Analyst Coverage Network and Corporate Financial Policies

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Abstract

This paper shows that sell-side analysts play an important role in propagating corporate financial policy choices, such as leverage and equity issuance decisions across firms. Using exogenous characteristics of analyst network peers as well as the "friends-of-friends" approach from the network effects literature to identify peer effects, we find that exogenous changes to financial policies of firms covered by an analyst leads other firms covered by the same analyst to implement similar policy choices. We find that a one standard deviation increase in peer firm average leverage is associated with a 0.35 standard deviation increase in a firm's leverage, and a one standard deviation increase in the frequency of peers' equity issuance leads to a 29.6% increase in the likelihood of issuing equity. We show evidence that these analyst network peer effects are distinct from industry peer effects and are more pronounced among peers connected by analysts that are more experienced and from more influential brokerage houses.

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1 Introduction

Sell-side analysts are important players in financial markets. Their role in acquiring, analyzing, and disseminating information for investors has been much studied (Frankel et al. (2006), Kadan et al. (2012); Muslu et al. (2014); Chang et al. (2006); Piotroski and Roulstone (2004)). In addition to their role as information intermediaries between firms and investors, there is growing evidence that analysts may also influence the policies of the firms they cover (Kaustia and Rantala (2015); Degeorge et al. (2013); Becher et al. (2015)). Analysts can communicate their preferred financial policy to management through conference calls, analyst reports, etc. Management in turn will be willing to adopt those policies either if they are perceived to be value enhancing or if management wishes to cater to the analyst (Degeorge et al. (2013)). An indirect channel of analyst influence is when managers, in their effort to meet analyst forecasts, alter firm financial and investment policies (Bhojraj et al. (2009); Gunny (2010); Hribar et al. (2006)).[1] In this paper, we argue that analysts may affect corporate financial policies by transmitting information across portfolio firms.

Analysts cover a portfolio of firms often spread across multiple industries. 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 may come across information that can effectively be transferred from one firm to another. Such information can be about the state of financial markets, growth opportunities, or about the suitability of a particular financial policy. If analysts communicate such intelligence to management and if the firms follow the analysts' recommendation, then we expect financial policies to be correlated among firms with common analysts. Note that although the policies of peer firms may be public knowledge, we believe analysts may still play an important role in communicating the suitability of the policy for a particular firm. We use the latest identification techniques from the social networks literature to document

[1] Managers sometimes engage in real activities manipulation. For instance, reducing R&D when actual earnings may be lower than the analyst consensus.

the causal effect of analyst peer firm financial policies on a firm's financial policy.

We identify "exogenous" changes to financial policies of firms covered by an analyst and test to see if other firms covered by the same analyst experience similar changes in policy. 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 use empirical methods from the social networks literature to identify peer effects in the analyst coverage network. As discussed by Manski (1993), a positive association between a firm's financial policy and that of its peers can arise from one of three sources. First, there can be one or more unobserved common characteristic between the firm and its peers. This is what Manski (1993) calls "correlated effects". For example, firms in the same analyst network are likely to operate in similar product markets and thus share common characteristics. These common characteristics can result in the firms choosing similar financial policies. To the extent analysts have "exogenous" preferences about financial policies and directly influence their portfolio firms to implement those policies, it can also generate correlated effects.

Second, firms may change their financial policy in response to changes in some peer firm characteristic. 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 referred to as "exogenous peer effects". The word exogenous refers to the change in the "exogenous" characteristic driving the change in financial policy. Finally, changes to peer firm financial policy may causally influence a firm's financial policy. This is referred to as "endogenous peer effect" and is the one that we wish to document. Our objective is to establish the presence of endogenous peer effects among firms covered by common analysts. Distinguishing between exogenous and endogenous effects is important 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 still generate multiplier effects through endogenous peer effects (Glaeser et al. (2003)).

We follow two methodologies to establish the existence of endogenous peer effects. First, to isolate correlated effects from endogenous and exogenous peer effects (we refer to these as social effects from now), we follow Leary and Roberts (2014) and use idiosyncratic equity return shocks as an exogenous source of variation in peer firm financial policy (and possibly characteristics). 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 (Baker and Wurgler (2002); Leary and Roberts (2005)). 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. Note that 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 in one or more of peers' characteristics.[2] To this extent this methodology will not allow us to distinguish between endogenous and exogenous peer effects.

To distinguish endogenous peer effects from exogenous peer effects we exploit the fact that analyst networks partially overlap. Thus 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. This is a key property of the analyst coverage network that allows for identification.[3] Following the

[2]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.

[3] 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.

"friends of friends" approach outlined in Bramoullé et al. (2009) and Goldsmith-Pinkham and Imbens (2013), we use the exogenous characteristic of firm k, namely idiosyncratic equity shock as an instrument for the financial policy of firm j to document its influence on firm i's financial policy. 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. Given our interest in controlling for exogenous peer effects another way to state this is, firm k's equity shock should not be correlated with either firm j or firm i's characteristic. To the extent we are able to isolate "idiosyncratic shocks" to equity values, this assumption is reasonable. It follows the same logic as outlined in Leary and Roberts (2014).

We begin by documenting a positive association between a firm's financial policy and that of its analyst peers. We find that this association extends to all the outcome variables we model and to analyst peers not from the same industry. Next we implement reduced-form regressions that documents 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 and characteristics of the firm's industry peers, as well as the characteristics of the firm and its analyst peers. The positive association exists for leverage, changes in leverage, equity issues and share repurchases. Thus our results are consistent with the existence of "social effects" for leverage, equity issues and share repurchases.

Next, we use the idiosyncratic shock to peer firms' stock prices (*Equity shock*) as an instrument for peer firm financial policies in a two-stage least squares (2SLS) specification and find that we obtain consistent results. To the extent this 2SLS does not isolate endogenous peer effects, we will not be able to interpret the estimates as the causal effect of peer firm financial policy on a firm's financial policy.

We take several steps to establish that our results capture the role of analyst networks and not other common factors such as industry. 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 relation between the return shocks of the pseudo peers and the firm's financial policy.

We further document cross-sectional variation in our estimated effects that are consistent with information propagating through the analyst network. First, we find that smaller and less successful firms are influenced by the larger and more successful ("leader") firms in their analyst network, but not vice versa. Second, 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 more experienced analysts and by analysts from brokerage houses with more "all-star" rated analysts.

Finally using the friends of friend methodology from the social network literature, we document the presence of endogenous peer effects among firms covered by analysts. Using the equity shock of indirect peer firms as an instrument for peer firm financial policies, we document an economically significant endogenous peer effect. A one standard deviation increase in peer firm average leverage is associated with a 0.35 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 peer firm's average equity issuance leads to a 29.6% increase in the likelihood of a firm issuing equity. Overall, after controlling for the endogeneity in the network formation we find that peer firms in the same analyst coverage network affect each other.

