Do Peer Firms Affect Corporate Financial Policy?*

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Preliminary and Incomplete

This Draft: March 1, 2010

*We thank Andy Abel, Ulf Axelson, Philip Bond, Itay Goldstein, Robin Greenwood, Richard Kihlstrom, Jiro Kondo, Arvind Krishnamurthy, Camelia Kuhnen, Ulrike Malmendier, David Matsa, Atif Mian, Mitchell Petersen, Nick Roussanov, and Moto Yogo; conference participants at the NBER Fall Corporate Finance Meeting; seminar participants at Cornell University, Pennsylvania State University, Purdue University, Rice University, University of Kentucky, University of Maryland, University of Pennsylvania, and University of Rochester. Roberts gratefully acknowledges financial support from a Rodney L. White Grant. Roberts: (215) 573-9780, mrrobert@wharton.upenn.edu; Leary: (607) 255-4002, mtl42@johnson.cornell.edu.

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Abstract

We show that corporate financial policies are highly interdependent; firms make financing decisions in large part by responding to the financing decisions of their peers, as opposed to changes in firm-specific characteristics. We identify these peer effects with a novel instrumental variables approach that uses the idiosyncratic equity shocks to peer firms as a source of exogenous variation. On average, a one standard deviation change in peer firms' leverage ratios is associated with a 9% change in own firm leverage ratios — a marginal effect that is significantly larger than that of any other observable determinant and one that is driven by underlying interdependencies among security issuance decisions. The presence of these peer effects creates an externality among financial policies that amplifies the effect of changes in firm-specific characteristics by over 11%, and transmits these changes onto the financial policies of other firms.

Competitor, or peer, firms play a central role in shaping a variety of corporate policies ranging from executive compensation to product market strategy. However, most research on corporate financial policy assumes that firms choose their capital structures independently of their peers. That is, theoretical and empirical work typically assume that a firm's capital structure is determined by some function of its marginal tax rate, expected deadweight loss in default, information environment, or incentive conflicts among claimants. Thus, the role for competitor firms' behavior in affecting corporate capital structures is often ignored, or at most an implicit one through its unmeasured impact on these firm-specific determinants.[1]

Despite this lack of attention, there is empirical evidence suggesting that peer effects are relevant for corporate financial policy. Median or average industry leverage is the single most important observable capital structure determinant in terms of explained variation and marginal effect. Further, survey evidence indicates that CFOs often consider the financing decisions of other firms in their industry when setting financial policy.[2] Understanding the extent to which peer firms play a role in shaping corporate financial policy is important for two reasons. First, it moves us closer to answering a fundamental question in corporate finance; namely, how do firms choose their capital structures? And, second, it has important implications for empirical, as well as theoretical, work because the presence of peer effects implies the existence of externalities in corporate financial policy.

While well motivated and empirically important, peer firm financial policy and its link to corporate capital structure does not have a unique interpretation because of the reflection problem (Manski (1993)). The reflection problem refers to a specific endogeneity problem that arises when trying to infer whether the behavior of a group influences the behavior of the individuals that comprise the group. In the current context, this problem is created by using a measure of peer firm financial policy, such as industry

[1] Theoretical examples include traditional tax-bankruptcy cost tradeoff theories, (Scott (1976)), agency-based theories (Jensen and Meckling (1976)), information asymmetry (Myers and Majluf (1984)), optimal contracting (DeMarzo and Fishman (2007)). Some exceptions include Brander and Lewis (1986), Maksimovic (1988), and Maksimovic and Zechner (1990). Empirically, there are no studies of which we are aware that explicitly model the interplay between financing decisions of peer firms, though several studies have examined reduced form relations linking leverage to median industry leverage (e.g., Frank and Goyal (2007)).

[2] Studies by Bradley, Jarrell, and Kim (1984), Frank and Goyal (2007), Lemmon, Roberts, and Zender (2008) all show that industry effects have the most economically important impact on leverage among observable leverage determinants. Graham and Harvey (2001) show that almost one quarter of surveyed CFOs identify the behavior of competitors as an important input into their financial decision making.

average leverage, as an explanatory variable for individual firm financial policy. In particular, any observed similarity in financing behavior among the firms within an industry — or any other peer group — can be attributed to two potential explanations.

The first explanation is that firms in the same industry face similar institutional environments or have similar firm characteristics, such as production technologies and investment opportunities. The inability to perfectly measure or observe these determinants generates a role for peer firm financial policy in so far as it proxies for these factors. In essence, the correlation between firms' leverage ratios and that of their peers reflects an omitted variables or measurement error bias.

The second explanation is that firms' financial policies are at least partly driven by a response to their peers. This response can be driven either by peer firm financial policy or by changes to peer firm characteristics. That is, peer firms can influence corporate financial policy via two distinct channels. The first, or direct, channel refers to firms' responding to the actions of their peers — in this case financial policy. The second, or indirect, channel refers to firms' responding to changes in the characteristics of their peers — profitability, risk, investment opportunities, etc.

The goal of this paper is to disentangle these explanations to better understand the role played by firms' peers in determining financial policy, and to identify the implications of these peer effects for empirical and theoretical research on corporate capital structure. To do so, we employ an instrumental variables approach designed to maximize both internal and external validity. Specifically, our identification strategy uses the lagged idiosyncratic component of peer firms' stock returns as an instrument for their financing decisions. This approach enables us to examine a large sample of firms over an extended period of time, thereby increasing the external validity of our study well beyond the confines of small sample natural experiments.

At the same time, we take advantage of a large literature in asset pricing to aid the internal validity of our study. Intuitively, the identifying assumption of our identification strategy is that an idiosyncratic shock to the stock price of firm A in period t has no affect on the financing decision of firm B in period $t+1$ but for its affect on firm A's financing decision in period $t+1$. To bolster confidence in this assumption, we estimate firm-specific, rolling regressions of stock returns on the usual asset-pricing factors and an industry factor. This specification produces an estimated residual (i.e., instrument) with a number of desirable properties.

