association is greater than that between firm financial policy and industry average financial policies.

In Table 3 we differentiate between analyst peers that are from the same industry and those that are from different industries to see if these two groups have a similar effect on firm financial decisions. We do this by replacing *Peer average* with two variables *Peer average (same industry)* and *Peer average (different industry).* These are the weighted averages of the outcome variable for same and different industry analyst peers. We calculate the weighted average using the methodology outlined in Section 3. From columns (1)-(2) of Table 3 we find that the coefficients on both same and different industry peer averages are positive and significant. The coefficients are also of similar size. This indicates that firm leverage is related similarly to the leverage of analyst peers from both the same and different industries. In unreported tests we find that the two coefficients in column (2) are not statistically distinguishable. The significant coefficient on *Peer average (different industry)* further reinforces the conclusion that the analyst network may have an independent effect on firm leverage apart from the industry effect documented in Leary and Roberts (2014). From columns (4)-(5) we find that same and different industry peer financial policies in terms of net debt issuance, net and gross equity issuance have a statistically significant association with a firm's respective financial policy. It is noteworthy that the different industry analyst peers have a larger influence on a firm's decision to issue equity as compared to same industry analyst peers.

4.2 Reduced Form and Structural Regressions

Having established a positive association between analyst peers' financial policies and a firm's own financial policy, we now go to our next set of tests wherein we employ *Equity Shock* as an exogenous peer firm characteristic to control for correlated effects. In Table 4 we report the results of a reduced form estimation wherein we include *Equity shock*^{ACN} and *Equity shock*^{IND} instead of peer and industry average financial policy and repeat our tests.[15] We perform the reduced form analysis to provide evidence of social effects (endogenous or exogenous). However, as discussed previously, this specification cannot distinguish endogenous from exogenous peer effects. In this table we also include *Equity shock*^{IND} to highlight that the effect of *Equity shock*^{ACN} is robust to controlling for industry characteristics, suggesting that our peer effect results are not only due to peer firms from the same industry. We explore this issue further in subsequent tests.

From columns (1)-(2) we find that all three equity shock variables (lagged one period), Equity shock^{OWN} , *Equity shock*^{IND} and *Equity shock*^{ACN} are negatively associated with a firm's market leverage (first difference and level). The negative and significant coefficient on *Equity shock*^{ACN} is consistent with the presence of social effects within the analyst network. When we model leverage (column 2), our coefficient estimates on *Equity shock*^{IND} and Equity shock^{OWN} are similar to those reported in Leary and Roberts (2014) (see Table IV). In the change specification, however, the industry average shock becomes statistically insignificant once we control for *Equity shock*^{ACN}.

In column (3) our dependent variable is *Net debt* and we find that while Equity shock^{OWN} is negatively associated with *Net debt*, both *Equity shock*^{ACN} and *Equity shock*^{IND} are not significantly associated with *Net debt*. Thus, we do not find any evidence consistent with the presence of social effects for debt issuances. In further tests, we do not include this as an outcome variable in our analysis. By contrast, columns (4) - (5) indicate a strong positive association between *Equity shock*^{ACN} in a year and the probability of a firm making equity

[15] We also include the own firm's equity shock (Equity shock^{OWN}) as an additional firm characteristic.

issues the next year. This suggests the presence of social effects in equity issuance decisions within analyst networks. Summarizing, our evidence in Table 4 shows that there appears to be strong social effects within analyst networks when it comes to leverage and equity issuance decisions.

In Table 5, we use alternate thresholds to define the equity issuance dummy (1%, 3% and 5% of total assets) and also separately look at net and gross equity issuance along with equity repurchases. From columns (1)-(3) we find that our results are robust to using different thresholds to identify equity issuance. In all three columns, the coefficients on *Equity shock*^{ACN} are positive and statistically significant. Regarding equity repurchases, we only find evidence of social effects when equity repurchases are higher than 1% of total assets (column 4). Columns (5) – (6) show only weak evidence that firms' repurchase decisions are related to the return shocks of their network peers. By contrast, columns (7) – (9) show strong evidence of analyst network effects in gross equity issuance. Thus, the social effects we identify in net equity issuance appear to come primarily from the issuance, rather than the repurchase, side.

Note that once we include *Equity shock*^{ACN}, the coefficients on *Equity shock*^{IND} are insignificant in all the columns except column (7). *Equity shock*^{ACN} is different from *Equity shock*^{IND} along two dimensions. First, it averages across firms connected through common analysts irrespective of their industry affiliation. Second, it is a weighted average with the weights equal to the number of common analysts. To see which of these is responsible for *Equity shock*^{IND} losing statistical significance, in unreported tests, we repeat the estimation after replacing *Equity shock*^{ACN} with *Equity shock*^{ACN} *(simple average)*. We find that the coefficients on *Equity shock*^{IND} continue to be insignificant (and the coefficient on *Equity shock*^{ACN} *(simple average)* significantly positive) in that specification. This highlights that it is the fact that *Equity shock*^{ACN} averages over a specific set of peers that is responsible for soaking up the effect of *Equity shock*^{IND} .

In Table 6 we provide the results of the two-stage least squares estimation that uses

Equity shock^{ACN} as an instrument for the average financial policies of peer firms. In all the specifications we also include the average financial policies of firms in the same industry as an additional control. On the top of Table 6, we provide the coefficients on the instruments from the first stage regression. Estimating the 2SLS has advantages and disadvantages relative to the reduced form. The advantage is that it allows us to estimate the magnitude of the impact of analyst peer firm policies on firms' financial decisions. The limitation, though, is that interpreting the magnitude in this way requires us to assume that the peer firms' equity shock influences firm *i's* financial policy only through its effect on peers' financial policies. As discussed earlier, it is possible that peers' equity shock influences firm i's policies because it is a shock to the peers' characteristic, such as investment opportunities or competitive position. This would represent an exogenous peer effect, in which case we would be wrong to attribute the entire magnitude to endogenous peer effects i.e., the effect of peers' policies on firm i's policies.

Despite this caveat, the results in Table 6 are instructive. The first stage results indicate that *Equity shock*^{ACN} is significantly related to peer firm leverage (columns 1 – 2) and equity issuance (columns 3 – 4) decisions. Further, the F-values for weak instrument tests shown at the bottom of the table are all large and greater than the threshold of 10.

Focusing on the results of the second stage, we find that the coefficient on the instrumented peer average leverage is positive and significant in columns (1)-(2), consistent with the presence of peer effects in leverage decisions that propagate through analyst networks. Our estimates are also economically significant. The coefficient on *Peer average* in column (2) indicates that a one standard deviation increase in peer firm weighted average leverage is associated with a 0.86 standard deviation increase in the firm's leverage (0.862 = 1.724 * (0.11 / 0.22)).

From columns (3)-(4) we find that the decision of peer firms to issue equity in a year is associated with the own firm's decision to issue equity. We find that the effect of analyst peers is greater than the effect of industry peers. Our estimates are also economically

significant. A one standard deviation increase in net (gross) equity issuance likelihood by peers is associated with a 0.306 (0.365) standard deviation increase in net (gross) equity issuance likelihood.

4.3 Robustness Tests– industry vs. analyst network effects

Our results thus far suggest that the peer group generated through shared analysts has a direct influence on corporate financial decisions. However, many firms in an analyst network are in the same industry as the firm in question. Leary and Roberts (2014) document the existence of peer effects in leverage among industry competitors. Although we control for industry averages in all our tests, and show that the effects are present for analyst peers not from the same industry (Table 3) this still raises the question of whether analyst network effects that we document are simply capturing industry peer effects. Our control for industry averages may prove inadequate if the number of analysts in common (which we use to form our weighted average peer equity shock) between pairs of firms in the same industry is higher in comparison to pairs of firms across industries. To the extent that firms in both the same industry and analyst network are more similar and more influential, our analyst peer weighted average may be a more precise measure of industry effects than the simple industry average.[16] We therefore perform several additional tests to address this issue.

In Table 7 we re-estimate the reduced form model employing three averages instead of two. These are the weighted average equity shock for firms that are both in the same industry and in the analyst network, *Equity shock*^{ACN} *(same industry)*, the weighted average equity shock for firms which are in the analyst network and not in the same industry, *Equity shock*^{ACN} *(different industry)* and the simple average equity shock for firms that are in the same industry but not in the analyst network, *Equity shock*^{IND} *(no common*

[16] Although, as we report earlier, our results are robust to using a simple average of analyst peer equity shock.

analyst). The construction of these variables can be illustrated with reference to Figure 1. In the figure the numbered shapes represent firms, the shapes themselves (*triangle*, *circle*, *etc.*) represent an industry. The lines connecting the shapes represent common analysts. Thus the firm *star-0* is connected to six other firms (*star-1, star-2, circle-1, pentagon-1, square-1 and triangle-1*) through common analysts. Of these, *star-1* and *star-2* are in the same industry as *star-0* while the others are in a different industry. Furthermore there are four other firms in the same industry as firm *star-0* (*star-3* through *star-6*). Our first peer average *Equity shock*^{ACN} *(same industry)*, for the firm *star-0* is the weighted average equity shock for the firms *star-1* and *star-2*. Our second weighted average *Equity shock*^{ACN} *(different industry)* is calculated across firms *circle-1, pentagon-1, square-1 and triangle-1*. Finally our third average *Equity shock*^{IND} *(no common analyst)* is calculated across firms *star-3* to *star-6*.

In Panel A, we report the results using the average equity shock of firms in the same industry as firm i, but not in the same analyst network. Results for leverage and equity issuances are directionally consistent with those in Table 4 and in Leary and Roberts (2014), but statistically and economically weaker. Note that one reason for the weaker result could be that these firms, given that they do not have any common analysts, may be less similar to the firm in question. Similarly, Panel B shows that leverage and equity issuance decisions are, respectively, negatively and positively related to equity shock of industry peers in the same analyst network, though for the case of change in leverage the relation is only marginally statistically significant and statistical insignificant for the net equity issuances. One potential reason for the marginal significance is that we have fewer firms that are both in the same industry and have common analysts. For example, for the average firm only 19% of the firms in its industry share common analysts. On the flip side, as seen from Table 1 only about 28% of the firms that have common analysts with a firm are from the same industry. Moreover, when we winsorize the *Equity shock*^{ACN} *(same industry)* at the 5th and 95th percentiles, the coefficient (for the case of change in leverage) becomes statistically significant at 5% level of

confidence, which suggests that outliers may also play a role affecting the results. By contrast, the relations in panel C, where the peer group includes only firms in the same analyst network, but not the same industry, are highly significant and of much larger magnitude. Similar results are found in Panel D, in which all three averages are included in the same specification. Overall, these results suggest that the peer effects operating through analyst networks do not simply reflect industry peer effects.