We make a number of important contributions. First, we document the important role of analysts in propagating financial policies across firms. An important question that we do not answer is whether such propagation is efficient or results in inefficient mimicking. Future research should explore this important question. Our second contribution is methodological. We are the first in the finance literature to use 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 provides the summary statistics and section 5 discusses the empirical evidence. Finally, section 6 concludes. Definitions of empirical variables are in Appendix A.

2 Literature Review

This paper is related to two main streams of literature. The first is related to the role of analysts in the financial markets and the second explores the effect of social networks in corporate finance. Our paper contributes to the literature by showing that analysts are an important mechanism underlying peer effects in financial policy and that analysts 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.[4] Evidence from Kelly and Ljungqvist (2012) suggests this information production of analysts is effective in reducing information asymmetry in financial markets. Additionally, a number of recent studies have shown evidence that analysts can

[4]Examples include Womack (1996); Piotroski and Roulstone (2004); Frankel et al. (2006); Kadan et al. (2012); Muslu et al. (2014), among others.

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 that analysts have preferred financial policies, which they influence firms to follow. Relative to these earlier studies, our study highlights a previously unexplored role of analysts that also impacts firm policies, namely that they facilitate peer effects by transmitting information among firms.

The second stream of the literature explores how peer effects, or the interaction among agents, can affect outcomes. There is a vast economics literature along this line and a growing literature in corporate finance analyzing the role of social networks on firm financial policy decisions. Shue (2013) shows that executive compensation and acquisitions strategies are significantly more similar among graduates from the same (randomly assigned) MBA section than among graduates from different sections. Fracassi (2016) studies the impact of social ties among managers from past employment and education and their corporate policy decisions. He finds that more connections two companies share with each other, more similar their capital investments are. Cai and Sevilir (2012) show that performance in M&A transaction of acquirers is better when the acquirer and the target share a common director. In the asset management area, Cohen et al. (2008) focus on the education network between mutual fund managers and corporate board members. They find that mutual fund managers invest more and perform significantly better on stock holdings for which the board members went to school together with the mutual fund managers. Matvos and Ostrovsky (2010) document peer effects among mutual fund managers in proxy voting.

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 studying the role of analysts in transmitting information among firms.

Our paper also differs methodologically from earlier studies of peer effects in corporate finance. We use recent econometric methodologies developed to identify peer effects (endogenous versus exogenous effects) in social networks. Our main model is an extended version of the Manski-type linear-in-means model studied in Goldsmith-Pinkham and Imbens (2013) and Bramoullé et al. (2009) (see also the survey by Blume et al. (2010)). A key property of the analyst coverage network that allows for identification of peer effects is that there exist many firms that are not directly connected to a firm through a common analyst, but that do share a common analyst with other firms in the analyst network. We refer to these as indirect analyst peers. We use the characteristics of the indirect analyst peers, including idiosyncratic equity shocks to indirect peers, as instruments for the financial policy of firm's direct peers to estimate peer effects in financial policy.

3 Data and Empirical Methodology

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 sample, 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 the end of the fiscal period and at least 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 37,745 firm-year observations.

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:

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

where the indices i, j and t refer to firm, industry and year respectively. The dependent variables that we model are, *Market leverage*, *Net debt issuance (1%)*, *Net equity issuance (1%)* and *Gross equity issuance (1%)*. Specifically, we employ the level and change in leverage. When we consider debt and equity issuances we use an indicator equal to one if the firm issues debt (equity) in excess of 1% of total assets, and zero otherwise.[5] All variables we use in our analysis are defined in the Appendix A. 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 represents the number of common analysts between firm l and firm i. Specifically:

$$y_{-it}^{ACN} = \frac{\sum^{I}{}_{(i \neq l)} n_{ilt} y_{lt}}{\sum^{I}{}_{(i \neq l)} n_{ilt}} \quad (2)$$

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

[5] 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.

more weight to peer firms with more analysts in common with a firm. Such peers may have a stronger influence on a firm's financial policy because there is a greater likelihood that one or more analysts 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^{ACN}_{-it-1}) as controls. These are the same set of characteristics included in X_{ijt-1} and discussed above. In calculating X^{ACN}_{-it-1}, we use the current network structure along with 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^{IND}_{-ijt} (excluding the firm i) and their average characteristics, X^{IND}_{-ijt-1}, as additional controls.[6] 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 industry- and year-fixed effects. 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

[6] We also create an alternative measure of industry average outcomes that includes only firms that are in the same industry as firm i, but they 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.

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.[7] For example, Muslu et al. (2014) and Israelsen (2014) show that shared coverage explains comovement and excess comovement between pairs of stock 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.[8] We then calculate, *Equity shock* for firm i in year t as 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, $\textit{Equity shock}_{-it}^{ACN}$, using the number of common analysts as the weights and the industry average equity shock, $\textit{Equity shock}_{-ijt}^{IND}$, as the simple average equity shock for all firms in the same industry as firm i.

We use $\textit{Equity shock}_{-it}^{ACN}$ 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 $\textit{Equity shock}_{-it}^{ACN}$ captures idiosyncratic

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

[8] 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.

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 $Equity\ shock^{ACN}_{-it}$ 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 (Baker and Wurgler (2002); Leary and Roberts (2005)) 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 ensures the relevance assumption is satisfied in our setting. Furthermore as we make clear later, the instrument is strongly correlated with firm financial policies in the first stage with a high F-statistic. The second assumption we make to isolate social effects is that $Equity\ shock^{ACN}_{-it}$ is uncorrelated with firm i's characteristics but through its effect on firm i's policies (or characteristics). To the extent our procedure for defining $Equity\ shock^{ACN}_{-it}$ isolates truly idiosyncratic shocks, this assumption is likely to be valid.

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 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 isolate the endogenous peer effects from exogenous peer effects, we exploit the fact that analyst networks partially overlap with each other. In other words, 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 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, Bramoullé et al. (2009) 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. In the example above if there was another firm m which is a peer of both firms i and j, Bramoullé et al. (2009) will allow one to use the average characteristics of both firms m and k as instruments for firm j's behavior. In our tests, we only use the characteristics of firm k as an instrument for the behavior of firm j. We exclude firm m because it is a direct peer of firm i. By construction, there are no analysts in common between firms i and k. The specific instrument we employ is the simple average *Equity shock.* The identifying assumptions necessary for us to isolate the endogenous peer effects are the following:

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. Our earlier results show that there are some social effects in our sample. Our second assumption is that firm k's equity shock should not be correlated with firm i's (and firm j's) characteristic. We believe this is a reasonable assumption because the firm and indirect peers do not have any analysts in common, and they are often not even from the same industry.[9] Furthermore *Equity shock* by construction identifies idiosyncratic shocks to a firm's equity value. Finally, since we focus on indirect peers we use a simple average of indirect peer equity shock instead of a weighted average.

[9]In a robustness test, we use only those indirect peers not in the same industry as firm i.