First, the conditional correlation between firms' idiosyncratic return and that of their peers is visrtually zero, ensuring that there are no common factors driving our estimated peer effect. Second, the shocks are conditionally serially uncorrelated and serially cross-uncorrelated implying that firms' shocks do not forecast future shocks for themselves or for other firms. Third, the shocks are uncorrelated with virtually every firm characteristic typically used to explain variation in capital structure. While these features do not guarantee validity of our instrument, they are reassuring and help guide our robustness tests aimed at addressing identification threats from alternative hypotheses.

Our first stage results show that idiosyncratic stock returns are strongly correlated with leverage levels and changes, primarily through their affect on security issuance decisions. Firms experiencing positive shocks to their stock prices are significantly more likely to issue equity, issue relatively more equity, and, consequently, reduce their leverage. These results are similar to previous evidence linking total stock returns to equity policy, but they show that the idiosyncratic component of stock returns is as important, if not more so, than the systematic component for the determination of financial policy. Statistically speaking, the first stage F-statistics are well above weak-instrument thresholds, ensuring that the instrument relevance test is easily passed. Economically speaking, this finding shows that managers respond to the firm-specific information contained in market equity prices when making financing decisions.

The second stage results show that firms' capital structure choices are strongly positively influenced by the financing choices of their peers. For example, firms change their market leverage ratios by nine percentage points, on average, in response to a one standard deviation change in leverage by peer firms. This marginal effect is the largest among observable determinants, including profitability, tangibility, firm size, and market-to-book, as well as a host of other explanatory variables. These results are extremely robust, found in both book and market measures of leverage, and in both levels and changes in leverage. Further, these results are unaffected by a number of specification changes and robustness tests examining alternative explanations. Closer inspection reveals that the commonality in leverage choices among peers is driven by a commonality in financing decisions; firms are significantly more likely to issue a security (e.g., equity or debt) when their peers issue that same security, resulting in similar changes to their leverage ratios.

Somewhat less important are the effects of peer firms' characteristics on financial policy. While often statistically significant, changes in the characteristics of peer firms have a relatively small impact on corporate financial policy. Rather, the primary channel through which peer affects operate is the direct channel of financing decisions, as opposed to the indirect channel of changing characteristics. Indeed, two way sorts on peer firms' average equity shocks — our instrument — and peer firms' average leverage changes

— our endogenous variable — reveal that firms only alter their leverage in response to peer firms' equity shocks when these shocks are accompanied by a change in peer firm leverage.

In addition to identifying an economically important source of variation in corporate capital structures and financial policies, our results reveal an amplification mechanism with significant implications for empirical studies. The externalities generated from the presence of peer effects alters the interpretation of estimated coefficients even in linear models. To illustrate, consider a change in firm A's profitability. This change not only affects firm A's financing choice, but also every other member of firm A's peer group via the direct and indirect peer effect channels. This impact on peer firms' financial policies feeds back onto firm A's financial policy, and so on, and so on. Thus, the marginal effect of a change in any capital structure determinant embeds multiple effects and can no longer be determined solely by the coefficient on that determinant.

We derive the marginal effects in the presence of both direct and indirect peer effects, and estimate the magnitude of each externality. To illustrate, a one standard deviation increase in profitability is associated with a 3.7% decline in book leverage. However, embedded in this estimated marginal effect are two countervailing forces. The direct channel of peer effects amplifies the effect of the profitability increase by 11%, from 3.7% to 4.1%. The indirect channel of peer effects leads to an offsetting contraction of a similar magnitude, so that the net effect of the profitability change is 3.7%. Interestingly, we see similar patterns for other capital structure determinants, whereby the amplification mechanism brought about by the direct peer effect is often offset by the indirect peer effect. While the net effect may be similar to that found in models without externalities, the interpretation of how and why leverage responds to changes in determinants is quite different.

To better understand precisely why these commonalities exist, we examine heterogeneity in the peer effect. While shedding light on the underlying mechanism, this analysis also reinforces our identification strategy as most alternative hypotheses leave little room for systematic heterogeneity in the peer effect. ***To be completed...***

Our study is most closely related to those documenting the importance of industry as a capital structure determinant. For example, Bradley et al. (1984) document that "almost 54% of the cross-sectional variance in firm leverage ratios can be explained by industrial classification." More recently, Frank and Goyal (2007) find that industry median leverage has the single most explanatory power for firm leverage among the 25 firm characteristics and macroeconomic variables they consider. However, these studies have left the interpretation of these industry effects largely unresolved. Indeed, Frank and Goyal (2007, 2008) explicitly note that capital structure similarities within an industry have several possible meanings. Ours is the first study to sift through these alternative meanings, identify policy interdependence as a substantial element of the industry leverage effect, and estimate the externalities induced by the presence of peer effects.[3]

Our study is also related to the work of Mackay and Phillips (2005), which identifies significant intra-industry variation in capital structures. Our study compliments theirs by showing that intra-industry leverage heterogeneity is accompanied by strong interdependencies in financial policy. In other words, within industry leverage distributions may be wide; but, they tend to shift over time as peer firms respond to one another, as opposed to just stretching or contracting when each firm acts in isolation.

The paper proceeds as follows. Section I introduces the data and presents summary statistics. Section II examines how economically important industry leverage is for corporate capital structures. Section III discusses the theoretical motivation for why firms financial policies might be related. Section IV details the empirical model and identification strategy. Section V presents the main results for both leverage and individual financing decisions. Section VI examines the potential mechanisms behind the estimated peer effects and Section VII concludes.

I. Data and Summary Statistics

Corporate accounting data come from Standard & Poor's (S&P) Annual Compustat database. We draw a sample of firm-year observations during the period 1965 to 2006, subject to the following criteria found in previous capital structure studies. We exclude all regulated entities including financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999), as well as government entities (SIC codes greater than or equal to 9000). We also exclude any firms that undertook a significant acquisition during the sample period as indicated by Compustat variable *aftnt1* equal to "AB"; however, all of our results are insensitive to this screen — motivated by consistency with previous studies — which affects less than 3% of the sample. We also exclude any observations with missing data for the primary variables used throughout the study (see Appendix A).