4.4 Placebo Tests

A potential concern with our analysis is that analysts may choose firms to cover that are economically connected, even if not in the same industry. For instance, analysts might choose firms in other industries but connected through costumer-supplier relationships. Thus, firms that are in the same analyst network, but in different industries, may exert influence on one another as a result of their product market connections rather than the analyst connection. In other words, the connection that an analyst creates between firms may proxy for economic linkages between those firms that as researchers we cannot perfectly observe.

We address this concern in Table 8 by performing a placebo test. Instead of using the average equity shock of firms in the same analyst network, we define a set of pseudo peers that are in the same industry as the peer firms in the analyst network, but do not share a common analyst with firm i. Referring to Figure 1, *circle-1, pentagon-1, square-1 and triangle-1* represent firms that are connected to *star-0* through common analysts but are in a different industry. To conduct our placebo test, we focus on the firms in the same industry as these firms but that do not have a common analyst with *star-0*. These are firms *pentagon-2* to *pentagon-4*, *square-2* to *square-4* and *triangle-2* to *triangle-4*. We refer to this average as the *Equity shock*^{ACN} *(pseudo-peer)* and repeat our tests with this average. If the analyst network captures links across firms in different industries then we should expect *Equity shock*^{ACN} *(pseudo-peer)* to be significantly related to the corporate policies of the

firm in question.

The results in Panel A of Table 8 show that there is no significant relationship between *Equity shock*^{ACN} *(pseudo-peer)* and a firm's financial policy. In Panel B, we repeat the tests with alternate industry definitions, including two-digit SIC codes, GICS codes, and the industry peer classification of Hoberg and Phillips (2010). Results are again insignificant when we calculate *Equity shock*^{ACN} *(pseudo-peer)* over firms that are in the same two-digit SIC code as the analyst peer firms and that do not have any common analyst with the firm in question. The only coefficients that are significant in the right direction are obtained when we focus on firms within the same GICS industries. Here we find that there is a negative (positive) association between *Equity shock*^{ACN} *(pseudo-peer)* and *Leverage (Gross Equity*), but no relation for leverage changes and net equity issuance. We also find a positive and significant coefficient for *Gross Equity* when we define pseudo-peers using the Hoberg-Phillips industry peer definition, but not for leverage (levels or changes) or net equity issues (Panel D). To summarize, we obtain very weak evidence for an association between *Equity shock*^{ACN} *(pseudo-peer)* and firm financial policies. This is in contrast to the strong relation between a firm's financial policies and those of the firms that are in the same industries as the pseudo peers, but that are in the analyst network of firm i. This suggests that our previous results were not simply driven by economic connections between industries, but that analyst networks play a particular role in propagating financial policies across firms.

4.5 Cross-Sectional Tests

In this section we perform cross-sectional tests to better illustrate the mechanism underlying the peer effects we document. In these tests, we focus on the level and change in leverage and net and gross equity issuances, as these are the outcome variables for which we find significant social effects in the previous analyses.

4.5.1 Leader vs. Followers

We first examine which firms within an analyst network are most influential. If firms are mimicking one another, we posit that the policy choices of leaders in the analyst network (i.e., more successful firms) will be more influential than those of other firms. In Table 9 we identify leader and follower firms within the analyst network using two alternative criteria: Sales and Profitability. We classify a firm as a leader if either its *Sales* or *Profitability* is above the sample median. We classify all other firms as follower firms.[17] In Panel A we evaluate the influence of leader firms on follower firms. That is, the model is estimated on the subsample of firms classified as followers and the independent variable of interest is the average equity shock of peer leader firms. In Panel B we perform the opposite analysis, i.e., we test for the influence of peer follower firms on leader firms.

The results in Panel A of Table 9 are similar to those in Leary and Roberts (2014); from columns (1),(2) and (4) we find that equity shock of leader firms (according to *Sales* and *Profitability* criteria) in an analyst network are correlated with leverage decisions of follower firms. Similar results are obtained for net and gross equity issuances. In Panel B we flip the analysis and test to see if equity shocks of follower firms affect the financial decisions of leader firms. Irrespective of the criteria used, we do not find any significant effects (also, the coefficients in Panel A are much larger are those in Panel B). Thus, there is no evidence of social effects from follower firms to leader firms. These results further reinforce our interpretation that the peer effects we document are a result of firms learning from (mimicking) the decisions of their analyst peer firms. In the next set of tests, we differentiate between analysts to better highlight their role in transmitting information across firms.

[17] To be more precise, we employ the analyst coverage network of each year to identify leaders and followers according to *Sales* and *Profitability*.

4.5.2 All-star brokerage houses and Analyst Experience

We argue that analyst networks are important in transmitting corporate policy decisions from one firm to another. If this is indeed the case, then the characteristics of the analyst herself may be important for the strength of these peer effects. More influential analysts should be more effective at transmitting policy-relevant information across firms. Firms are also likely to take the comments of such analysts more seriously. We construct two measures that capture the potential influence of analysts. Specifically, from *Institutional Investor* magazine we collect the names of the top four analysts (first, second, third, and runner-up) for each industry during 1990-2013. We classify an analyst as being influential from the first year she appears in the *Institutional Investor* ranking. We classify brokerage houses that employ three or more influential analysts as *All-star brokerage houses.* These roughly represent about 10% of all brokerage houses in our sample. We differentiate between all-star brokerage houses and non-all-star brokerage houses to see if there is any difference in the extent of peer effects within their networks. Next we differentiate analysts based on their level of experience. Each year, we define analysts to have more (less) experience if they are above (below) sample median in terms of the number of years since they first appear on IBES.

Table 10 examines the impact of all-star brokerage houses (Panel A) and analyst experience (Panel B) on the strength of the analyst network peer effect. In Panel A, we present the results of the reduced form in which we include the weighted average equity shock for the two groups of peers (All-Star and Non All-Star). The all-star average is calculated over peers that share at least one analyst from an all-star brokerage house while the non all-star average is calculated over peers connected only by analysts not from all-star brokerage houses. For all outcome variables (first difference and level of leverage, net and gross equity issuance), we find a larger coefficient on the averages for peers connected through analysts from all-star brokerage houses relative to peers connected through non-all-star brokerage houses, although we find that the coefficients are statistically different only for leverage and

net equity issuances.

Similar, but stronger results are obtained in Panel B where we differentiate analysts based on their experience (More Experienced vs. Less Experienced).[18] In all specifications, we find stronger peer effects among firms that are connected through more experienced analysts. All of these differences are statistically significant, with the exception of the coefficient for net equity issuances. Interestingly, the peer effect is not statistically different from zero for firms connected through less experienced analysts, but always significant for firms connected through more experienced ones.

4.5.3 Regulation FD

Regulation Fair Disclosure (Reg FD) was adopted by the U.S. Securities and Exchange Commission in October 2000 with the intent to stop selective disclosure, a practice in which companies give material information only to a few analysts and institutional investors prior to disclosing it publicly.

Arguably the passage of the Reg FD reduced the ability of analysts to obtain information and diminished their influence on top management. For example, Cohen et al. (2010) show that while analysts with school ties to senior corporate officers produced stock recommendations pre-Reg FD that significantly outperformed analysts without such school ties, post-Reg FD, the school-tie premium disappeared. Gintschel and Markov (2004) also show that Reg FD reduced the informativeness of analysts' output. They find that the absolute price impact of information disseminated by financial analysts was lower post-Reg FD.

We expect the analyst information channel to become less important in the period after Reg FD. To test this, we create a dummy variable, *Post-RegFD,* that takes the value of one for the sample period 2002-2013 and takes the value of zero for the sample period 1990-1999 (before Reg FD). We exclude the year 2000-2001 from this analysis to avoid confounding ef-

[18] We repeat the process and create two weighted average equity shocks for the two peer groups : Equity shock^{ACN}(More experienced) and Equity shock^{ACN}(Less experienced)

fects around the implementation of the law. We repeat our tests from Table 4 after including the dummy variable *Post-RegFD* and the interaction term *Equity shock*^{ACN} *X Post-RegFD*. Our results in Panel A of Table 11 show that for leverage in level terms and equity issuances, the coefficient on the interaction term *Equity shock*^{ACN} *X Post-RegFD* is statistically significant with the opposite sign of the coefficient associated with *Equity shock*^{ACN}. Thus our results indicate that after the implementation of Reg FD, the analyst peer effects become weaker. This is consistent with the reduced level of communication between the analysts and firm management. Note that while Reg-FD shocked the analyst's ability to get information from the firms she covers, it did not equivalently shock the economic linkages between the firms. Hence our weaker results Post-FD indicates that the peer effects we document are not just due to fundamental economic linkages across firms.

Additionally, in Panel B of Table 11 we perform a placebo test similar to the one in Panel A of Table 7, using the equity shock for firms that are in the same industry but not in the analyst network (*Equity shock*^{IND} *(no common analyst)*). We replicate the reduced form model after including the interaction term *Equity shock*^{IND} *(no common analyst)X Post-RegFD* and the dummy variable *Post-RegFD*.

We do not expect to find a reduction in the effect of industry peers post-Reg FD. Indeed, the results in Panel B of Table 11 indicate that the coefficient associated with *Equity shock*^{IND} *(no common analyst) X Post-RegFD* is not statistically different from zero for leverage and equity issuance. This provides further evidence that our results are not entirely due to some unobserved economic linkages across the firms with common analysts.

4.6 Indirect Peer Approach

Finally, in Table 12 we use the friends-of-friends methodology to help isolate exogenous peer effects from endogenous peer effects. Specifically, we identify indirect peer firms for every firm. These are firms that are not directly connected to a firm through common analysts

but are connected to one or more of its analyst network peers. We then estimate a two-stage least squares model in which we use the average equity shock of these "indirect peers" as an instrument for the financial policies of a firm's direct peers to identify endogenous peer effects in financial policy.[19]

As discussed in Section 3, in order to separate contextual from endogenous peer effects, the key identification assumption is that the characteristics of the indirect peers used as instruments are uncorrelated with the characteristics of the direct peers. This is likely to be true for idiosyncratic return shocks as they isolate value-relevant events that are unique to the indirect peers (i.e., this is the identification assumption employed in the previous section).