4 Summary Statistics

Panel A of Table 1 provides descriptive statistics for the analysts' network. On average, a firm is connected to 41.3 other firms through common analysts. Interestingly, only 10.46 (28%) of these connections are from the same three digit-SIC code industry as the firm. The low percentage of within industry connections helps us independently estimate peer effects arising from both industry and analyst networks. 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 405.54 (373) and the 25th percentile of the number of indirect connections is 218 while the 75th percentile is 563. 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 385 (352)).

Our next set of variables measure the number of common analysts between two firms. We find that on average, two connected firms in our sample have 1.89 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 2.34. 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.

Panel B reports the average value of the outcome variables we use in our analysis. We find that the average *Market leverage* in first difference (level) for the firms in our sample is 1% (21%). In comparison, the industry average *Market leverage* in first difference (level) and the peer average *Market leverage* in first difference (level) are 1% (23%) and 1% (20%) respectively. 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 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. Based on this definition, firms issue equity 23% of the sample period. 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, 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 *Equity shock* in our sample is close to zero at -.03, it has sufficient dispersion with a standard deviation of 0.50. Not surprisingly, *Equity shock* becomes much less dispersed when 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 the full CRSP-Compustat-IBES merged sample. We winsorize all our variables of interest at the 1st and 99th percentiles.

5 Empirical Results

5.1 Baseline Regressions

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 to investigate the hypothesis that more influential analysts are more effective in transmitting information about financial policies between firms. In our final set of tests, we employ the friends-of-friends approach to isolate endogenous peer effects from exogenous peer effects.

In Table 2, we provide the results of estimating equation (1) in our full sample. The outcome variable in columns (1) and (3) is *Market 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 (2008)). 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 significantly 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 the *Peer average* reduces the size of the coefficient on *Industry average* in first difference (level) from .461 (.405) to .253 (.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 issuance* 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 within and across industry analyst peers 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 (within industry)* and *Peer average (across industry).* These are the weighted averages of the outcome variable for within and across 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 within and across industry peer averages are positive and significant. The coefficients are also of similar size. This indicates that both within and across industry analyst peers appear to exert a similar level of influence on firm leverage. Specifically, in unreported tests we find that the two coefficients in column (2) are not statistically distinguishable. The significant coefficient on *Peer average (across 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 within and across 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 across industry analyst peers have a larger influence on a firm's decision to issue equity as compared to within industry analyst peers.

5.2 Reduced Form and Structural Regressions

Having established a positive association between peer firm financial policy and own firm's financial policy, we now go to our next set of tests wherein we employ *Equity Shock* as an exogenous peer firm characteristic in an effort to control for correlated effects.[10] In Table 4 we report the results of a reduced form estimation wherein we include *Peer Equity Shock* and *Industry Equity Shock* instead of peer and industry average financial policy and repeat our tests. We perform the reduced form analysis to provide evidence of social effects (endogenous or exogenous). However, at this point we cannot identify which one of these effects drives the results. In this table we also include *Industry Equity Shock* to highlight that the effect of *Peer Equity Shock* is robust to controlling for industry characteristics, suggesting that our peer effects 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), *Own Equity Shock*, *Industry Equity Shock* and *Peer Equity Shock* are negatively associated with a firm's market leverage (first difference and level). To the extent that equity shock provides an exogenous shock to a firm's financial policy and characteristic, the negative and significant coefficient on *Peer Equity Shock* is consistent with the presence of social effects within the analyst network. When we model leverage (column 2), our coefficient estimates on *Industry Equity Shock* and *Own Equity Shock* 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 *Peer Equity Shock*.

[10]Following Leary and Roberts (2014), we use the *Equity Shock* instrument lagged one period.

In column (3) our dependent variable is *Net debt issuances* and we find that while *Own Equity Shock* is negatively associated with *Net debt issuances*, both *Peer Equity Shock* and *Industry Equity Shock* are not significantly associated with *Net debt issuances*. By contrast, columns (4) - (5) indicate a strong positive association between *Peer Equity Shock* in a year and the probability of a firm making equity 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 decision.

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 *Peer Equity Shock* and *Peer average* are positive and statistically significant. Moreover, from column (4) we also find some evidence for peer effects in equity repurchases.[11]

In Table 6 we provide the results of the two-staged least squares estimation that uses *Peer Equity Shock* 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 shocks influence firm i through their 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

[11]The lack of statistical significance in columns 5 – 6 is understandable in light of the rarity of equity repurchases in excess of 3% (5%) of assets.

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 *Peer Equity Shock* 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). This is consistent with the presence of peer effects in leverage decisions that propagate through analyst network. 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 0.788 standard deviation increase in the firm's leverage (0.788 = 1.575 * (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. The coefficient estimates indicate that a one standard deviation increase in peer firm average net (gross) equity issuance results in a 12.51% (16.78%) increase in the likelihood of a firm issuing equity as identified by changes in net (gross) equity. In comparison a one standard deviation increase in industry average gross equity issuance (the only coefficient statistically significant) results in a 2.4% increase in the likelihood of a firm making a gross equity issue.

5.3 Robustness Tests

Our results thus far suggest that the peer group generated through shared analysts has a direct influence on corporate policy 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, 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 because 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 still not be able to fully disentangle industry effects from analyst network effects. 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 of *Equity Shock* for firms that are both in the same industry and in the analyst network of a firm (Industry=Yes, ACN=Yes), the weighted average of *Equity Shock* for firms which are in the analyst network and not in the same industry (Industry=No, ACN=Yes) and the simple average of *Equity Shock* for firms that are in the same industry but not in the analyst network (Industry=Yes, ACN=No). The construction of these variables can be illustrated with reference to Figure 1. In the figure the numbered shapes represent firms with each shape (*triangle*, *circle*, *etc*) representing 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 *start-2* are in the same industry as *star-0* while the others are in a different industry. Furthermore there are six other firms in the same industry as firm *star-0*. Our first peer average (Industry=Yes, ACN=Yes), for the firm *star-0* is the weighted average of *Equity Shock* for the firms *star-1* and *star-2*. Our second weighted average (Industry=No, ACN=Yes) is calculated across firms *circle-1, pentagon-1, square-1 and triangle-1*. Finally our third average (Industry=Yes, ACN=No) is calculated across firms *start-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. 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 these relations are only marginally statistically significant. 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.

5.4 Placebo Tests

A potential limitation with the previous analysis is that analysts may choose firms to cover that are economically connected, even if not in the same industry. 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 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 analyst 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 *Pseudo-peer average* and repeat our tests with this average. If the analyst network captures links across firms in different industries then we should expect the *Pseudo-peer average Equity Shock* to be significantly related to the corporate policies of the firm in question.

The results in Table 8 show that there is no significant relationship between *Pseudo-peer average* and a firm's financial policy. This suggests that firms respond to other firms in their analyst network not simply because they are in the same industry or in economically connected industries.

5.5 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 peer effects in the previous analysis.