[3]More broadly, our study is related to a long line of works examining peer effects in various settings including mutual fund voting (Matvos and Ostrovsky (2009)), student performance (Kremer and Levy (2003)), investment decisions (Duflo and Saez (2002)), and entrepreneurship (Lerner and Malmendier (2009)).

Stock return data for our sample of Compustat firms are obtained from the Center for Research in Security Prices (CRSP) monthly stock price database. We merge CRSP and Compustat data using the historical header file from CRSP. Our final sample consists of firm-year observations in the intersection of our Compustat sample and CRSP. We use several other data sources for robustness tests, but postpone a discussion of these ancillary data sources until the analysis is presented below.

Table I presents summary statistics for our sample. The aforementioned screens produce 76,501 firm-year observations corresponding to 9,293 unique firms. There are 178 industries, defined by three-digit SIC code, represented in our sample. The typical industry contains approximately 18 firms, though the distribution is right skewed as indicated by the median number of firms, 12. To address potential measurement concerns regarding the definition of an industry, as well as the documented intra-industry heterogeneity (Mackay and Phillips (2005)), we investigate more refined peer groups in some of our empirical analysis below. Though, recent research by Hoberg and Phillips (2009) shows that more refined industry definitions based on data from SEC filings provides little improvement over SIC codes in the ability of industry fixed effects to explain variation in corporate investment and financing.

Summary statistics for a variety of variables used throughout this study are presented after Winsorizing all ratios at the upper and lower one percentiles. All variables are formally defined in Appendix A. At this point, we simply note the similarity of these summary statistics to those found in previous studies (e.g., Frank and Goyal (2007)). We also note that these statistics will be useful for assessing economic significance in the analysis below.

II. The Correlation Between Firm and Industry Leverage

We begin by examining the empirical link between industry leverage and corporate capital structures using the existing empirical literature as our guide. The goal is threefold. First, we want to highlight the significance of this determinant. Second, we want to provide results against which we can benchmark subsequent findings. Finally, we want to ensure that this result is not spurious.

Table II presents OLS estimates, t-statistics, and model statistics for several variations of the following model of leverage,

$$y_{ijt} = \alpha + \beta \bar{y}_{-ijt} + \lambda' X_{ijt-1} + \phi' \nu_t + \delta' \mu_j + \psi' \omega_i + \varepsilon_{ijt}. \quad (1)$$

The indices i, j, and t correspond to firm, industry, and year, respectively. The outcome variable, y_{ijt}, is financial leverage. For robustness, we examine both book and market leverage.

The first independent variable, $\bar{y}_{-ijt}$, denotes the average leverage for all firms in industry j, excluding firm i, at the end of year t. We focus on the average throughout this study, though substituting the median produces similar findings. This variable corresponds to the direct peer effect, though the extent to which its coefficient (β) captures variation in leverage due to peer firm behavior is unclear at this stage. This point is worth emphasizing. OLS estimation of equation (1) only indicates the direction and magnitude of association between leverage and average industry leverage, as well as the other explanatory variables. As such, we postpone our economic inferences until we appropriately address the identification concerns below.

Previous studies typically lag average industry leverage, and other explanatory variables, in an attempt to account for delayed responses and to mitigate the endogeneity concerns which are the focus of this study. Empirically, the choice between contemporaneous or lagged values is largely irrelevant — the estimated coefficients are similar in both signs and magnitudes. Theoretically, we believe a contemporaneous peer effect is more appealing as it mitigates the opportunity for confounding forces to infect our identification strategy while still allowing firms a sufficient amount of time — up to one year — to react to their peers' financing decisions.

The second term, X_{ijt-1}, is a K-dimensional vector of firm-specific determinants of financial policy, lagged one period. (As mentioned above, lagging one period has a negligible effect on the parameter estimates.) In Table II, we focus on the most common and robust determinants of capital structure (see, for example, Rajan and Zingales (1995) and Frank and Goyal (2003, 2007)). We incorporate year (ν_t), and industry (μ_j) or firm (ω_i) fixed effects to capture common components of leverage ratios. We assume that the error term, ε_{ijt}, is potentially correlated within firms and heteroscedastic. As such, all standard errors and test-statistics are robust to these two departures from the classical regression model (Petersen (2009)).

The results in Panel A show that, in a pooled regression, average industry leverage is the most economically important observable determinant of capital structure, in terms of either marginal effect or explained variation Multiplying each coefficient estimate by the corresponding variable standard deviation (see Table I) standardizes the units for comparison. For example, using the results in column (3), a one standard deviation change in average industry book leverage is associated with a 5.4% change in individual firms' book leverage ratios. This effect is over 50% larger, in magnitude, than the next most important determinant, profitability, whose standard deviation scaled coefficient is -3.6%. Additionally, a comparison of the adjusted R-squares for specifications (1) and (2) reveals that industry average leverage, by itself, explains more variation in book leverage ratios than the other observable determinants combined.

Specifications (4) and (5) incorporate industry and firm fixed effects to address unobserved heterogeneity concerns. Estimates of the latter specification are obtained by a within estimator, though first difference estimates produce similar findings. While no longer the most important characteristic, changes in average industry leverage still have an economically and statistically large impact on within-industry and within-firm variation in leverage.

Specifications (6) through (10) are identical to (1) through (5), only replacing book leverage with market leverage. The results are strikingly similar, particularly when one accounts for the greater volatility of market leverage relative to book leverage (see Table I). Thus, the larger magnitudes of the estimated coefficients do not necessarily imply greater economic significance. Rather, they reflect greater volatility in market leverage relative to book leverage (see Table I).

In unreported analysis, we examine several additional specifications for robustness. A dynamic specification that includes lagged leverage reveals that industry average leverage is statistically significant and the most economically significant determinant after the lagged dependent variable. Likewise, the importance of industry leverage is undiminished by the inclusion of additional determinants, such as the marginal tax rate, stock returns, earnings volatility, Altman's Z-Score, capital expenditures, research and development expenditures, and sales and general administrative expenses.