The first row of Table 12 presents the coefficients on the indirect peer average equity shock from the first stage. We find that the equity shocks of indirect peer firms are significantly related to the level and change in leverage and net and gross equity issuances of direct peers. Further, the F-values indicate that for these policy variables the instrument easily passes the weak instrument test.

Regarding the second stage, in Panel A we find a significant relation between a firms' financial policies and those of their direct peers for the level of leverage and both net and gross equity issuances. The positive and significant coefficients on *Peer average* for those corporate policies suggest that the average outcome variable of analyst peer firms has a causal effect on a firm's outcome variable. Our results are also economically significant. From the coefficient in column (2) we find that a one standard deviation increase in peer firm average leverage is associated with a 0.39 standard deviation increase in a firm's leverage (0.388 = 0.776 * (0.11 / 0.22)). For equity issuances, we find that a one standard deviation increase in net (gross) equity issuance likelihood by peers leads to a 0.33 (0.6) standard deviation

[19] Note that in these regressions when we control for industry average financial policy, we focus on firms that do not have common analysts because the policy of firms with common analyst (and in the same industry) is the endogenous variable and is instrumented by the indirect peer average.

increase in net (gross) equity issuance likelihood.

In Panel B, we repeat our tests using an instrument that excludes all indirect peers in the same industry as firm i. As compared to Panel A we now find peer effects for changes in firm leverage and equity issuance. While the coefficient for the level of leverage is insignificant, it is of similar magnitude as that in column (2). Overall, the results in Panel B suggest that our results are robust to excluding same-industry indirect peers.

It is important to remark that the coefficients associated with industry averages of the outcome variables are also positive and statistically significant but they are substantially smaller in comparison to peer firm endogenous variables. Our results suggest that analyst networks are likely an important source for industry peer effects.

One concern with the test in Table 12 is that the number of indirect peers in each group is considerably larger that the number of direct peers (or industry peers). This diminishes variation in the average equity shock across indirect peer groups. While the results in Table 12 indicate that enough power remains to identify the endogenous peer effects, in Table IA-7 of Internet Appendix (IA) we report results of a robustness check to address this concern. Specifically, we limit the set of indirect peers to those with at least three analysts in common with a direct peer (while still imposing that they have no analysts in common with the firm in question). This limits the size of the indirect peer groups and produces cross-group dispersion in average equity shock only slightly below that of the direct peer groups. The results are similar to those in Table 12 with two exceptions. In the first stage, we find an insignificant coefficient on the indirect peers' equity shock when the dependent variable is the level of leverage, likely because we are now relying on only a subset of the peers of the direct peers. Though, we continue to find strong first-stage coefficients for the other three policy variables. We therefore exclude the leverage level from the second-stage analysis. In the second stage, we now find a significant relation between the instrumented peer average policy and own-firm policies for the change in leverage, as well as for gross equity issues. Overall, these results support the findings in Table 12 of endogenous peer effects working

through analyst networks and show that these results are robust to varying definitions of indirect peers.

4.7 Other unreported tests

We perform a number of additional robustness tests whose results are presented in the Internet Appendix (IA). We briefly discuss their results here. Recent literature shows that firms with common institutional shareholders tend to follow similar financial policies (Cronqvist and Fahlenbrach (2008)). In Table IA-2 of the IA, we repeat our tests after including the characteristics of firms that share institutional shareholders with the firm in question and find our results on analyst peers to be robust. Consistent with prior literature we find evidence for peer effects within institutional shareholder networks. We also repeat our tests with four alternate industry definitions: two-digit SIC code, Fama-French industry classification, GICS codes and Hoberg-Phillips peers. We find our results to be robust across these industry classifications (Tables IA-3 to IA-6).

5 Conclusion

Sell-side analysts are important information intermediaries in financial markets. There is growing evidence that they may influence the financial policies of firms that they cover. In this paper we provide evidence that sell-side analysts are an important mechanism underpinning peer effects in financial policy choices. Building on recent empirical methods from the network effects literature to identify peer effects, we find that exogenous changes to financial policies of firms covered by an analyst, such as leverage and equity issuance, lead other firms covered by the same analyst to make similar changes in policy.

We use an extended Manski-type linear-in-means model, and use the idiosyncratic equity

shocks of analyst peer firms, as well as the return shocks of indirect peers ("friends of friends"), as instruments for analyst peer firm financial policies. We show that the network effects that we document are distinct from industry peer effects and that these effects are more pronounced among peers connected by analysts that are more experienced and from more influential brokerage houses. Moreover, the peer effects are weaker post-Reg FD which regulation affected the ability of analysts to get information from the firms.

An important question that we leave for future research is to establish if the propagation that we document is value enhancing or value destroying. Future research can also explore if there is similar propagation in other corporate policies such as investment and governance provisions such as design of executive compensation. Apart from research analysts, firms are also connected by other channels such as social ties or commonality of board of directors, executives, commercial/investment bankers or other professional advisors, and institutional or active investors. The methodology used in this paper can be fruitfully used to identify peer effects in these other settings.

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Appendix A: Variable Definitions

- *Total Assets*: Book value of Assets *(Compustat item: at).*
- *Equity Repurchase*: Dummy variable that takes the value of one if equity repurchases normalized by book assets at the beginning of the year is greater than a threshold *(Compustat items: prstkc/at(t-1)>1%,3%,5%).*
- *Equity Shock*: Idiosyncratic returns defined as the difference between realized and expected returns based on the methodology provided by Leary and Roberts (2014).
- *Gross Equity*: Dummy variable that takes the value of one if gross equity issuances normalized by book assets at the beginning of the year is greater than a threshold *(Compustat items: sstk/at(t-1)>1%,3%,5%).*
- *Leverage*: The ratio of the sum of total long-term debt plus total debt in current liabilities scaled by the market value of assets *(Compustat items:(dltt+dlc)/(prcc_f*cshpri+dlc+dltt+pstkl-txditc)).*
- *Log(Sales)*: Natural logarithmic of sales *(Compustat items: log(sale)).*
- *Market to Book*: The ratio of the sum of the total book value of debt plus market value of equity divided by book value of total assets *(Compustat items: (prcc_f*cshpri+dlc+dltt+pstkl-txditc)/at).*
- *Market Value of Assets*: The sum of the market value of equity plus total long-term debt plus current liabilities *(Compustat items: prcc_f*cshpri+dlc+dltt+pstkl-txditc).*
- *Net Debt Issuances*: The sum of the total long-term debt plus total debt in current liabilities for the current fiscal year minus the sum of the total long-term debt plus total debt in current liabilities in the previous fiscal year *(Compustat items: (dltt+dlc-(dltt(t-1)+dlc(t-1)))).*
- *Net Debt*: Dummy variable that takes the value of one if net debt issuances normalized by book assets at the beginning of the year is greater than 1%. *(Compustat items: (dltt+dlc-(dltt(t-1)+dlc(t-1)))/at(t-1)>1%).*
- *Net Equity Issuances*: Difference between equity issuances and equity repurchases *(Compustat items: sstk-prstkc).*
- *Net Equity*: Dummy variable that takes the value of one if net equity issuances normalized by book assets at the beginning of the year is greater than a threshold *(Compustat items: (sstk-prstkc)/at(t-1)>1%,3%,5%).*
- *Profitability*: The ratio of the EBITDA divided by book value of total assets *(Compustat items: oibdp/at).*
- *Stock Return*: Annual return for the firm's stock over the current fiscal year *(Compustat items: ((prcc_f/ajex+dvpsx_f/ajex)/(prcc_f(t-1)/ajex(t-1)))-1).*

- *Tangibility*: The ratio of the book value of Net Property Plant and Equipment divided by book value of total assets *(Compustat items: ppent/at).*

Figure 1: An example of analyst coverage network

In this figure we present a hypothetical analyst network for illustration purposes. In the figure, the shape-families represent industries while the shapes represent individual firms. The lines connecting the shapes represent common analysts.