5.5.1 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 industry leaders will be more influential than those of other firms. In Table 9 we identify leader and follower firms within an industry using four alternate criteria. We use *Market share, Profitability*, *Return* and *EPS growth* as the alternate metrics to identify leader and follower firms. We classify a firm as a leader if either its *Market share* and *Return* (only equity issuances) is above sample median or it is in the top quartile in terms of *Profitability*, *Return* (only leverage) or *EPS growth*.[12] We classify all other firms as follower firms. 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)-(4) we find that irrespective of the criteria used, *Equity Shock* of leader firms in an industry are correlated with market leverage decisions of follower firms.[13] Similar results are obtained for net and gross equity issuances. In Panel B we flip the analysis and test to see if *Equity Shock* of follower firms affect the financial decisions of leader firms. Irrespective of the criteria used, we do not find any significant effect. 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 is a result of firms learning from (mimicking) the decisions of the analyst peer firms. In the next set of tests, we differentiate between analysts to better

[12] In addition, we use the firms' stock returns (*Return*) in the previous year to identify leaders and follower firms when the dependent variable is either net or gross equity issuances. For the case of leverage, we employ stock returns in the current period.

[13] For brevity we only report the results of leverage in level.

highlight their role in transmitting information across firms.

5.5.2 All-star Analysts, Brokerage houses and Analyst Experience

Our paper argues that analyst networks are important in transmitting corporate policy decisions from one firm to another. If this is the case, 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. We construct two measures that capture the potential influence of analysts. Specifically, from *Institutional Investor* magazine we collect the information of the top four ranked 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 two 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. For every year, we calculate the number of years since an analyst first appears on IBES. We then define analysts to have more (less) experience if they are above (below) sample median in terms of the number of years since they first appeared 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 use two separate peer averages as independent variables. The first, *Peer Average (All-Star)*, uses only peers that share at least one analyst from an all-star brokerage house. For the second, we use only those peers connected by analysts not from all-star brokerage houses. For each dependent variable (change and level of leverage, net and gross equity issuance), we estimate the model in two ways: a baseline OLS regression in which the peer firm average is the average financial policy of each group of peers, and the reduced form regression in which we employ two weighted average for the *Equity Shock* (All-Star and No All-Star). In all specifications, we find a larger coefficient on peer averages for peers connected through analysts from all-star brokerage houses relative to peers connected through non-all-star brokerage houses. For the OLS regressions, the coefficients are statistically different across the two peer averages. In the case of reduced form regressions, 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. Here we again form two peer averages, based on firms connected through more (less) experienced analysts. 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 reduced form model for net equity issuances. Interestingly, in the reduced form models, the peer effect is never statistically different from zero for firms connected through less experienced analysts, but always significant for firms connected through more experienced ones.

5.6 Indirect Peer Approach

Finally in Table 11 we attempt to isolate the exogenous peer effects from endogenous peer effects by using the friends-of-friends methodology. Specifically, we identify indirect peer firms for every firm. These are firms that are not directly connected to a firm through analyst networks 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 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.

There are several reasons for the equity shock of indirect peers to be exogenous to the financial characteristics of both the firm in question and the direct peer firm. First, the asset pricing model we employ includes market and industry network return factors that are likely to remove common variation due to shocks to the economy or to related groups of firms. Importantly though, not only are the indirect peers in different analyst networks but the vast majority are also in a different industry from the firm in question. Thus, even if the asset pricing model does not completely remove common return shocks, what remains is unlikely to be correlated with the fundamentals of the firm in question. Furthermore, since the indirect peers are in different analyst networks, we can control for the average stock return in each firm's analyst network to further rule out any correlation between the indirect peers' return shocks and the fundamentals of the firm in question. 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.

The first row of Table 11 presents the coefficients on the indirect peer average *Equity Shock* from the first stage. We find that *Equity Shock* of indirect peer firms is 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. In the second stage, we find a significant relation between 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 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 0.352 standard deviation increase in a firm's leverage (0.352 = 0.704 * (0.11 / 0.22)). For equity issuances, we find that a one standard deviation increase in peer firm simple average net and gross equity issuances leads to 13.1% and 29.6% increase in the likelihood of a firm issuing equity, respectively.

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 smaller in comparison to peer firm endogenous variables. Our results suggest that analyst networks are likely an important source for industry peer effects.

6 Conclusion

Sell-side analysts are an important information intermediary 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 consistent with sell-side analysts being 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, equity issuance and repurchases, 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 characteristic of indirect analyst peer firms and idiosyncratic equity shocks to peer firms as instruments for analyst peer firm financial policy. We find that firms' leverage and equity issuance decisions are significantly impacted by the peer firms in their analyst network. We show that these network effects 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, less successful firms are more influenced by the financial policies of their more successful analyst peers, but not the other way around.

Research analysts are intermediaries connecting firms to each other. However, 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 developed in this paper can also be used to identify peer effects in these other settings, and we hope future research will further explore these issues.

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Appendix A: Variable Definitions

- Book Value of Total Assets: Book value of Assets *(Compustat item: at).*
- Equity Repurchase Indicator: Dummy variable that takes the value of one if equity repurchases normalized by book assets at the beginning of the year is greater than 1% (3%) (5%) *(Compustat items: prstkc/at(t-1)>1%,3%,5%).*
- Equity Shock: Idiosyncratic returns defined as the difference between effective and expected returns based on the methodology provided by Leary and Roberts (2014).
- Gross Equity Issuance Indicator: 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 1% (3%) (5%) *(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 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 contemporaneous 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 Issuance Indicator: 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 minus equity repurchases *(Compustat items: sstk-prstkc).*

- Net Equity Issuance Indicator: 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 1% (3%) (5%). *(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: ACN