Panel B examines the impact on the estimated coefficients of varying the peer group definition. In addition to quantifying the sensitivity of the estimates, these tests highlight the importance of defining peer groups in an economically meaningful manner. We re-estimate the book and market leverage specifications presented in columns (3) and (8) of Panel A using four different definitions for industry. Because the results are similar in their implications, we present and discuss only the book leverage findings.

The first definition randomly assigns firms to industries which are similar in size to industries defined by 3-digit SIC codes, approximately 18 firms per industry-year, on average. To avoid our results being driven by "one odd draw," we repeat the process of random assignment and model estimation 100 times to reduce the impact of simulation error. We then average the estimated coefficients and construct a corresponding standard error from the standard deviation of the 100 estimated coefficients. The R^2 is the average across the 100 estimations. The results reveal that there is no link — statistically or economically — between leverage and industry average leverage, whose coefficient and t-statistic are both zero.

The second, third, and fourth definitions define industry using one-digit, two-digit, and three-digit SIC codes, respectively. The results show that the coefficient of average industry leverage, as well as its precision, increases monotonically moving from the one-digit to the three-digit peer group definitions, with a particular sharp increase from two-digit to three-digit classifications. In concert with the randomly assigned industries, these results B show that the relation between leverage and industry average leverage, while still subject to multiple interpretations, is not spurious. The results in Panel A show that this relation is economically large. We now turn to understanding what this relation means.

III. Empirical Model

Our empirical framework follows closely that found in Manski (1993) and begins with a linear model of financial policy. We start with a linear specification to emphasize the intuition and highlight the salient econometric issues. We discuss and investigate a variety of extensions to the model further below.

Using the notation introduced in section II, we model measures of financial policy, such as leverage, by the following equation,

$$y_{ijt} = \alpha + \beta \bar{y}_{-ijt} + \lambda' X_{ijt-1} + \gamma' \bar{X}_{-ijt-1} + \delta' \mu_j + \phi' \nu_t + \varepsilon_{ijt}. \tag{2}$$

Equation (2) is similar to existing models found in the capital structure literature, such as equation (1), but for the addition of the K-dimensional vector, $\bar{X}_{-ijt-1}$. This vector contains average peer firm characteristics, each of which is constructed in manner similar to that of the peer group leverage measure. Economically, this vector corresponds to the indirect channel of peer effects where the characteristics, as opposed to the actions, of peer firms affect the actions of firm i. Each term in this vector corresponds to a firm-specific determinant in X_{ijt} implying that the average investment opportunities, profitability, tangibility, etc. of peer firms play a role in shaping firm i's financial policy.

The parameter vector is $(\alpha, \beta, \lambda', \gamma', \delta', \phi')$. We refer to these parameters as structural parameters only to distinguish them from the composite, or reduced form, parameters that appear in the context of instrumental variables. Like the vast majority of the empirical capital structure literature, we leave unspecified the precise optimization problem undertaken by the firm.[4] Externalities are captured by β, which measures the direct peer effect occurring through peers' financial policies, and γ', which measures the indirect peer effect occurring through the characteristics of peers. The coefficients λ, δ, and ϕ measure the effect of firm specific and common factors on financial policy. In doing so, the variables corresponding to these parameters mitigate, but do not eliminate, the possibility that firms in the same industry have similar financial policies because they share common (possibly unobserved) characteristics or operate in the same institutional environment.[5]

The model is easily extended along a number of dimensions. Each firm may be influenced by multiple peer groups. Direct and indirect peer effects may be transmitted via distributional features other than the mean, such as the median. The linear functional form can be relaxed to accommodate nonlinear or nonparametric specifications. These extensions, as well as others, are considered below.

A. The Identification Problem

The empirical goal is to disentangle the various explanations for financial policy variation by statistically identifying the structural parameters, $(\alpha, \beta, \lambda', \gamma', \delta')$. The primary difficulty arises from the presence of $\bar{y}_{-ijt}$ as a regressor in equation (2). Intuitively, if firms' financing decisions are influenced by one another, then firm i's capital structure is a function of firm j's and vice versa. That is, the explanatory variable encompassing firm j's capital structure, $\bar{y}_{-ijt}$, is simultaneously determined with the dependent variable representing firm i's capital structure, y_{ijt}. Thus, industry average leverage $\bar{y}_{-ijt}$ is an endogenous regressor.

This identification problem can be seen by focusing on the population version of equation (2) and invoking the equilibrium condition $E(y_{ijt}|\mu_j) = E(y_{-ijt}|\mu_j)$. Ignoring the time dimension for notational convenience, we can derive the following reduced form model using the results in Manski (1993):

$$E(y|X, \mu_j) = \alpha^* + {\gamma^*}' E(X|\mu_j) + {\delta^*}' \mu_j + {\lambda^*}' X. \tag{3}$$

where the superscript "*" refers to reduced form or composite parameters that are func-

[4]See Hennessy and Whited (2005, 2007) for examples of a fully specified economic model and structural estimation.

[5]The implicit assumption is that these common *unobserved* characteristics are either time-invariant or, at least, slow-changing so that they may be captured by the industry fixed effects. Time varying differences are captured by the firm-specific controls, X_{ijt-1}, and year fixed effects, ν_t.

tions of the underlying structural parameters. Specifically,

$$\begin{aligned}
\alpha^* &= \frac{\alpha}{1-\beta} \\
\gamma^{*'} &= \left(\frac{\beta\lambda+\gamma}{1-\beta}\right)' \\
\delta^{*'} &= \left(\frac{\delta}{1-\beta}\right)' \\
\lambda^{*'} &= \lambda'
\end{aligned}$$

(See Appendix B for a formal derivation.) Immediately apparent is that the structural parameters cannot be recovered from the estimable composite parameters since we are left with five unknowns and only four equations. What is needed to recover the structural parameters is an exogenous source of variation in peer firm financial policy.