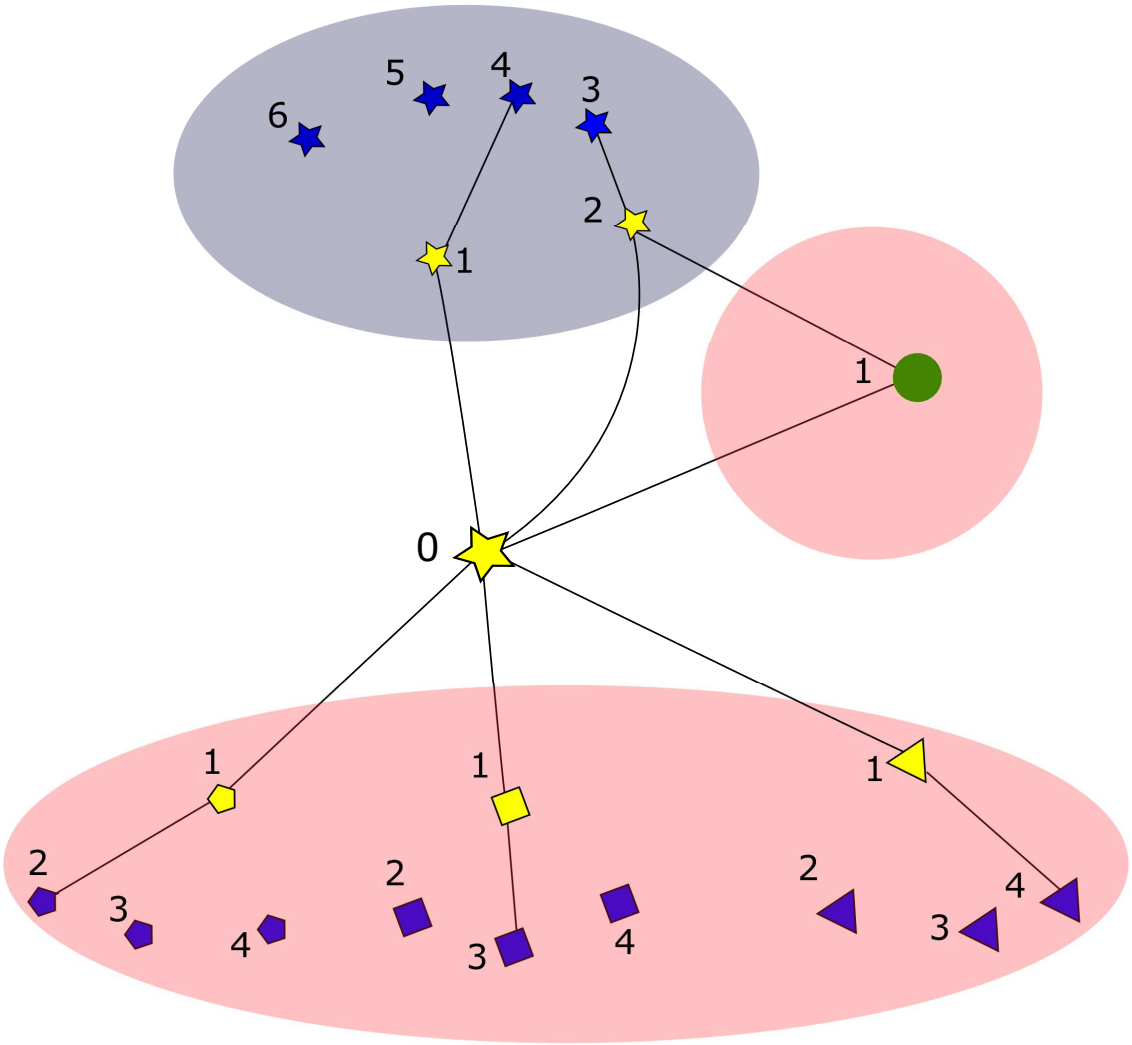

Table 1: Summary Statistics. Analyst Coverage Network and Equity Shock

This table presents the descriptive statistics for the analyst coverage network and the variables used in the regressions analysis. Panel A shows the characteristics of analyst networks in terms of number of direct and indirect peers, the number of common analysts broken down into within and across industries. Panel B reports the summary statistics for the outcome variables that we employ in our analysis. Panel C and D show the summary statistics of equity shock and control variables respectively. All variables used in the regression analysis are winsorized at the 1st and 99th percentiles and are defined in Appendix A.

Panel A: Analyst Coverage Network																	
		Number of Connections					Connections (%)					Number of analysts in common					
Direct Peers	N	Mean	Std	P25	P50	P75	Mean	Std	P25	P50	P75	N	Mean	Std	P25	P50	P75
Overall	37960	41.50	26.97	20.00	37.00	58.00						37960	1.88	1.04	1.10	1.50	2.33
Within industry (3Digit-Sic code)	37960	10.41	12.52	2.00	5.00	15.00	0.28	0.30	0.05	0.16	0.46	32461	3.11	2.73	1.19	2.00	4.00
Across industries (3Digit-Sic code)	37960	31.09	25.53	11.00	25.00	45.00	0.72	0.30	0.54	0.84	0.95	36799	1.54	0.71	1.00	1.25	1.77
Within industry (F-F Industry)	37960	17.05	16.14	4.00	12.00	26.00	0.43	0.31	0.15	0.39	0.68	35002	2.51	1.88	1.14	1.80	3.25
Across industries (F-F Industry)	37960	24.44	21.83	8.00	19.00	36.00	0.57	0.31	0.32	0.61	0.85	36203	1.43	0.63	1.00	1.19	1.58
Within industry (GICS Industry)	37960	17.19	14.13	5.00	14.00	26.00	0.44	0.29	0.19	0.42	0.67	35114	2.60	1.91	1.18	1.88	3.39
Across industries (GICS Industry)	37960	24.31	22.13	8.00	18.00	35.00	0.56	0.29	0.33	0.58	0.81	36554	1.34	0.52	1.00	1.14	1.45
Connected Firms (%)	21	0.94	0.02	0.92	0.94	0.96											
Indirect Peers		Number of Connections					Connections (%)										
Overall	37960	411.64	235.83	221.00	379.00	570.00											
Within industry (3Digit-Sic code)	37960	20.07	31.99	1.00	5.00	25.00	0.07	0.13	0.00	0.01	0.08						
Across industries (3Digit-Sic code)	37960	391.56	237.04	202.00	357.00	550.00	0.93	0.13	0.92	0.99	1.00						
Within industry (F-F Industry)	37960	43.45	41.56	12.00	30.00	62.00	0.14	0.15	0.03	0.08	0.21						
Across industries (F-F Industry)	37960	368.19	232.77	181.00	332.00	521.00	0.86	0.15	0.79	0.92	0.97						
Within industry (GICS Industry)	37960	26.14	20.30	9.00	23.00	39.00	0.10	0.12	0.02	0.06	0.12						
Across industries (GICS Industry)	37960	385.50	236.03	195.00	352.00	545.00	0.90	0.12	0.88	0.94	0.98						

Panel B: Outcome Variables										
		Firm specific			Industry average (Three-Digit SIC Code)			Peer firm simple average.		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
ΔLeverage	37960	0.01	0.10	0.00	0.01	0.05	0.00	0.01	0.04	0.00
Leverage	37960	0.21	0.22	0.15	0.23	0.13	0.20	0.20	0.11	0.19
Net debt	37960	0.36	0.48	0.00	0.33	0.16	0.30	0.37	0.16	0.36
Net equity	37960	0.23	0.42	0.00	0.23	0.15	0.22	0.23	0.17	0.19
Gross equity	37960	0.36	0.48	0.00	0.31	0.18	0.30	0.39	0.22	0.35
		Peer firm weighted average								
		Full sample			Same industry			Different industry		
ΔLeverage	37960	0.01	0.05	0.00	0.01	0.06	0.00	0.01	0.05	0.00
Leverage	37960	0.20	0.11	0.19	0.17	0.17	0.13	0.19	0.11	0.19
Net debt	37960	0.37	0.18	0.36	0.32	0.30	0.27	0.36	0.20	0.35
Net equity	37960	0.22	0.18	0.17	0.20	0.26	0.08	0.21	0.20	0.15
Gross equity	37960	0.39	0.24	0.35	0.34	0.34	0.26	0.36	0.25	0.33

Panel C: Equity Shock						
	N	Mean	SD	P25	Median	P75
Equity shock^{OWN}	37960	-0.03	0.50	-0.32	-0.10	0.14
Equity shock^{IND} (three-digit SIC code)	37960	-0.03	0.16	-0.12	-0.05	0.04
Equity shock^{ACN} (weighted average)	37960	-0.04	0.12	-0.11	-0.04	0.02
Equity shock^{ACN} (simple average)	37960	-0.04	0.11	-0.10	-0.04	0.02
Equity shock^{ACN} (indirect peer)	37960	-0.03	0.06	-0.07	-0.04	-0.00
Equity shock^{ACN} (indirect peer excl. same industry)	37960	-0.03	0.06	-0.07	-0.04	-0.00

Panel D: Control Variables										
		Firm specific			Industry average (Three-Digit SIC Code)			Peer firm simple average		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Log(Sales)	37960	6.69	1.78	6.60	5.77	1.13	5.62	7.07	0.94	7.12
Market to book	37960	1.66	1.26	1.27	1.60	0.66	1.43	1.82	0.75	1.65
Profitability	37960	0.13	0.11	0.13	0.09	0.07	0.10	0.14	0.05	0.15
Tangibility	37960	0.29	0.23	0.22	0.28	0.19	0.22	0.30	0.16	0.26
Δ Log(Sales)	37960	0.10	0.22	0.09	0.10	0.11	0.10	0.11	0.10	0.11
ΔMarket to book	37960	-0.06	0.81	-0.01	-0.07	0.40	-0.05	-0.08	0.45	-0.02
Δ Profitability	37960	-0.00	0.07	0.00	-0.01	0.03	-0.00	-0.00	0.02	-0.00
Δ Tangibility	37960	-0.00	0.04	-0.00	-0.00	0.02	-0.00	-0.00	0.01	-0.00

		Peer firm weighted average								
		Full sample			Same industry			Different industry		
Log(Sales)	37960	7.24	1.04	7.26	6.19	2.81	6.91	7.06	1.65	7.32
Market to book	37960	1.85	0.81	1.65	1.59	1.16	1.40	1.72	0.78	1.60
Profitability	37960	0.14	0.05	0.15	0.12	0.08	0.13	0.14	0.05	0.15
Tangibility	37960	0.30	0.17	0.26	0.26	0.23	0.19	0.28	0.15	0.26
Δ Log(Sales)	37960	0.11	0.11	0.11	0.10	0.14	0.09	0.11	0.11	0.11
ΔMarket to book	37960	-0.08	0.48	-0.02	-0.07	0.55	0.00	-0.07	0.46	-0.00
Δ Profitability	37960	-0.00	0.03	-0.00	-0.00	0.03	0.00	-0.00	0.03	0.00
Δ Tangibility	37960	-0.00	0.01	-0.00	-0.00	0.02	0.00	-0.00	0.01	-0.00

Table 2: Baseline Specification I. Analyst peer firms vs. industry peers

The table presents the OLS coefficients for the following regression:

$$y_{ijt} = \alpha + \beta_1 y_{-it}^{ACN} + \beta_2 y_{-ijt}^{IND} + \gamma_1' X_{-it-1}^{ACN} + \gamma_2' X_{-ijt-1}^{IND} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