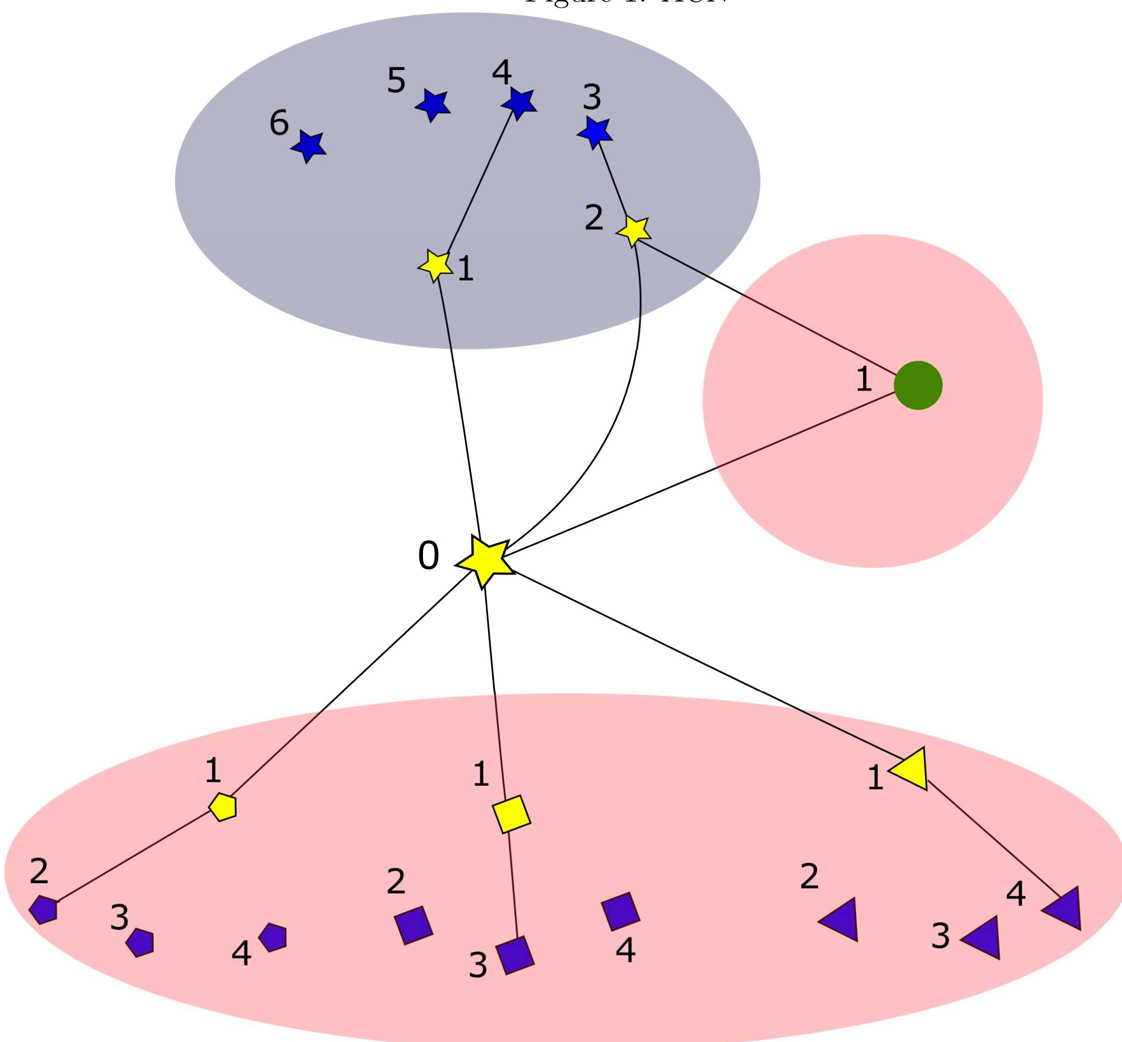

Table 1: Summary Statistics. Analyst Coverage Network and Equity Shock

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 connections of direct and indirect peers. Panel B reports the statistics for the outcome variables. Panel C and D show the statistics of the equity shock instrument (lagged one period) and control variables (lagged one period), respectively, used in the regression analysis. All variables used in the regression analysis are winsorized at the 1st and 99th percentile.

Panel A: Analysts Network						
	Number of Connections					
Direct Peers	N	Mean	Std	P25	P50	P75
Overall	37745	41.30	26.86	20.00	37.00	57.00
Within industry	37745	10.46	12.56	2.00	5.00	15.00
Across industries	37745	30.84	25.36	11.00	25.00	45.00
Within industry connection (%)	37745	0.28	0.30	0.05	0.16	0.46
Connected Firms (%)	21	0.94	0.02	0.92	0.94	0.96
Indirect Peers						
Overall	37745	405.54	232.08	218	373	563
Within industry	37745	20.27	32.22	1	5	25
Across industries	37745	385.27	233.1	199	352	541
	Number of analysts in common (Direct Peers)					
Overall	37745	1.89	1.04	1.10	1.50	2.34
Within industry	32326	3.11	2.73	1.18	2.00	4.00
Across industries	36581	1.54	0.72	1.00	1.26	1.78

Panel B: Outcome Variables													
		Firm specific			Industry average			Industry average (No Overlap)			Peer firm simple avg.		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
ΔMarket leverage	37745	0.01	0.1	0	0.01	0.06	0.00	0.01	0.06	0.00	0.01	0.04	0.00
Market leverage	37745	0.21	0.22	0.15	0.23	0.14	0.20	0.21	0.16	0.16	0.20	0.11	0.19
Net debt issuance (1%)	37745	0.36	0.48	0.00	0.33	0.16	0.30	0.32	0.26	0.29	0.37	0.16	0.36
Net equity issuance (1%)	37745	0.23	0.42	0.00	0.23	0.15	0.22	0.22	0.22	0.19	0.23	0.17	0.19
Gross equity issuance (1%)	37745	0.36	0.48	0.00	0.31	0.18	0.30	0.32	0.27	0.31	0.39	0.23	0.35
		Peer firm weighted average											
		Full sample			Within industry			Accross industry					
ΔMarket leverage	37745	0.01	0.05	0.00	0.01	0.06	0.00	0.01	0.05	0.00			
Market leverage	37745	0.20	0.11	0.19	0.17	0.17	0.13	0.19	0.11	0.18			
Net debt issuance (1%)	37745	0.37	0.18	0.36	0.32	0.30	0.27	0.35	0.20	0.35			
Net equity issuance (1%)	37745	0.22	0.18	0.17	0.20	0.26	0.08	0.21	0.20	0.15			
Gross equity issuance (1%)	37745	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
Own equity shock	37745	-0.03	0.50	-0.32	-0.10	0.15
Industry equity shock	37745	-0.03	0.16	-0.12	-0.05	0.04
Industry equity shock (no overlap)	37745	-0.03	0.21	-0.14	-0.04	0.04
Peer equity shock (weighted average)	37745	-0.04	0.12	-0.11	-0.04	0.02
Indirect Peer equity shock (simple average)	37745	-0.03	0.06	-0.07	-0.03	0.00

Panel D: Control Variables

		Firm specific			Industry average			Industry average (No overlap)			Peer firm simple average		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Log(Sales)	37745	6.69	1.78	6.60	5.78	1.13	5.62	5.81	1.87	5.95	7.07	0.94	7.12
Market to book	37745	1.67	1.26	1.27	1.60	0.66	1.44	1.49	0.81	1.37	1.82	0.75	1.65
Profitability	37745	0.13	0.11	0.13	0.09	0.07	0.10	0.10	0.07	0.11	0.14	0.05	0.15
Tangibility	37745	0.29	0.23	0.22	0.28	0.19	0.22	0.26	0.20	0.20	0.29	0.16	0.26
Δ Log(Sales)	37745	0.10	0.22	0.09	0.10	0.11	0.10	0.08	0.12	0.09	0.11	0.10	0.11
ΔMarket to book	37745	-0.06	0.82	-0.01	-0.07	0.40	-0.05	-0.08	0.43	-0.02	-0.08	0.46	-0.02
Δ Profitability	37745	0.00	0.07	0.00	-0.01	0.03	0.00	0.00	0.03	0.00	0.00	0.03	0.00
Δ Tangibility	37745	0.00	0.04	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.01	0.00