However, as long as the intercept, the average peer characteristics, the group fixed effects, and the firm-specific factors are linearly independent, we can identify the reduced-form parameters $(\alpha^*, \gamma^{*'}, \delta^{*'}, \lambda^{*'})$. This result is useful because estimation of the reduced form model (equation (3)) can identify the presence of a peer effect without the use of an instrument. Specifically, the coefficients on the peer firm characteristics, $\gamma^{*'}$ will be zero only if both β and $\gamma^{*'}$ are zero. Thus, as a test for the presence of peer effects we estimate several variations of equation (3) via OLS.

The results are presented in Table III. The layout and specifications mimic those found in Table II, but for the replacement of the endogenous direct peer effect $\bar{y}_{-ijt}$ with exogenous lagged average peer firm characteristics, $\bar{X}_{-ijt-1}$. Two findings are particularly relevant. First, the R-squares in Columns (1) and (6) show that average industry characteristics capture 6.4% and 16% of the variation in book and market leverage ratios, respectively. These estimates are just over half of the variation captured by the industry average leverage ratios (see the corresponding columns in Table II). The difference in variation is due to some combination of firm-specific effects and direct peer effects.

Second, in every specification at least two, and often more, average peer firm characteristics are statistically significant. Related, tests of the null hypothesis that these coefficients are jointly zero are all rejected at better than the one percent level (F-stat towards the bottom of the table). The coefficients of the peer firm characteristics tend to be smaller than those of firm-specific effects, as is their net contribution to explained variation. Both of these results are expected. Peer firm characteristics, in isolation, are imperfect proxies for the industry average leverage, and the coefficients are nonlinear combinations of the underlying structural parameters.

Ultimately, these results indicate the presence of peer effects. What they cannot tell us is the channel through which peer effects operate, direct versus indirect, or the magnitude of the peer effects and associated externalities. For these features, we turn to an instrumental variables approach.

IV. The Identification Strategy

A valid instrument satisfies both the relevance and exclusion conditions. In our setting, these conditions translate into a variable that affects the peer groups' financing decisions (relevance), and affects the firm's financing decision *only* through the peer groups' financing decisions (exclusion). In other words, we require a "shock" to the decision process behind peer firms' financing decisions. Equivalently, we need a perturbation to the equilibrium condition in equation (3).

We argue that the idiosyncratic component of peer firms' equity returns from the previous year is a good candidate. First, the idiosyncratic component of stock returns is, by definition, firm-specific and unrelated to other firms via common factors, consistent with the requirements of the exclusion restriction. Second, a vast empirical asset pricing literature suggests that estimation of this component of stock returns is plausible and, to a degree, empirically testable. Third, the empirical relevance of stock returns for financial policy is well documented (e.g., Loughran and Ritter (1995), Baker and Wurgler (2002), and Welch (2004)) and consistent with several theories.[6] Thus, there is suggestive evidence that this instrument may satisfy the relevance condition.

What is unknown is whether or not the idiosyncratic component of stock returns contains information relevant for future financial policy. Though, fortunately, this condition is empirically testable and all analysis below contain formal test results. What is untestable is whether this instrument satisfies the exclusion restriction. Before addressing this issue, we first describe the construction of this instrument, followed by a discussion of potential identification threats to motivate our empirical analysis.

[6] For example, Myers and Majluf (1984) suggest that financial policy is linked to stock prices because of information asymmetry between managers and investors. Likewise, Myers (1977) suggests that financial policy is linked to stock prices because of debt overhang considerations.

A. Construction of The Instrument

To isolate the idiosyncratic component of stock returns, we specify the following augmented factor model for returns, r_{ijt}:

$$\begin{aligned} R_{ijt} = \alpha_{ijt} &+ \beta^{M}_{ijt}(RM_t - RF_t) + \beta^{SMB}_{ijt} SMB_t + \beta^{HML}_{ijt} HML_t + \beta^{MOM}_{ijt} MOM_t \\ &+ \beta^{IND}_{ijt}(R_{jt} - RF_t) + \eta_{ijt}, \end{aligned} \tag{4}$$

where R_{ijt} refers to the total return for firm i in industry j over month t. The first four factors are those typically found in empirical asset pricing studies (e.g., Fama and French (1993) and Carhart (1997)): the excess market return ($RM_t - RF_t$), the small minus big portfolio return (SMB_t), the high minus low portfolio return (HML_t), and the momentum portfolio return (MOM_t) The fifth factor is the excess return on an equal weighted industry portfolio, ($R_{jt} - RF_t$). While not a priced risk factor, this last factor is included to remove any variation in returns that is common across firms in the same industry. Inclusion of this factor ensures that the estimated residual, our instrument, is orthogonal to industry shocks.

We estimate equation (4) for each firm on a rolling annual basis using historical monthly returns. We require at least 24 months of historical data and use up to 60 months of data in the estimation. The observed returns, estimated coefficients, and realized factor returns enable us to compute the expected and idiosyncratic components of monthly stock returns.

For example, to obtain expected and idiosyncratic returns for January 1990 through December 1990 for IBM, we first estimate equation (4) using monthly returns from January 1985 through December 1989. Using the estimated coefficients and the factor returns from January 1990 through December 1990, we use equation (4) to compute the expected and idiosyncratic returns as follows:

$$\begin{aligned} \text{Expected Return}_{ijt} \equiv \hat{R}_{ijt} &= \hat{\alpha}_{ijt} + \hat{\beta}^{M}_{ijt}(RM_t - RF_t) + \hat{\beta}^{SMB}_{ijt} SMB_t + \hat{\beta}^{HML}_{ijt} HML_t \\ &\quad + \hat{\beta}^{MOM}_{ijt} MOM_t + \hat{\beta}^{IND}_{ijt}(R_{jt} - RF_t) \\ \text{Idiosyncratic Return}_{ijt} \equiv \hat{\eta}_{igt} &= R_{igt} - \text{Expected Return}_{igt} \end{aligned}$$

To obtain expected and idiosyncratic returns for 1991, we repeat the process by updating the estimation sample from 1986 through 1990 and using factor returns during 1991. This process generates betas that are firm-specific and time-varying but constant within a calendar year.[7] Thus, our construction of idiosyncratic shocks allows for heterogeneous — both cross-sectionally and longitudinally — sensitivities to aggregate shocks.