The outcome variables are Δ *Leverage* (columns (1) - (2)), *Leverage* (columns (3) - (4)), *Net Debt* (columns (5) - (6)), *Net Equity* (columns (7) - (8)) and *Gross Equity* (columns (9) - (10)). The main independent variables are *Peer average* and *Industry average*, which measure the contemporaneous averages of the respective outcome variable for analyst and industry peers respectively. All other control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage		Leverage		Net Debt		Net Equity		Gross Equity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer average		.550		.375		.218		.309		.278
		(.021)***		(.025)***		(.022)***		(.024)***		(.021)***
Industry average	.491	.271	.412	.286	.226	.171	.332	.237	.361	.273
	(.017)***	(.017)***	(.024)***	(.023)***	(.024)***	(.024)***	(.025)***	(.025)***	(.025)***	(.025)***
Own characteristics										
Log(Sales)	.029	.024	.036	.035	-.045	-.048	-.105	-.100	-.081	-.080
	(.003)***	(.003)***	(.004)***	(.004)***	(.008)***	(.009)***	(.008)***	(.008)***	(.009)***	(.009)***
Market to book	.0009	.002	-.019	-.018	.014	.013	.066	.064	.072	.072
	(.0005)*	(.0005)***	(.001)***	(.001)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.032	-.025	-.299	-.298	.359	.352	-.151	-.159	.184	.177
	(.009)***	(.009)***	(.018)***	(.018)***	(.047)***	(.048)***	(.044)***	(.044)***	(.045)***	(.045)***
Tangibility	.094	.087	.071	.076	.323	.329	.085	.088	.055	.053
	(.014)***	(.013)***	(.024)***	(.024)***	(.050)***	(.050)***	(.046)*	(.046)*	(.048)	(.048)
Peer characteristics										
Log(Sales)		.016		-.009		.004		.005		.013
		(.007)**		(.003)***		(.007)		(.006)		(.006)**
Market to book		-.004		.006		-.0001		-.006		-.020
		(.001)***		(.002)***		(.007)		(.007)		(.007)***
Profitability		-.047		.084		-.007		.144		.015
		(.027)*		(.037)**		(.106)		(.095)		(.096)
Tangibility		.055		-.063		-.097		-.005		.028
		(.045)		(.025)**		(.064)		(.051)		(.054)
Industry characteristics										
Log(Sales)	-.005	-.011	-.009	-.008	-.0007	.001	.004	.002	-.003	-.003
	(.006)	(.007)	(.005)*	(.005)*	(.013)	(.013)	(.010)	(.009)	(.012)	(.011)
Market to book	-.006	-.003	-.005	-.006	.010	.010	.005	.0006	.003	.007
	(.002)***	(.002)*	(.003)	(.003)*	(.009)	(.010)	(.008)	(.008)	(.008)	(.009)
Profitability	.055	.054	.148	.122	.089	.047	.049	.035	-.077	-.100
	(.021)***	(.022)**	(.029)***	(.030)***	(.082)	(.086)	(.071)	(.075)	(.079)	(.082)
Tangibility	-.071	-.068	.007	.007	-.075	-.043	.074	.047	.082	.063
	(.038)*	(.039)*	(.043)	(.042)	(.104)	(.104)	(.082)	(.081)	(.094)	(.094)
Obs.	37960	37960	37960	37960	37960	37960	37960	37960	37960	37960
R^2	.149	.176	.778	.783	.242	.244	.392	.397	.458	.462

Table 3: Baseline Specification II. Same vs. different industry analyst peers

The table presents the OLS coefficients for the following regression:

$$y_{ijt} = \alpha + \beta_1 \left[y_{-it}^{ACN}\right]_{SI} + \beta_2 \left[y_{-it}^{ACN}\right]_{DI} + \beta_3 y_{-ijt}^{IND} + \gamma_1' \left[X_{-it-1}^{ACN}\right]_{SI} + \gamma_2' \left[X_{-it-1}^{ACN}\right]_{DI} + \gamma_3' X_{-ijt-1}^{IND} + \gamma_4' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Debt* (column (3)), *Net Equity* (column (4)) and *Gross Equity* (column (5)). The main independent variables are *Peer average (within industry)* and *Peer average (across industry)*, which measure the contemporaneous averages of the respective outcome variable for analyst peers that are within and outside the firm's industry respectively. All other control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Debt	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)
Peer average (same industry)	.218	.144	.059	.072	.084
	(.014)***	(.015)***	(.012)***	(.014)***	(.013)***
Peer average (different industry)	.274	.151	.087	.157	.135
	(.018)***	(.019)***	(.017)***	(.018)***	(.016)***
Industry average	.284	.292	.172	.254	.270
	(.018)***	(.024)***	(.026)***	(.026)***	(.026)***
Peer characteristics (within industry)					
Log(Sales)	.015	-.006	-.002	-.002	.002
	(.005)***	(.001)***	(.003)	(.002)	(.003)
Market to book	-.004	-.0002	-.002	.0006	-.006
	(.001)***	(.002)	(.005)	(.005)	(.006)
Profitability	-.025	.019	.052	-.038	-.080
	(.020)	(.027)	(.078)	(.071)	(.077)
Tangibility	.038	-.028	-.042	.047	-.021
	(.030)	(.018)	(.047)	(.038)	(.043)
Peer characteristics (across industry)					
Log(Sales)	.009	-.003	.0003	.0008	-.0009
	(.006)	(.001)**	(.004)	(.003)	(.003)
Market to book	.0002	.002	.004	-.013	-.021
	(.001)	(.002)	(.005)	(.006)**	(.005)***
Profitability	-.028	.051	-.083	.193	.144
	(.024)	(.031)*	(.090)	(.085)**	(.086)*
Tangibility	.053	-.034	-.041	-.022	.013
	(.039)	(.018)*	(.048)	(.037)	(.039)
Own characteristics	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960	37960
R^2	.169	.782	.243	.395	.461

Table 4: Reduced form regression with idiosyncratic equity shock

The table presents the results of the following OLS regression:

$$y_{ijt} = \alpha_0 + \alpha_1 Eq.Shock^{ACN}_{-it-1} + \alpha_2 Eq.Shock^{IND}_{-ijt-1} + \alpha_3 Eq.Shock^{OWN}_{ijt-1} + \gamma_1' X^{ACN}_{-it-1} + \gamma_2' X^{IND}_{-ijt-1} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Debt* (column (3)), *Net Equity* (column (4)) and *Gross Equity* (column (5)). The main independent variables are *Equity Shock*^{ACN} and *Equity Shock*^{IND} which measure the lagged averages of the idiosyncratic equity shock for analyst peers and industry peers respectively. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent variable:	ΔLeverage	Leverage	Net Debt	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)
Equity shock^{ACN}	-.027	-.025	-.031	.061	.081
	(.005)***	(.006)***	(.023)	(.019)***	(.020)***
Equity shock^{IND}	-.003	-.016	.014	.007	.027
	(.004)	(.004)***	(.018)	(.013)	(.014)*
Equity shock^{OWN}	-.006	-.016	-.011	.059	.071
	(.001)***	(.002)***	(.005)**	(.005)***	(.005)***
Own characteristics					
Log(Sales)	.028	.035	-.046	-.097	-.076
	(.003)***	(.004)***	(.009)***	(.008)***	(.009)***
Market to book	.003	-.017	.015	.059	.065
	(.0006)***	(.001)***	(.004)***	(.004)***	(.004)***
Profitability	-.026	-.296	.364	-.171	.155
	(.010)***	(.019)***	(.048)***	(.045)***	(.045)***
Tangibility	.085	.061	.322	.110	.076
	(.014)***	(.025)**	(.051)***	(.046)**	(.049)
Peer characteristics					
Log(Sales)	.048	-.002	.007	-.011	.002
	(.008)***	(.003)	(.007)	(.006)*	(.006)
Market to book	-.004	-.009	.00006	.015	.003
	(.002)**	(.002)***	(.007)	(.007)**	(.007)
Profitability	-.078	-.063	.063	-.011	.007
	(.029)***	(.038)*	(.106)	(.095)	(.096)
Tangibility	.154	.024	-.059	.013	.008
	(.047)***	(.024)	(.064)	(.051)	(.055)
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960	37960
R^2	.118	.772	.239	.392	.458

Table 5: Reduced form regression with idiosyncratic equity shock: equity issuance and equity repurchase

The table presents the results of the following OLS regression:

$$y_{ijt} = \alpha_0 + \alpha_1 Eq.Shock^{ACN}_{-it-1} + \alpha_2 Eq.Shock^{IND}_{-ijt-1} + \alpha_3 Eq.Shock^{OWN}_{ijt-1} + \gamma_1' X^{ACN}_{-it-1} + \gamma_2' X^{IND}_{-ijt-1} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

The outcome variables are *Net Equity* (columns (1)- (3)), *Equity Repurchase* (columns (4) - (6)) and *Gross Equity* (columns (7) - (9)). The main independent variables are *Equity Shock*^{ACN} and *Equity Shock*^{IND} which measure the lagged averages of the idiosyncratic equity shock for analyst peers and industry peers respectively. All control variables are lagged one period. In all the specifications we include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	Net Equity			Equity Repurchase			Gross Equity		
	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equity shock^{ACN}	.061	.056	.044	.039	.031	.023	.081	.055	.050
	(.019)***	(.016)***	(.015)***	(.019)**	(.017)*	(.015)	(.020)***	(.018)***	(.016)***
Equity shock^{IND}	.007	.009	.009	.012	.005	.013	.027	.013	.006
	(.013)	(.010)	(.009)	(.015)	(.013)	(.011)	(.014)*	(.011)	(.010)
Equity shock^{OWN}	.059	.045	.039	.0004	-.0007	-.0002	.071	.052	.044
	(.005)***	(.004)***	(.004)***	(.004)	(.004)	(.003)	(.005)***	(.005)***	(.004)***
Own characteristics									
Log(Sales)	-.097	-.080	-.067	.058	.045	.035	-.076	-.076	-.069
	(.008)***	(.007)***	(.006)***	(.009)***	(.008)***	(.007)***	(.009)***	(.007)***	(.007)***
Market to book	.059	.054	.042	-.004	.012	.019	.065	.065	.048
	(.004)***	(.004)***	(.003)***	(.004)	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.171	-.295	-.288	.632	.566	.457	.155	-.172	-.233
	(.045)***	(.040)***	(.040)***	(.046)***	(.040)***	(.036)***	(.045)***	(.042)***	(.041)***
Tangibility	.110	.168	.173	-.213	-.114	-.084	.076	.157	.176
	(.046)**	(.037)***	(.033)***	(.050)***	(.042)***	(.036)**	(.049)	(.039)***	(.035)***
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960	37960	37960	37960	37960	37960
R^2	.392	.35	.322	.427	.395	.378	.458	.376	.327

Table 6: Two-stage least square instrumentals variable regression using equity shock

The table presents the results of the 2SLS regression that relates peer firm average financial policy to firm financial policy. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2), *Net Equity* (column (3) and *Gross Equity* (column (4). The main endogenous variables are peer averages of the outcome variables. The excluded instrument in the first stage is *Equity shock*^{ACN} which measures the lagged averages of the idiosyncratic equity shock for analyst peers. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
First stage				
Equity shock^{ACN}	-.012	-.014	.079	.105
	(.002)***	(.003)***	(.007)***	(.008)***
Second stage				
Instrumented peer average	1.841	1.724	.713	.730
	(.463)***	(.529)***	(.230)***	(.182)***
Industry average	-.234	-.152	.115	.125
	(.182)	(.172)	(.073)	(.062)**
Own characteristics				
Equity shock^{OWN}	-.005	-.015	.059	.071
	(.001)***	(.002)***	(.004)***	(.005)***
Log(Sales)	.019	.028	-.090	-.069
	(.004)***	(.004)***	(.008)***	(.008)***
Market to book	.003	-.018	.057	.064
	(.0007)***	(.001)***	(.004)***	(.004)***
Profitability	-.009	-.297	-.187	.151
	(.011)	(.019)***	(.042)***	(.043)***
Tangibility	.073	.099	.102	.066
	(.015)***	(.026)***	(.042)**	(.045)
Peer characteristics	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960
Kleibergen-Paap F-value	43.447	23.638	125.706	171.729
Cragg-Donald F-value	73.349	40.217	260.887	341.540
Anderson-Rubin F-value	20.088	16.841	10.078	17.322
Anderson-Rubin P-value	7.58e-06	.00004	.002	.00003