		Peer firm weigthed average									Indirect peer firm simple average		
		Full sample			Within industry			Across industry					
Log(Sales)	37745	7.24	1.04	7.26	6.20	2.81	6.90	7.06	1.65	7.32	7.15	0.52	7.18
Market to book	37745	1.85	0.82	1.66	1.59	1.16	1.40	1.72	0.79	1.60	1.83	0.57	1.71
Profitability	37745	0.14	0.05	0.15	0.12	0.08	0.13	0.14	0.05	0.15	0.14	0.03	0.14
Tangibility	37745	0.30	0.17	0.26	0.26	0.23	0.18	0.28	0.15	0.26	0.29	0.12	0.27
Δ Log(Sales)	37745	0.11	0.11	0.11	0.10	0.14	0.09	0.11	0.11	0.11	0.11	0.08	0.12
ΔMarket to book	37745	-0.08	0.48	-0.02	-0.07	0.55	0.00	-0.07	0.47	0.00	-0.08	0.38	-0.03
Δ Profitability	37745	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.02	0.00
Δ Tangibility	37745	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00

Table 2: Baseline Specification I. Peer Firms vs. Industry

The table presents the OLS estimated coefficients for the baseline regressions. The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables, but excluding *Peer average* and *Industry average*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

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

Dependent Variable:	ΔLeverage		Leverage		Net Debt I.		Net Equity I.		Gross Equity I.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer average		.555		.372		.215		.316		.284
		(.022)***		(.025)***		(.022)***		(.024)***		(.021)***
Industry average	.461	.253	.405	.286	.218	.166	.307	.215	.346	.262
	(.017)***	(.017)***	(.023)***	(.022)***	(.023)***	(.024)***	(.025)***	(.024)***	(.024)***	(.024)***
Own characteristics										
Log(Sales)	.029	.024	.035	.034	-.043	-.046	-.105	-.100	-.081	-.079
	(.003)***	(.003)***	(.004)***	(.004)***	(.008)***	(.009)***	(.008)***	(.008)***	(.009)***	(.009)***
Market-to-book	.0008	.002	-.019	-.018	.013	.013	.066	.064	.072	.071
	(.0005)	(.0005)***	(.001)***	(.001)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.033	-.026	-.298	-.297	.354	.347	-.147	-.155	.187	.180
	(.009)***	(.009)***	(.018)***	(.018)***	(.047)***	(.048)***	(.044)***	(.044)***	(.045)***	(.045)***
Tangibility	.095	.089	.071	.076	.313	.320	.085	.087	.051	.049
	(.014)***	(.013)***	(.025)***	(.024)***	(.050)***	(.050)***	(.046)*	(.046)*	(.049)	(.049)
Peer characteristics										
Log(Sales)		.015		-.009		.004		.005		.013
		(.008)**		(.003)***		(.007)		(.006)		(.006)**
Market-to-book		-.004		.006		-.0001		-.005		-.019
		(.001)***		(.002)***		(.007)		(.007)		(.007)***
Profitability		-.044		.081		-.00004		.143		.013
		(.028)		(.037)**		(.105)		(.095)		(.095)
Tangibility		.043		-.061		-.097		.008		.037
		(.045)		(.025)**		(.064)		(.052)		(.055)
Industry characteristics										
Log(Sales)	-.006	-.011	-.009	-.008	-.005	-.003	.002	.0008	-.008	-.008
	(.007)	(.007)	(.005)	(.005)	(.013)	(.013)	(.009)	(.009)	(.012)	(.012)
Market-to-book	-.006	-.003	-.004	-.006	.008	.008	.006	.0004	.003	.006
	(.002)***	(.002)	(.003)	(.003)*	(.009)	(.010)	(.008)	(.008)	(.008)	(.009)
Profitability	.055	.053	.149	.124	.098	.054	.040	.029	-.073	-.096
	(.021)***	(.023)**	(.029)***	(.030)***	(.082)	(.086)	(.071)	(.074)	(.079)	(.083)
Tanigibility	-.062	-.059	.010	.006	-.088	-.054	.054	.024	.061	.041
	(.038)	(.039)	(.043)	(.043)	(.104)	(.105)	(.080)	(.080)	(.093)	(.093)
Obs.	37745	37745	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.149	.176	.778	.783	.241	.243	.392	.398	.458	.463

Table 3: Baseline Specification II. Within vs. Across Industry

The table presents the OLS estimated coefficients for the baseline regressions. Moreover, we split the peer average corporate policy and control variables in two depending on the three digit industry classification of peer firms. We calculate the weighted average of corporate policies and control variables for peer firms that are in the same industry classification (within industry) and for peer firms that are in a different industry classification (across industry).The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables, but excluding *Peer average* and *Industry average,* are lagged one period. When the dependent variable is Δ*Leverage* all the control variables are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

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

Dependent Variable:	ΔLeverage	Leverage	Net Debt I.	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)	(5)
Peer average (within industry)	.221	.145	.060	.072	.082
	(.014)***	(.016)***	(.012)***	(.014)***	(.013)***
Peer average (across industry)	.277	.149	.084	.162	.139
	(.018)***	(.019)***	(.017)***	(.018)***	(.016)***
Industry average	.265	.291	.166	.231	.260
	(.018)***	(.023)***	(.025)***	(.026)***	(.025)***
Peer characteristics (within industry)					
Log(Sales)	.017	-.006	-.001	-.002	.003
	(.005)***	(.001)***	(.003)	(.002)	(.003)
Market-to-book	-.004	-.0001	-.002	.0008	-.006
	(.001)***	(.002)	(.005)	(.005)	(.006)
Profitability	-.027	.026	.054	-.044	-.088
	(.020)	(.026)	(.078)	(.071)	(.076)
Tangibility	.035	-.027	-.044	.043	-.028
	(.030)	(.019)	(.047)	(.038)	(.043)
Peer characteristics (across industry)					
Log(Sales)	.007	-.003	.0003	.0004	-.001
	(.006)	(.001)**	(.004)	(.003)	(.003)
Market-to-book	.0002	.002	.003	-.013	-.021
	(.001)	(.002)	(.005)	(.005)**	(.005)***
Profitability	-.024	.044	-.077	.204	.153
	(.024)	(.031)	(.090)	(.085)**	(.085)*
Tangibility	.044	-.033	-.043	-.022	.014
	(.039)	(.018)*	(.048)	(.038)	(.039)
Own characteristics	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745
R^2	.169	.781	.242	.396	.461

Table 4: Reduced Form using Equity Shock

The table presents the OLS estimated coefficients for the reduced for regression using a modified version of Leary and Roberts (2014) equity shock. The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instruments are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock instruments, are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