[7]Performing the estimation on a rolling monthly basis has no effect on our results or inferences.

Table IV presents sample means and medians for the estimated coefficients. On average, each of the rolling regressions has 58 monthly observations, though the majority rely on a full five-year window. Additionally, we see that the average R-squared is approximately 30%. Unsurprisingly, the regressions load strongly positively on the industry factor, followed by the market and size factors. The average realized monthly return is 1.4%. The expected return is slightly larger at 1.5% — a difference exacerbated by rounding — which results in a slight negative average idiosyncratic monthly return. Economically speaking, these differences are negligible.

For consistency with our annual accounting data, we transform the monthly returns in two ways. First, we annualize the returns through compounding. Second, we compute average monthly returns for each calendar year and annualize by multiplying by 12. To avoid repetition, we focus attention on the former measure, though our results are qualitatively similar when using the latter.

Our instrument is obtained from the firm-specific annual shocks by computing the average over peer firms. Using averaging as a form of aggregation ensures consistency with the direct ($\bar{y}_{-ijt}$) and indirect ($\bar{X}_{-ijt-1}$) peer effects. For notational consistency, we denote the instrument by $\bar{\hat{\eta}}_{-ijt-1}$. Note that the instrument is lagged one year relative to the direct peer effect so that relevance requires that the average equity shock to peer firms from last year influences peer firms' average financing decisions this year.

Before discussing the properties of the instrument, we note that, conditional on a properly specified asset pricing model (equation (4)), the instrument need not be zero. Our instrument is a conditional average, conditional on industry and year. Additionally, the instrument is not exactly the industry average since it excludes the i^{th} observation. Figure 1 illustrates this variation by presenting the empirical histogram for our instrument. Of course, the average of this average (i.e., the unconditional mean) should be close to zero. This conjecture is confirmed by the approximately zero average idiosyncratic return shown at the bottom of Table IV, and the zero balance point of the empirical histogram in Figure 1.[8]

[8] The zero unconditional mean result is also consistent with the asymptotic notion that the probability limit, as the number of firms approaches infinity, of the average industry equity shock should be zero. Of course, the notion of a peer group of infinite size is economically nonsensical, so that our economic motivation is consistent with the asymptotic properties of our instrument. More concretely, the economic notion of a peer group places a restriction on both the composition and size of the group. As the size of the group approaches infinity, any corresponding peer effect should approach zero, evidence to which is found in Panel B of Table II.

B. Identification Threats

Identification threats come from correlations between our instrument and the error term, ε_{ijt}, in equation (2) due to either omitted or mismeasured variables. More precisely, the concern is that the instrument is correlated with an omitted or mismeasured firm i-specific effect (e.g., investment opportunities or bankruptcy risk) or common factor (e.g., latent risk factors or overlapping product markets), in which case our estimates of the structural parameters may still contain traces of bias. A more subtle issue arises in distinguishing the precise channel through which the peer effect occurs — directly via financial policy or indirectly via characteristics. This subsection takes a first step towards addressing these issues by examining the statistical and economic properties of our instrument.

B.1. Distinguishing Peer Effects from Omitted Firm Characteristics & Common Factors

Previous empirical work shows that observable leverage determinants do a relatively poor job of controlling for systematic variation in capital structures (e.g., Welch (2004), Lemmon, Roberts and Zender (2008), and Stebulaev and Yang (2009)). These findings suggest that there are likely a number of firm characteristics or common factors that are relevant for capital structure, but that are either poorly measured or omitted from equation (2). The relevant issue for identification purposes is whether these omitted variables or measurement errors are correlated with our instrument, the average idiosyncratic equity shock to peer firms. Thus, we focus on ensuring, as much as possible, that the average idiosyncratic equity shock to peer firms is (1) not a better measure of firm i's capital structure determinants, and (2) not capturing a common factor shared among firms within the peer group.

Consider an obvious threat, such as investment opportunities, which are poorly measured and correlated with both stock returns and financial policy. In order for an alternative hypothesis based on mismeasured investment opportunities to contaminate the results, it must be that other firms' idiosyncratic returns better capture firm i's investment opportunities than do all of firm i's observable measures, which include not only the accounting measures and firm i's market-to-book ratio but also firm i's stock return. Likewise, other hard to measure or unobservable capital structure determinants, such as risk and liquidation values, can only contaminate the results in so far as they are correlated with the instrument, conditional on all of firm i's characteristics.

This argument highlights the importance of isolating the idiosyncratic component of stock returns rather than using total returns as an instrument. If the variation in individual stock prices is dominated by the idiosyncratic component, then the average total return of other firms in an industry may provide a less noisy measure of the investment opportunities facing each individual firm than their own individual stock returns. Intuitively, the averaging of returns can net out the noise in each individual stock return. Thus, we rely solely on the idiosyncratic component of stock returns for identification.

Table V examines the extent to which our instrument, peer firm average idiosyncratic equity returns ($\bar{\hat{\eta}}_{-ijt-1}$), correlates with firm i characteristics (X_{ijt-1}). We examine the correlations with both contemporaneous and one-period lead effects, to determine whether the instrument contains information about current or future firm i characteristics.[9] Note that correlation with the characteristics is not problematic because the characteristics are all included in the regression as control variables. In other words, identification of the peer effect cannot come from variation in the instrument that is correlated with any observable firm characteristics. However, economically large associations between the instrument and firm characteristics raises potential concerns about the extent to which our instrument may be correlated with unobservable factors, and the extent to which we have removed common variation among firms' returns via equation (4).

The results reveal no statistically or economically significant associations between our instrument and firm i's characteristics measured either contemporaneously or one-period ahead. All of the coefficients are statistically and economically indistinguishable from zero. A joint test of coefficient significance also reveals a statistically insignificant result, as revealed by the row denoted F-Stat P-Value. Unreported analysis reveals similar findings when we expand the specification to include additional firm i controls including the marginal tax rate, stock returns, earnings volatility, and Altman's Z-Score. In other words, the instrument contains no information about firm i's observable capital structure determinants, present or near future.