Table 7: Differentiating between same industry and different industry analyst peers

The table presents the results of OLS regressions that relate peer firm idiosyncratic equity shock to firm capital structure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Equity* (column (3)) and *Gross Equity* (column (4)). The main independent variables are *Equity shock*^{IND} (no common analyst) , *Equity shock*^{ACN} (same industry) *and Equity shock*^{ACN} (different industry). *Equity shock*^{IND} (no common analyst) is the simple average equity shock of all firms in the same industry and that do not have a common analyst. *Equity shock*^{ACN} (same industry) *(Equity shock*^{ACN} (different industry)) is the weighted average equity shock of analyst peers (not) from the same industry. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Panel A: All firms in the same industry as firm i and that do not have a common analyst				
Equity shock^{IND} (no common analyst)	-.003	-.009	.014	.026
	(.003)	(.003)***	(.010)	(.011)**
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Industry characteristics (no common analyst)	Yes	Yes	Yes	Yes
R^2	.114	.771	.392	.458
Panel B: Analyst peers from the same industry				
Equity shock^{ACN} (same industry)	-.005	-.007	.010	.021
	(.003)*	(.003)**	(.010)	(.011)**
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Peer characteristics (same industry)	Yes	Yes	Yes	Yes
R^2	.116	.771	.392	.458
Panel C: Analyst peers not from the same industry				
Equity shock^{ACN} (different industry)	-.014	-.016	.049	.071
	(.004)***	(.005)***	(.016)***	(.016)***
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Peer characteristics (different industry)	Yes	Yes	Yes	Yes
R^2	.115	.77	.392	.458
Panel D: All together				
Equity shock^{IND} (no common analyst)	-.004	-.009	.013	.025
	(.003)	(.003)***	(.010)	(.011)**
Equity shock^{ACN} (same industry)	-.005	-.006	.009	.019
	(.003)*	(.003)*	(.010)	(.011)*
Equity shock^{ACN} (different industry)	-.016	-.016	.050	.071
	(.004)***	(.005)***	(.016)***	(.016)***
R^2	.118	.772	.392	.458
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Industry characteristics (no common analyst)	Yes	Yes	Yes	Yes
Peer characteristics (same industry)	Yes	Yes	Yes	Yes
Peer characteristics (different industry)	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960

Table 8: Placebo test with pseudo peers

The table presents the results of OLS regressions that relate pseudo peer firm idiosyncratic equity shock to firm capital structure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Equity* (column (3)) and *Gross Equity* (column (4)). The main independent variable is *Equity shock*^{ACN} *(pseudo-peer)* which is the simple average equity shock of all firms that are in the same industry as a firm's analyst peers but that do not have any common analysts with the firm in question. We use alternate industry definitions to identify the pseudo-peers in the different panels. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. In all the specifications we include as control variables individual firm and pseudo-peer characteristics. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Panel A: Three-Digit SIC Code				
Equity shock^{ACN} *(pseudo-peer)*	.0003	-.017	-.025	.001
	(.011)	(.013)	(.038)	(.041)
Obs.	37159	37159	37159	37159
R^2	.116	.772	.39	.459
Panel B: Two-Digit SIC Code				
Equity shock^{ACN} *(pseudo-peer)*	-.013	-.029	-.073	.013
	(.019)	(.023)	(.065)	(.069)
Obs.	36883	36883	36883	36883
R^2	.112	.772	.39	.459
Panel C: Fama-French industry Cclassification				
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
Equity shock^{ACN} *(pseudo-peer)*	.032	-.0002	-.100	-.038
	(.020)	(.022)	(.066)	(.070)
Obs.	36675	36675	36675	36675
R^2	.111	.773	.392	.46
Panel D: GICS industry classification				
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
Equity shock^{ACN} *(pseudo-peer)*	-.002	-.039	.034	.128
	(.015)	(.017)**	(.053)	(.053)**
Obs.	36894	36894	36894	36894
R^2	.111	.772	.395	.462
Panel D: Hoberg-Phillips Peers				
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
Equity shock^{ACN} *(pseudo-peer)*	.008	-.026	.065	.135
	(.013)	(.017)	(.050)	(.053)***
Obs.	30057	30057	30057	30057
R^2	.121	.779	.407	.469
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Pseudo-peer characteristics	Yes	Yes	Yes	Yes

Table 9: Cross-sectional test: Leaders vs. Followers

The table presents the results of OLS regressions that relate peer firm idiosyncratic equity shock to firm capital structure. The outcome variables are Δ*Leverage* (columns (1)-(2)), *Leverage* (columns (3)-(4)), *Net* Equity (columns (5)-(6)) and *Gross Equity* (columns (7)-(8)). The main independent variables are *Equity shock*$^{ACN}_{-it}$ (Leaders) and *Equity shock*$^{ACN}_{-it}$ (Followers) which measure the weighted average equity shock of analyst peers which are industry leaders and followers respectively. We classify firms that rank above median in terms of sales (columns (1), (3), (5) and (7)) or profitability (columns (2), (4), (6) and (8)) as leaders and the rest as followers. In Panel A our sample comprises of follower firms while in Panel B we focus on leader firms. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Leaders' equity shock on followers' financial policy

Dependent Variable:	ΔLeverage		Leverage		Net Equity		Gross Equity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales	Profitability	Sales	Profitability	Sales	Profitability	Sales	Profitability
Equity shock^{ACN} (Leaders)	-.013	-.014	-.005	-.014	.088	.056	.080	.058
	(.005)***	(.005)***	(.007)	(.007)**	(.023)***	(.021)***	(.023)***	(.021)***
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17973	18446	17973	18446	17973	18446	17973	18446
R^2	.1	.144	.781	.819	.434	.465	.497	.51

Panel B: Followers' equity shock on leaders' financial policy

Dependent Variable:	ΔLeverage		Leverage		Net Equity		Gross Equity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales	Profitability	Sales	Profitability	Sales	Profitability	Sales	Profitability
Equity shock^{ACN} (Followers)	-.006	.0005	-.006	-.002	.016	.016	.022	.022
	(.004)	(.004)	(.005)	(.005)	(.015)	(.019)	(.017)	(.020)
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18288	18822	18288	18822	18288	18822	18288	18822
R^2	.157	.131	.792	.802	.324	.444	.435	.515

Table 10: Cross-sectional test: All-Star brokerage houses and analyst experience

The table presents the results of OLS regressions that relate peer firm average financial policy and idiosyncratic equity shock to firm capital structure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net* Equity (column (3)) and *Gross Equity* (column (4)). We classify brokerage houses that employ at least two all-star analysts as All-star brokerage houses. We classify analysts with above median experience as being more experienced. In Panel A we differentiate *Equity shock*$^{ACN}_{-it}$ across all-star and non-all-star brokerage houses while in Panel B we differentiate it across more and less experienced analysts. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: All-Star Brokerage Houses (All-Star vs. Non All-Star)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Equity shock^{ACN} (All-Star)	-.020	-.025	.064	.063
	(.005)***	(.006)***	(.019)***	(.020)***
Equity shock^{ACN} (Non All-Star)	-.013	-.009	.004	.032
	(.004)***	(.004)*	(.014)	(.015)**
(All-Star)-(Non All-Star)	-0.007	-.016**	0.06***	0.031
Equity shock^{IND}	No	Yes	Yes	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Peer characteristics (All-Star)	Yes	Yes	Yes	Yes
Peer characteristics (Non All-Star)	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960
R^2	.118	.772	.393	.459

Panel B: Analyst Experience (More Experienced vs. Less Experienced)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Equity shock^{ACN}(More experienced)	-.027	-.027	.044	.070
	(.005)***	(.006)***	(.019)**	(.020)***
Equity shock^{ACN} (Less experienced)	-.003	-.003	.011	.012
	(.003)	(.003)	(.011)	(.011)
(More)-(Less)	-0.024***	-0.024***	0.034	0.058***
Equity shock^{IND}	Yes	Yes	Yes	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Peer characteristics (More experienced)	Yes	Yes	Yes	Yes
Peer characteristics (Less experienced)	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960
R^2	.118	.772	.393	.459

Table 11: Cross-sectional test: Regulation FD

This table presents the coefficients of the reduced form regression and the effect associated with the passage of the Regulation Fair Disclosure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Equity* (column (3)) and *Gross Equity* (column (4)). The main independent variables are *Equity Shock*^{ACN} and *Equity Shock*^{IND} *(no common analysts)* which measure the lagged averages of the idiosyncratic equity shock for analyst peers and industry peers respectively. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. The dummy variable *Post-RegFD* takes the value of one for the sample period 2002-2013 and takes the value of zero for the sample period 1990-1999 *(Pre-RegFD)*. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Reduced-form using direct peer Equity Shock				
	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Equity shock^{ACN}	-.028	-.045	.162	.168
	(.009)***	(.012)***	(.039)***	(.038)***
Equity shock^{ACN} *X Post-RegFD*	.003	.028	-.153	-.121
	(.010)	(.014)**	(.047)***	(.047)**
Post-RegFD	-.003	-.004	.011	.083
	(.003)	(.014)	(.025)	(.030)***
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Obs.	34549	34549	34549	34549
R^2	.129	.775	.397	.462

Panel B: Reduced-form using all firms in the same industry as firm i and that do not have a common analyst				
	ΔLeverage	Leverage	Net Equity	Gross Equity
Equity shock^{IND}(no common analyst)	-.003	-.011	.006	.028
	(.005)	(.006)*	(.018)	(.020)
Equity shock^{IND}(no common analyst)*X Post-RegFD*	-.005	.002	.007	-1.00e-05
	(.006)	(.007)	(.022)	(.024)
Post-RegFD	-.005	-.014	-.023	.049
	(.003)	(.010)	(.020)	(.024)**
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes
Obs.	34549	34549	34549	34549
R^2	.126	.774	.397	.462

Table 12: Two-stage least square instrumentals variable regression using indirect peers