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

Dependent variable:	ΔLeverage	Leverage	Net Debt I.	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)	(5)
Peer Equity Shock	-.027	-.025	-.029	.059	.077
	(.005)***	(.006)***	(.023)	(.019)***	(.020)***
Industry Equity Shock	-.004	-.015	.009	.008	.028
	(.004)	(.004)***	(.018)	(.013)	(.014)*
Own Equity Shock	-.006	-.016	-.011	.058	.071
	(.001)***	(.002)***	(.005)**	(.005)***	(.005)***
Own characteristics					
Log(Sales)	.028	.035	-.045	-.097	-.075
	(.003)***	(.004)***	(.009)***	(.008)***	(.009)***
Market-to-book	.003	-.017	.014	.059	.065
	(.0006)***	(.001)***	(.004)***	(.004)***	(.004)***
Profitability	-.027	-.295	.360	-.165	.158
	(.010)***	(.018)***	(.048)***	(.044)***	(.045)***
Tangibility	.086	.059	.312	.111	.075
	(.014)***	(.025)**	(.051)***	(.046)**	(.049)
Peer characteristics					
Log(Sales)	.047	-.003	.007	-.011	.002
	(.008)***	(.003)	(.007)	(.006)*	(.006)
Market-to-book	-.004	-.009	-.00009	.016	.004
	(.002)**	(.002)***	(.007)	(.007)**	(.007)
Profitability	-.075	-.063	.071	-.012	.007
	(.029)***	(.038)*	(.106)	(.094)	(.096)
Tangibility	.143	.025	-.059	.021	.012
	(.047)***	(.024)	(.063)	(.052)	(.055)
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745
R^2	.118	.771	.238	.393	.459

Table 5: Reduced Form. Equity Issuance and Equity Repurchase

The table presents the OLS estimated coefficients for the reduced form using a modified version of Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are equity repurchases and issuances. In columns (1)-(3), (4)-(6) and (7)-(9) the dependent variables are Net Equity Issuance Indicator, Equity Repurchase Indicator and Gross Equity issuance Indicator, respectively. All the control variables and the equity shock instruments are lagged one period. All variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and standard errors are clustered at the firm level. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	Net Equity Issuance			Equity Repurchase			Gross Equity Issuance		
	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Equity Shock	.059	.055	.041	.040	.027	.019	.077	.053	.046
	(.019)***	(.016)***	(.015)***	(.019)**	(.017)	(.015)	(.020)***	(.018)***	(.016)***
Industry Equity Shock	.008	.008	.012	.006	.008	.020	.028	.013	.009
	(.013)	(.010)	(.009)	(.015)	(.013)	(.011)*	(.014)*	(.011)	(.010)
Own characteristics									
Equity Shock	.058	.045	.039	.001	-.0003	-.0005	.071	.052	.044
	(.005)***	(.004)***	(.004)***	(.005)	(.004)	(.003)	(.005)***	(.005)***	(.004)***
Log(Sales)	-.097	-.081	-.068	.057	.045	.035	-.075	-.077	-.069
	(.008)***	(.007)***	(.007)***	(.009)***	(.008)***	(.007)***	(.009)***	(.008)***	(.007)***
Market-to-book	.059	.054	.042	-.004	.012	.019	.065	.064	.048
	(.004)***	(.004)***	(.003)***	(.004)	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.165	-.292	-.286	.629	.562	.454	.158	-.169	-.231
	(.044)***	(.040)***	(.040)***	(.046)***	(.040)***	(.036)***	(.045)***	(.042)***	(.041)***
Tangibility	.111	.165	.170	-.219	-.118	-.086	.075	.154	.171
	(.046)**	(.037)***	(.033)***	(.051)***	(.042)***	(.036)**	(.049)	(.040)***	(.035)***
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.393	.351	.323	.426	.395	.377	.459	.377	.328

Table 6: Structural Regression using Equity Shock

The table presents the 2SLS estimated coefficients for the structural regression using a modified version of Leary and Roberts (2014) equity shock as instrument. The endogenous variable is the peer firm weighted average of the dependent variable. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instrument, but excluding *Industry average*, are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. We report the Kleibergen-Paap rk Wald, Cragg-Donald and Anderson-Rubin F-statistics for the weak identification tests.

Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
First stage :				
Peer Equity Shock	-.013	-.015	.079	.105
	(.002)***	(.003)***	(.007)***	(.008)***
Instrumented peer average	1.785	1.575	.695	.699
	(.429)***	(.477)***	(.228)***	(.180)***
Industry average	-.199	-.090	.108	.134
	(.158)	(.149)	(.068)	(.058)**
Own characteristics				
Equity Shock	-.005	-.015	.058	.070
	(.001)***	(.002)***	(.004)***	(.005)***
Log(Sales)	.019	.028	-.090	-.068
	(.004)***	(.004)***	(.008)***	(.008)***
Market-to-book	.003	-.018	.057	.064
	(.0007)***	(.001)***	(.004)***	(.004)***
Profitability	-.010	-.295	-.183	.152
	(.011)	(.019)***	(.042)***	(.043)***
Tangibility	.077	.097	.100	.063
	(.015)***	(.025)***	(.042)**	(.046)
Peer characteristics	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
Kleibergen-Paap F-value	48.186	27.013	128.238	172.549
Cragg-Donald F-value	83.952	45.873	264.594	341.505
Anderson-Rubin F-value	21.638	16.309	9.683	15.954
Anderson-Rubin P-value	3.39e-06	.00005	.002	.00007

Table 7: Robustness Test

The table presents the OLS estimated coefficients for the reduced form using a modified version of Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are leverage and equity issuances. We include as control variables own and reference group characteristics. All the control variables and the equity shock instruments are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. Panel A, B and C presents the estimated coefficients of the reduced form using the three reference groups independently. Specifically, in Panel A, the coefficients are estimated using as peers all the firms in the same industry as firm i, but they are not in the analysts network of the firm i. In Panel B (C) the coefficients are estimated using as peers all the firms in the same industry (different industries) as firm i, and they are in the network of firm i. Finally, Panel D presents the estimated coefficients of the OLS regressions using the three reference groups all together, industry peers, direct peers within industry and across industries. 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	(1)	(2)	(3)	(4)
Panel A: Peer Equity Shock (Industry=Yes, ACN=NO)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.003	-.009	.012	.025
	(.003)	(.003)***	(.010)	(.011)**
R^2	.114	.77	.392	.458
Panel B: Peer Equity Shock (Industry=Yes, ACN=YES)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.005	-.006	.009	.019
	(.003)*	(.003)*	(.010)	(.011)*
R^2	.116	.77	.392	.458
Panel C: Peer Equity Shock (Industry=NO, ACN=YES)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.014	-.016	.050	.069
	(.004)***	(.005)***	(.016)***	(.016)***
R^2	.115	.769	.392	.458
Panel D: Peer Equity Shock (All together).				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer (Industry=Yes, ACN=NO)	-.004	-.009	.012	.024
	(.003)	(.003)***	(.010)	(.011)**
Peer (Industry=YES, ACN=YES)	-.005	-.006	.008	.017
	(.003)*	(.003)*	(.010)	(.011)
Peer (Industry=NO, ACN=YES)	-.016	-.017	.051	.070
	(.004)***	(.005)***	(.016)***	(.016)***
R^2	.118	.771	.393	.459
Obs.	37745	37745	37745	37745