With regard to an ommitted common factor, we note that each specification contains year fixed effects. However, a more salient concern is with regards to an ommitted common factor in equity returns, i.e., a misspecification of the asset pricing model. Unreported results reveal that the contemporaneous conditional correlation between the instrument and firm i's idiosyncratic equity shock is economically tiny (approximately

[9]Though using future values on the right hand side of a regression is unorthodox, our goal with this analysis is not to identify the determinants of industry average idiosyncratic equity returns. Rather, we merely want to document the extent of any correlations, without attempting to draw any economic inferences or causal conclusions.

0.02). Further, the conditional correlation between our instrument and the one-period ahead firm i idiosyncratic equity shock is even smaller (less than 0.01).

While we take additional measures below to address concerns over misspecification of the asset pricing model, these tiny magnitudes are reassuring for three reasons. First, they show that the factor regression (equation (4)) purges most all of the intra-industry correlations present in raw returns. In other words, our instrument does not contain any information about firm i's contemporaneous shock. Second, they show that our instrument does not contain any information about firm i's future shock. Finally, they show that mismeasurement of the peer group will more likely attenuate our findings, as opposed to compromise our identification strategy.

This last point is worth clarifying. If there exist peer groups within an industry, then the asset pricing model may be insufficient to remove common variation among the subgroups, thereby compromising the identification strategy. However, because the correlation between firm i's idiosyncratic equity shock and other firms' equity shocks is near zero, the existence of economically significant subgroups would require a combination of significantly positively and negatively correlated returns within the industry. To examine this possibility, we randomly select subgroups within each industry year combination and estimate the correlation between firm i and these subgroups. Fewer than 5% of the estimated correlation coefficients are negative and less than 1% of these estimates are statistically significant. Thus, any mismeasurement of the peer group will more likely attenuate our findings, as opposed to biasing our results, a conjecture we empirically investigate below.

Ultimately, this analysis and discussion illustrates that our instrument has a number of appealing properties for the purpose of identifying financing externalities. We will refer back to these properties below when we examine alternative hypotheses.

B.2. Distinguishing Direct from Indirect Peer Effects

A more subtle issue concerns distinguishing between the two channels through which a peer effect works — directly through financial policy and indirectly through characteristics. We can control for observable characteristics of peer firms via the term $\bar{X}_{-ijt-1}$. Inclusion of this term, and various fixed effects, alleviates some concern that the direct effect coefficient, β, captures indirect effects. However, the fact that firm i's relevant characteristics are hard to observe and measure, implies the same for its peers. Thus, the other identification concern is that our estimate of the direct effect of peer firm financial policy may be tainted by mismeasured or omitted peer firm characteristics.

To illustrate this problem, consider the following hypothetical example. Firm k introduces a new product, which positively impacts the idiosyncratic component of its stock return. In the following period, firm k issues equity to finance increased production, and reduces its leverage ratio towards a new optimum. In response, peer firm i, issues equity and reduces its leverage too. The question is to what is firm i responding: the introduction of the new product (the indirect peer effect), or the change in financial policy (the direct peer effect)? Relying solely on the equity shock of firm k, in conjunction with observable peer firm characteristics, to identify firm i's response may be insufficient to distinguish between these two channels. Thus, in our robustness section below, we provide additional analysis towards this end.

V. The Role and Implications of Peer Effects

A. Leverage

Panel A of Table VI presents the estimated coefficients, t-statistics (in parentheses), and model statistics from two-stage least squares (2SLS) regressions of equation (2). We present results for book and market leverage in both levels and first differences. The latter specification helps address concerns over omitted firm i characteristics, since it is equivalent to a levels specification that includes firm fixed effects. The level specifications uses the levels for all of the variables on both left and right hand sides of the equation. The first difference specifications uses first differences for all of the variables on both left and right hand sides of the equation. The only exception is the instrument, average peer firm idiosyncratic equity returns, which is the same across all specifications. Thus, we instrument for the endogenous direct peer effect in year t, $\bar{y}_{ijt}$, with the average idiosyncratic stock returns of peer firms in year $t-1$, $\bar{\hat{\eta}}_{-ijt-1}$.

The first stage results reveal that the average equity shock is strongly negatively associated with both the level and first difference in average industry leverage ratios. The sign of the estimate is consistent with previous findings relating total returns to leverage and with theoretical arguments relating investment opportunities and risk to optimal leverage and financing choices (e.g., Myers (1977) and Scott (1976)). The magnitude of the effects are economically significant as well, stronger than many of the included determinants (not reported). Statistically speaking, the instrument easily passes weak instrument tests (e.g., Stock and Yogo (2005)).

The second stage results reveal that peer firm financial policies are strongly positively related to leverage. The economic magnitude is slightly larger in the 2SLS estimation than the OLS estimation. For example, specification (1) in Panel A of Table VI implies that a one standard deviation change in average peer firm leverage is associated with a 6.4% change in firm i's leverage ratio. The OLS estimate found in column (4) of Panel A, Table II implies only a 2% change in firm i's leverage ratio. While this increase in magnitude may at first seem surprising, the identification discussion of section III shows that the estimated reduced form parameters are nonlinear functions of the structural parameters (see Appendix B for the derivation).

Columns (3) and (4) in Panel A of Table VI reinforce these findings by showing similar results for changes in leverage ratios. A comparison of the coefficients scaled by their corresponding variable standard deviations reveals that the direct peer effect has a larger impact on leverage ratio changes than any other included determinant. This finding is reassuring because it shows that the unobserved firm specific heterogeneity found by Lemmon, Roberts, and Zender (2008) is not responsible for our findings.

As an aside, we note that the estimated firm-specific effects are similar to those found in Table II and the existing literature (e.g., Frank and Goyal (2007)). For example, comparing column (1) in Panel A of Table VI with column (4) in Table II shows that the coefficients on each firm specific characteristic are all within one percentage point of one another. Similarly, column (2) from Panel A of Table VI reveals coefficients that are quantitatively close to those in column (9) of Table II. These similarities are unsurprising in light of the orthogonality between our instrument and firm-specific characteristics (Table V), and they emphasize the fact that the identifying variation behind the estimated peer effect is specific to the idiosyncratic stock return of peer firms from the previous period.