The table presents the results of the 2SLS regression that relates peer firm average financial policy to firm capital structure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2), *Net Equity* (column (3) and *Gross Equity* (column (4). The main endogenous variables are peer averages of the outcome variables. The excluded instrument in the first stage is *Equity shock*^{ACN} (indirect peers) which measures the lagged averages of the idiosyncratic equity shock for indirect analyst peers. Panel A shows the results of the indirect peer approach using the *Equity Shock* of all indirect peers. Panel B shows the results of the indirect peer approach using the *Equity Shock* of indirect peers that are only in different industries as firm i. All control variables, but excluding *Industry average (no overlap)*, are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	Panel A: All Indirect Peers				Panel B: Indirect Peers (in different industries)			
Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First stage								
Equity shock^{ACN} (indirect peers)	-.034	-.050	.105	.163	-.034	-.031	.124	.155
	(.004)***	(.007)***	(.016)***	(.019)***	(.005)***	(.007)***	(.017)***	(.019)***
Second stage								
Instrumented peer average	.512	.776	.818	1.314	.791	.714	.882	1.294
	(.354)	(.297)***	(.466)*	(.324)***	(.346)**	(.460)	(.384)**	(.329)***
Industry average (no overlap)	.112	.027	.040	.024	.077	.030	.038	.025
	(.046)**	(.014)**	(.020)**	(.015)	(.045)*	(.019)	(.017)**	(.016)
Peer average stock return	-.0004	-.008	.003	-.033	-.004	-.009	-.002	-.031
	(.007)	(.006)	(.041)	(.030)	(.006)	(.008)	(.035)	(.031)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37960	37960	37960	37960	37960	37960	37960	37960
Kleibergen-Paap F-value	55.79	49.061	42.962	74.217	53.358	19.176	55.509	66.447
Cragg-Donald F-value	91.074	74.494	75.123	131.565	96.429	31.574	111.001	127.125
Anderson-Rubin F-value	1.956	6.811	3.184	19.109	4.906	2.415	5.545	18.522
Anderson-Rubin P-value	.162	.009	.074	1.00e-05	.027	.12	.019	.00002

Internet Appendix for "*Analyst Coverage Networks and Corporate Financial Policies*"

Table IA- 1: Summary Statistics: Industry averages based on alternate industry definitions

The table reports the summary statistics for the industry averages of the outcome variables, equity shock and control variables that we employ in our analysis based on alternate industry definitions. All variables used in the regression analysis are winsorized at the 1st and 99th percentiles and are defined in Appendix A.

Outcome Variables-Industry Average (Simple Average)																
	Two-Digit SIC Code				Fama-Frech Industry Classification				GICS				HP-Peers			
	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median
ΔMarket leverage	37960	0.01	0.05	0.01	37960	0.01	0.05	0.00	37947	0.01	0.05	0.01	30076	0.01	0.05	0.00
Market leverage	37960	0.23	0.11	0.19	37960	0.23	0.11	0.22	37947	0.23	0.11	0.23	30076	0.21	0.14	0.18
Net debt	37960	0.33	0.11	0.31	37960	0.33	0.11	0.32	37947	0.33	0.12	0.32	30076	0.34	0.21	0.31
Net equity	37960	0.23	0.11	0.23	37960	0.23	0.12	0.21	37947	0.23	0.14	0.20	30076	0.24	0.21	0.21
Gross equity	37960	0.31	0.14	0.31	37960	0.31	0.14	0.28	37947	0.31	0.16	0.28	30076	0.40	0.26	0.37
Control Variables-Industry Average (Simple Average)																
	Two-Digit SIC Code				Fama-Frech Industry Classification				GICS				HP-Peers			
	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median
Equity shock^{IND}	37960	-0.03	0.09	-0.04	37960	-0.03	0.09	-0.04	37917	-0.03	0.10	-0.04	30076	-0.03	0.16	-0.04
Log(Sales)	37960	5.72	0.92	5.58	37960	5.72	0.90	5.67	37947	5.75	0.96	5.70	30076	6.69	1.05	6.77
Market to book	37960	1.61	0.53	1.51	37960	1.61	0.60	1.45	37947	1.60	0.61	1.42	30076	1.73	0.79	1.52
Profitability	37960	0.08	0.06	0.09	37960	0.09	0.06	0.10	37947	0.09	0.07	0.11	30076	0.11	0.07	0.13
Tangibility	37960	0.28	0.17	0.22	37960	0.28	0.17	0.22	37947	0.28	0.17	0.23	30076	0.28	0.19	0.23
Δ Log(Sales)	37960	0.10	0.09	0.10	37960	0.10	0.09	0.11	37947	0.10	0.10	0.10	30076	0.10	0.12	0.10
ΔMarket to book	37960	-0.08	0.35	-0.07	37960	-0.08	0.38	-0.05	37947	-0.07	0.39	-0.04	30076	-0.07	0.49	-0.03
Δ Profitability	37960	-0.01	0.02	-0.00	37960	-0.00	0.02	-0.00	37947	-0.00	0.02	-0.00	30076	-0.00	0.03	-0.00
Δ Tangibility	37960	-0.00	0.01	-0.00	37960	-0.00	0.01	-0.00	37947	-0.00	0.01	-0.00	30076	-0.00	0.02	-0.00

Table IA- 2: Reduced form and 2SLS IV regression controlling for institutional investor network

The table presents the reduced form OLS (Panel A) and 2SLS (Panel B) regression that relates firm financial policy to analyst peer firm financial policy after controlling for the financial policy of firms that share institutional shareholders. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2), *Net Equity* (column (3) and *Gross Equity* (column (4). In Panel B, the main endogenous variables are peer averages of the outcome variables. All the control variables and the equity shock instruments are lagged one period. When the dependent variable is Δ*Leverage* all the control variables, except the equity shock instruments are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A of the paper for complete variable definitions. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Reduced Form				
Dependent variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
Equity shock^{ACN}	-.020	-.022	.076	.091
	(.006)***	(.007)***	(.021)***	(.022)***
Equity shock$^{Inst.Investor}$	-.191	-.175	.594	.573
	(.025)***	(.032)***	(.087)***	(.090)***
Equity shock^{IND}	-.004	-.015	-.0009	.022
	(.004)	(.004)***	(.013)	(.014)
Equity shock^{OWN}	-.004	-.014	.052	.066
	(.001)***	(.002)***	(.005)***	(.005)***
Own characteristics	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes
Inst. Inv characteristics	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37205	37205	37205	37205
R^2	.121	.773	.399	.463

Panel B: Structural Regression				
Dependent variable:	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)
First stage :				
Equity shock^{ACN}	-.012	-.014	.090	.112
	(.002)***	(.003)***	(.008)***	(.009)***
Instrumented peer average	1.551	1.485	.888	.807
	(.483)***	(.556)***	(.227)***	(.190)***
Inst. Investor average	.462	.382	.842	.574
	(.205)**	(.161)**	(.130)***	(.109)***
Industry average	-.054	-.007	.086	.145
	(.165)	(.154)	(.060)	(.052)***
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes
Inst. Inv characteristic	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37205	37178	37178	37178
Kleibergen-Paap F-value	36.856	18.629	139.17	156.075

Table IA- 3: Baseline Specification I. Peer firms using alternate industry classifications

The table presents the OLS coefficients for the following regression:

$$y_{ijt} = \alpha + \beta_1 y_{-it}^{ACN} + \beta_2 y_{-ijt}^{IND} + \gamma_1^{'} X_{-it-1}^{ACN} + \gamma_2^{'} X_{-ijt-1}^{IND} + \gamma_3^{'} X_{ijt-1} + \delta^{'} u_i + \phi^{'} v_t + \epsilon_{ijt}$$

The outcome variables are Δ *Leverage* (columns (1) - (2)), *Leverage* (columns (3) - (4)), *Net Debt* (columns (5) - (6)), *Net Equity* (columns (7) - (8)) and *Gross Equity* (columns (9) - (10)). The main independent variables are *Peer average* and *Industry average*, which measure the contemporaneous averages of the respective outcome variable for analyst and industry peers respectively. We use alternate industry definitions to calculate industry averages. Following the specification of Table 2, we control for firm, industry and peer characteristics. All other control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage		Leverage		Net Debt		Net Equity		Gross Equity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Two-Digit Sic Code					
Peer average		.546		.368		.215		.320		.293
		(.022)***		(.025)***		(.022)***		(.025)***		(.021)***
Industry average	.719	.390	.620	.415	.409	.298	.469	.289	.496	.312
	(.024)***	(.024)***	(.037)***	(.036)***	(.042)***	(.043)***	(.042)***	(.042)***	(.042)***	(.042)***
Obs.	37960	37960	37960	37960	37960	37960	37960	37960	37960	37960
R^2	.146	.172	.778	.783	.242	.244	.39	.396	.456	.461
					Fama-French Industry Classification					
Peer average		.550		.376		.213		.300		.282
		(.022)***		(.026)***		(.022)***		(.025)***		(.021)***
Industry average	.772	.404	.669	.443	.485	.362	.630	.438	.621	.417
	(.026)***	(.027)***	(.039)***	(.039)***	(.047)***	(.048)***	(.046)***	(.047)***	(.049)***	(.050)***
Obs.	37960	37960	37960	37960	37960	37960	37960	37960	37960	37960
R^2	.145	.171	.777	.783	.242	.244	.392	.397	.457	.461
					GICS					
Peer average		.509		.345		.211		.271		.257
		(.023)***		(.026)***		(.023)***		(.024)***		(.022)***
Industry average	.748	.409	.652	.440	.394	.262	.595	.419	.600	.419
	(.023)***	(.024)***	(.034)***	(.033)***	(.042)***	(.044)***	(.040)***	(.041)***	(.040)***	(.041)***
Obs.	37947	37947	37947	37947	37947	37947	37947	37947	37947	37947
R^2	.153	.173	.779	.783	.241	.244	.394	.398	.459	.462
					HP-Peers					
Peer average		.531		.444		.242		.284		.293
		(.025)***		(.029)***		(.027)***		(.029)***		(.026)***
Industry average	.510	.288	.304	.194	.147	.100	.222	.152	.164	.096
	(.019)***	(.019)***	(.019)***	(.018)***	(.019)***	(.019)***	(.021)***	(.021)***	(.018)***	(.018)***
Obs.	30076	30076	30076	30076	30076	30076	30076	30076	30076	30076
R^2	.164	.186	.784	.791	.255	.258	.407	.411	.467	.471

Table IA- 4: Reduced form regression with idiosyncratic equity shock and alternate industry classifications