Table 8: Placebo Test

The table presents the OLS estimated coefficients for our placebo test using the reduced form specification and a modified version of the Leary and Roberts (2014) equity shock as instrument. We use industry peers of firms in the network of firm i, but we do **NOT** include firms in the same industry of firm i. The exogenous variable is the *Pseudo-peer Equity Shock*. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instrument are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
Pseudo-peer Equity Shock	-.003	-.013	.002	.021
	(.011)	(.013)	(.037)	(.040)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Pseudo-peer characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
R^2	.114	.769	.392	.458

Table 9: Leaders vs. Followers

The table presents the OLS estimated coefficients for the reduced form. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. We classify leader and followers based on their within industry-year ranking associated to market share, EPS growth, profitability and stock return. A firm is classified as industry leader if it belongs to the top quarter in each industry-year subsample for the case of EPS, Profitability and stock return (only for leverage) and a firm is classified as leader when its market share and stock return (only for equity issuances) is above the median. All the control variables and the equity shock instruments are lagged one period. The exogenous variable is the weighted average *Equity Shock* of peer leader (follower) firms. Panel A(B) shows the effects of leader (follower) firms on individual follower's (leader's) corporate policy decisions. All variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and standard errors are clustered at the firm level. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Leaders affect Followers												
Follower Firm Dependent Variable:	Leverage				Net Equity Issuance (1%)				Gross Equity Issuance (1%)			
	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Peer Equity Shock (Leaders)	-.022	-.010	-.016	-.008	.061	.020	.032	.039	.062	.013	.034	.021
	(.009)**	(.003)***	(.004)***	(.004)**	(.028)**	(.010)**	(.014)**	(.019)**	(.029)**	(.010)	(.014)**	(.020)
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14150	29938	28586	29710	14150	29938	28586	19360	14150	29938	28586	19360
R^2	.801	.782	.781	.788	.457	.405	.42	.433	.493	.482	.46	.493
Panel B: Followers affect Leaders												
Leader Firm Dependent Variable:	Leverage				Net Equity Issuance (1%)				Gross Equity Issuance (1%)			
	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return
Peer Equity Shock (Followers)	-.006	-.013	-.011	-.012	.015	.011	.013	.014	.002	.066	.050	.047
	(.004)	(.019)	(.008)	(.017)	(.013)	(.061)	(.040)	(.031)	(.013)	(.063)	(.039)	(.032)
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23595	7807	9159	8035	23595	7807	9159	18005	23595	7807	9159	18005
R^2	.782	.846	.832	.851	.395	.616	.516	.501	.48	.639	.587	.548

Table 10: All-Star Brokerage Houses and Analyst Experience

The table presents the OLS estimated coefficients for the baseline regression (BR) and reduced form (RF) using a modified version of the Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. We classify analysts with larger experience if within a year the number of years that they appear on IBES is above the median. For the case of all-star brokerage houses, we classify them according to the number of all-star analysts that they employ (at least two all-star analysts, which is approximately the top decile of the distribution). We calculate the weighted averages of the *Equity Shock*, outcome and control variables for peer firms that share at least one analysts with larger experience (all-star brokerage houses) and for peer firms that do not share any analysts with larger experience (brokerage houses). Panel A display the results with respect to all-star brokerage houses and Panel B shows the results using analyst experience. All the control variables and the equity shock instruments, but excluding *Peer and Industry average*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions 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 is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: All-Star Brokerage Houses (All-Star vs. No All-Star)								
Dependent Variable:	ΔLeverage		Leverage		Net Equity I.		Gross Equity I.	
	BR	RF	BR	RF	BR	RF	BR	RF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer average (All-Star)	.512		.354		.251		.237	
	(.019)***		(.022)***		(.022)***		(.019)***	
Peer average (No All-Star)	.225		.126		.138		.126	
	(.017)***		(.017)***		(.017)***		(.016)***	
Peer Equity Shock (All-Star)		-.019		-.024		.060		.059
		(.005)***		(.006)***		(.019)***		(.020)***
Peer Equity Shock (No All-Star)		-.014		-.009		.003		.031
		(.004)***		(.004)**		(.014)		(.015)**
(All-Star)-(No All-Star)	0.287	-0.006	0.228	-.015	0.114	0.057	0.111	0.027
P-value	**0.000**	0.364	**0.000**	**0.038**	**0.000**	**0.012**	**0.000**	0.262
Industry average (No overlap)	Yes	No	Yes	No	Yes	No	Yes	No
Industry Equity Shock	No	Yes	No	Yes	No	Yes	No	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (All-Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (No All-Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.169	.118	.78	.771	.4	.394	.465	.459

Panel B: Analyst Experience (Larger vs Smaller)								
Dependent Variable:	ΔLeverage		Leverage		Net Equity I.		Gross Equity I.	
	BR	RF	BR	RF	BR	RF	BR	RF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer average (Larger)	.570		.401		.293		.282	
	(.020)***		(.024)***		(.022)***		(.019)***	
Peer average (Smaller)	.132		.062		.073		.058	
	(.014)***		(.012)***		(.013)***		(.012)***	
Peer Equity Shock (Larger)		-.027		-.027		.042		.067
		(.005)***		(.006)***		(.019)**		(.020)***
Peer Equity Shock (Smaller)		-.004		-.005		.014		.019
		(.003)		(.003)		(.011)		(.012)
(Larger)-(Smaller)	0.438	-0.023	0.339	-0.022	0.219	0.028	0.224	0.048
P-value	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	0.195	**0.000**	**0.036**
Industry average (No overlap)	Yes	No	Yes	No	Yes	No	Yes	No
Industry Equity Shock	No	Yes	No	Yes	No	Yes	No	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (Larger)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (Smaller)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.168	.118	.78	.772	.401	.394	.465	.459

Table 11: Indirect Peer Firms and Structural Regression

The table presents the 2SLS estimated coefficients for the structural regression using indirect peer firms equity shock as instrument. In addition, we employ a modified version of the Leary and Roberts (2014) equity shock. The endogenous variable is the peer firm simple average of the dependent variable. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns All the control variables and instruments, but excluding *Industry average (no overlap)*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables, except the equity shock and peer average stock return, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. For brevity we supress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. We report, the Kleibergen-Paap rk Wald F statistic, Cragg-Donald F statistic and Anderson-Rubin F-statistic for the weak identification tests.

	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
First Stage: Indirect peers'				
Equity Shock	-.034	-.048	.106	.161
	(.004)***	(.007)***	(.016)***	(.018)***
Instrumented peer average	.462	.704	.770	1.287
	(.349)	(.305)**	(.459)*	(.324)***
Industry average (No overlap)	.119	.033	.038	.025
	(.046)***	(.014)**	(.020)*	(.015)
Peer average stock return	.0003	-.008	.007	-.030
	(.007)	(.006)	(.040)	(.030)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes
Ind. characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
Kleibergen-Paap F-value	57.042	45.865	44.978	75.613
Cragg-Donald F-value	92.994	69.487	77.211	129.445
Anderson-Rubin F-value	1.647	5.252	2.883	17.988
Anderson-Rubin P-value	.199	.022	.09	.00002