The table presents the results of the following OLS regression:

$$y_{ijt} = \alpha_0 + \alpha_1 Eq.Shock^{ACN}_{-it-1} + \alpha_2 Eq.Shock^{IND}_{-ijt-1} + \alpha_3 Eq.Shock_{ijt-1} + \gamma_1' X^{ACN}_{-it-1} + \gamma_2' X^{IND}_{-ijt-1} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2)), *Net Debt* (column (3)), *Net Equity* (column (4)) and *Gross Equity* (column (5)). The main independent variables are *Equity Shock*^{ACN} and *Equity Shock*^{IND} which measure the lagged averages of the idiosyncratic equity shock for analyst peers and industry peers respectively. We use alternate industry definitions to calculate industry averages. Following the specification in Table 4, we include as control variables the firm, industry and peer characteristics. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent variable:	ΔLeverage	Leverage	Net Debt	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)
			Two-Digit SIC Code		
Equity shock^{ACN}	-.027	-.024	-.027	.063	.086
	(.005)***	(.006)***	(.023)	(.019)***	(.020)***
Equity shock^{IND}	-.005	-.030	-.001	.007	.013
	(.007)	(.008)***	(.031)	(.023)	(.025)
Equity shock^{OWN}	-.006	-.016	-.010	.059	.072
	(.001)***	(.002)***	(.005)**	(.005)***	(.005)***
Obs.	37960	37960	37960	37960	37960
R^2	.114	.772	.239	.392	.458
			Fama-French Industry Classification		
Equity shock^{ACN}	-.025	-.024	-.022	.061	.081
	(.005)***	(.006)***	(.023)	(.019)***	(.020)***
Equity shock^{IND}	-.013	-.032	-.025	.033	.069
	(.007)*	(.008)***	(.035)	(.026)	(.028)**
Equity shock^{OWN}	-.006	-.016	-.010	.059	.071
	(.001)***	(.002)***	(.005)*	(.005)***	(.005)***
Obs.	37960	37960	37960	37960	37960
R^2	.114	.772	.239	.393	.459
			GICS		
Equity shock^{ACN}	-.030	-.025	-.030	.058	.084
	(.005)***	(.006)***	(.023)	(.020)***	(.020)***
Equity shock^{IND}	.007	-.023	.007	.029	.034
	(.006)	(.007)***	(.029)	(.024)	(.026)
Equity shock^{OWN}	-.006	-.016	-.011	.059	.072
	(.001)***	(.002)***	(.005)**	(.005)***	(.005)***
Obs.	37913	37913	37913	37913	37913
R^2	.114	.771	.239	.393	.459
			HP-Peers		
Equity shock^{ACN}	-.035	-.032	-.044	.056	.081
	(.006)***	(.007)***	(.027)	(.023)**	(.023)***
HP-Peer Equity Shock	.004	-.014	.014	-.024	-.002
	(.004)	(.005)**	(.020)	(.016)	(.017)
Equity shock^{OWN}	-.004	-.017	-.012	.056	.069
	(.001)***	(.002)***	(.006)**	(.005)***	(.005)***
Obs.	30076	30076	30076	30076	30076
R^2	.125	.78	.253	.408	.47

Table IA- 5: Two-stage least square instrumentals variable regression using equity shock and alternate industry classifications

The table presents the results of the 2SLS regression that relates peer firm average financial policy to firm financial policy. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2), *Net Equity* (column (3) and *Gross Equity* (column (4). The main endogenous variables are peer averages of the outcome variables. The excluded instrument in the first stage is *Equity shock*^{ACN} which measures the lagged averages of the idiosyncratic equity shock for analyst peers. We use alternate industry definitions to calculate industry averages. Following the specification in Table 6, we include as control variables firm, industry and peer characteristics. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Two-Digit SIC Code				GICS			
First stage :								
Equity shock^{ACN}	-.010	-.013	.081	.106	-.012	-.013	.078	.105
	(.002)***	(.003)***	(.007)***	(.008)***	(.002)***	(.003)***	(.007)***	(.008)***
Second stage								
Instrumented peer average	2.018	1.727	.735	.760	2.011	1.818	.733	.777
	(.565)***	(.541)***	(.225)***	(.180)***	(.482)***	(.558)***	(.233)***	(.183)***
Industry average	-.487	-.313	.061	.011	-.574	-.427	.121	.045
	(.338)	(.291)	(.130)	(.120)	(.316)*	(.329)	(.155)	(.134)
Obs.	37960	37960	37960	37960	37947	37947	37947	37947
Kleibergen-Paap F-value	31.468	23.007	136.893	180.137	44.592	23.052	129.876	179.328
	Fama-French Industry Classification				HP-Peers			
First stage :								
Equity shock^{ACN}	-.013	-.015	.083	.107	-.015	-.017	.074	.100
	(.002)***	(.003)***	(.007)***	(.008)***	(.002)***	(.003)***	(.008)***	(.008)***
Second stage								
Instrumented peer average	1.838	1.673	.739	.766	1.682	1.657	.551	.700
	(.426)***	(.480)***	(.221)***	(.179)***	(.426)***	(.449)***	(.278)**	(.221)***
Industry average	-.437	-.295	.159	.058	-.185	-.113	.085	.0003
	(.280)	(.274)	(.146)	(.138)	(.176)	(.114)	(.071)	(.053)
Obs.	37960	37960	37960	37960	30076	29882	29882	29882
Kleibergen-Paap F-value	52.327	28.517	141.167	184.128	53.172	30.93	95.824	137.755

Table IA- 6: Two-stage least square instrumentals variable regression using indirect peers and alternate industry classifications

The table presents the results of the 2SLS regression that relates peer firm average financial policy to firm capital structure. The outcome variables are Δ *Leverage* (column (1)), *Leverage* (column (2), *Net Equity* (column (3) and *Gross Equity* (column (4). The main endogenous variables are peer averages of the outcome variables. The excluded instrument in the first stage is *Equity shock*^{ACN} (indirect) which measures the lagged averages of the idiosyncratic equity shock for indirect analyst peers. We use alternate industry definitions to calculate industry averages. Following the specification in Table 12, we include as control variables firm, industry and peer characteristics and peer average stock return. All control variables are lagged one period. In the specification with Δ*Leverage* as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects. The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity	Gross Equity	ΔLeverage	Leverage	Net Equity	Gross Equity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Two-Digit SIC Code				GICS			
First stage								
Equity shock^{ACN} (indirect peers)	-.031	-.049	.102	.159	-.025	-.047	.090	.143
	(.004)***	(.007)***	(.016)***	(.019)***	(.004)***	(.007)***	(.016)***	(.019)***
Second stage								
Instrumented peer average	.492	.772	.834	1.346	.259	.803	.716	1.325
	(.388)	(.301)**	(.478)*	(.332)***	(.485)	(.312)**	(.542)	(.369)***
Industry average (No overlap)	.221	.057	.021	-.015	.286	.035	.083	-.0003
	(.102)**	(.031)*	(.058)	(.039)	(.152)*	(.039)	(.078)	(.051)
Obs.	37960	37960	37960	37960	37947	37947	37947	37947
Kleibergen-Paap F-value	47.441	48.389	41.558	71.955	34.017	45.902	32.476	58.796
	Fama-French Industry Classification				HP Peers			
First stage								
Equity shock^{ACN} (indirect peers)	-.026	-.047	.093	.149	-.028	-.056	.091	.173
	(.004)***	(.007)***	(.016)***	(.019)***	(.005)***	(.007)***	(.017)***	(.020)***
Second stage								
Instrumented peer average	.313	.749	.760	1.365	.381	.598	.758	1.329
	(.454)	(.310)**	(.523)	(.356)***	(.471)	(.287)**	(.616)	(.346)***
Industry average (No overlap)	.318	.079	.085	-.044	.195	.047	.040	.007
	(.154)**	(.047)*	(.079)	(.060)	(.080)**	(.015)***	(.032)	(.018)
Obs.	37960	37960	37960	37960	30076	29882	29882	29882
Kleibergen-Paap F-value	36.226	45.911	34.826	63.801	33.662	60.779	27.939	78.33

Table IA- 7: Robustness test of indirect peer approach

This table presents the results for the indirect peer approach, where indirect peers are defined as the firms connected to the firms' direct peers by at least three analysts in common. Panel A shows the characteristics of analyst networks in terms of indirect peers and the equity shock of indirect peers. Panel B reports the results of the 2SLS regression that relates peer firm average financial policy to firm capital structure employing the indirect peer approach. Following the specification in Table 12, we include as control variables firm, industry and peer characteristics and peer average stock return. All control variables are lagged one period. In the specification with $\Delta Leverage$ as the dependent variable all the control variables are in first difference form and we include year and industry fixed effects (three-digit SIC code). The remaining specifications include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile and are defined in Appendix A. For brevity we suppress the constant. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Summary statistics for the indirect peer connections and equity shock

Indirect Peers		Number of Connections					Connections (%)				
	N	Mean	SD	P25	Median	P75	Mean	SD	P25	Median	P75
Overall	37451	81.74	64.77	35	65	111					
Within industry (3Digit-Sic code)	37451	6.91	11.97	0	1	8	0.12	0.21	0	0.02	0.15
Across industries (3Digit-Sic code)	37451	74.83	64.43	27	58	103	0.88	0.21	0.85	0.98	1
Within industry (F-F Industry)	37451	14.85	16.42	2	9	23	0.25	0.27	0.03	0.14	0.4
Across industries (F-F Industry)	37451	66.89	62.96	21	48	93	0.75	0.27	0.6	0.86	0.97
Within industry (GICS Industry)	37451	10.01	10.31	2	7	15	0.19	0.23	0.02	0.1	0.29
Across industries (GICS Industry)	37451	71.73	64.53	24	54	100	0.81	0.23	0.71	0.9	0.98
Equity shock^{ACN} (indirect peer)	37451	-0.04	0.1	-0.09	-0.04	0.01					

Panel B: 2SLS employing indirect peer approach

Dependent Variable:	ΔLeverage	Net Equity	Gross Equity
	(1)	(2)	(3)
First stage			
Equity shock^{ACN} (indirect peers)	-.019	.032	.035
	(.002)***	(.008)***	(.009)***
Second stage			
Instrumented peer average	.791	1.082	1.874
	(.318)**	(.771)	(.825)**
Industry average (no overlap)	.077	.031	.007
	(.041)*	(.029)	(.025)
Peer average stock return	-.005	-.024	-.089
	(.006)	(.068)	(.074)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes
Ind. characteristics	Yes	Yes	Yes
Obs.	37451	37409	37409
Kleibergen-Paap F-value	68.143	17.1	14.788