The significant coefficients on the peer firm averages suggest that capital structure decisions are affected not only directly by the leverage choices of a firm's competitors, but also indirectly by their competitors' characteristics. That is, controlling for firm i's characteristics, the results in column (1) imply that firms whose competitors are smaller, more profitable or have higher market-to-book ratios tend to have higher leverage ratios. These latter two results appear consistent with the industry equilibrium argument of Shleifer and Vishny (1992), for example. As a firm's competitors become more financially healthy, liquidation values increase. As such, debt becomes less costly and firms can take on more debt — leverage rises.

More generally, these peer characteristic findings suggest that firms consider not only their own characteristics in forming financial policy, but their characteristics *relative* to their competitors. For example, the positive coefficient on firm i's log(Sales) in column (1) suggests that larger firms on average have higher leverage ratios. However, the negative coefficient on *other* firms' size implies that a firm of a given size will use more leverage when its competitors are smaller than when its competitors are larger. This pattern of opposite signs between firm-specific and peer firm characteristics also holds for the other included and significant characteristics. We note that while the coefficients of each firm specific and peer firm average are of similar magnitudes, the corresponding impacts on firm i's leverage ratio are very different. The typical variation in average peer firm characteristics is an order of magnitude smaller than the variation in the firm-specific measure. Therefore, typical changes in peer firm characteristics lead to significantly smaller changes in firm i's leverage ratio relative to changes in firm i's characteristics.

Unfortunately, it is difficult to place a precise interpretation on peer firm characteristics. There is little theory beyond that mentioned that speaks directly to these findings, and the proxies are relatively coarse. However, these results are consistent with the findings of MacKay and Phillips (2005), who suggest that a firm's relative position within its industry is an important determinant of capital structure. More relevant to our study, these results show that competitor characteristics represent an additional channel through which peer firms influence capital structure.

In summary, this analysis shows that peer firms play a significant role in shaping corporate capital structures, in terms of both the level and change in leverage ratios. Further, the primary channel through which peers affect capital structures appears to be via financial policy, as opposed to changing characteristics. The next two subsections investigate the robustness of these findings to alternative interpretations.

A.1. Robustness Tests - Peer Effects Vs. Omitted Firm Characteristics & Common Factors

In Panels B and C of Table VI we present a number of robustness checks to mitigate identification concerns related to distinguishing peer effects from omitted and mismeasured firm i characteristics and common factors. The analysis here builds on that found in section IV.B. Panel B presents results for levels, Panel C for first differences. We run all robustness tests on both book and market leverage; however, because of the similarity of findings, we report only the results for book leverage. Further, we focus attention on the key variables of interest: the first stage estimate of the instrument parameter, and the second stage estimate of the direct peer effect parameter.

The specification in Column (1) in Panel B incorporates control variables in addition to all of the ones presented in Panel A. Specifically, we expand both the firm specific factors (X_{ijt-1}) and the peer characteristics ($\bar{X}_{-jt-1}$) to also include: an indicator identifying whether a dividend was paid, Altman's Z-score, Graham's marginal tax rate, capital investment, R&D expenditures, SG&A expenditures, and intra-industry leverage dispersion. The motivation behind these additional factors comes from the parsimonious nature of our baseline specification. The results show a negligible effect on both first and second stage estimates suggesting that there are no obvious observed variables ommitted from the model.

The specification in column (2) addresses the concern that commonality among firms' capital structures is due to the use of common banks (commercial or investment) within the industry. In other words, firms within an industry may be behaving similarly with respect to their financial policies because they are using the same banker, who is giving similar advice. We use Thompson's SDC and Reuters Loan Pricing Corporation's Dealscan database to identify lead underwriters and arrangers or agents for public and private, debt and equity issuances.[10] We then create bank fixed effects for each firm in the overlap of our sample and these two databases by forward imputation. That is, we assume that the firm uses the same bank each year until either the end of the sample or until we find a different bank being used, regardless of the security being issued. For example, if IBM floated equity with Goldman Sachs as the lead underwriter in 1991, we assume that IBM used Goldman Sachs for each year including and after 1991, until the end of our sample or until they used another bank for a future equity *or* debt issuance. (Results obtained by backward imputation — assuming that the firm used the same bank in all years prior to the issuance until either the beginning of our sample or a new bank was found — are similar.)

We make two points concerning the results in column (2). First, incorporating bank fixed effects has no impact on the first stage estimate and actually amplifies the second stage estimate. Second, bank effects explain a significant amount of variation in leverage ratios. In unreported analysis using identical samples, the difference in *adjusted* R-squares due to the bank effects is nine percentage points. So, while banks seem to have significant influence over corporate capital structures, they are not responsible for the commonality in financial policies that we are identifying.

In column (3), we incorporate firm i's lagged leverage ratio and the average lagged leverage ratio for the peer group, to capture any targeting behavior or dynamic feedback from the explanatory variables onto leverage ratios. Note, that this specification is similar

[10]Specifically, SDC provides underwriter information for public debt and equity offerings, as well as Rule 144a offerings. We rely on Dealscan to identify the lead bank (or arranger) on sole-lender and syndicated loans.

to that used in studies studying targeting behavior (e.g., Flannery and Rangan (2006) and Kayhan and Titman (2007)). Specifically, a simple reparameterization shows that this specification is identical to a model in which firms adjust to a time-varying target consisting of firm and peer characteristics. (The first difference model found in Panel C implicitly incorporates firm fixed effects into the specification.) Again, both first and second stage estimates are largely unaffected.

In column (4), we incorporate contemporaneous controls, both firm-specific (X_{ijt}) and peer ($\bar{X}_{-ijt}$), in addition to the one-period lagged controls. The motivation here is to ensure that our choice of lag structure is not driving our results, as well as to account for any delays in the response of firm i to the shock to its peers. For example, competitors contemporaneous market-to-book ratio may capture the impact of a shock to peer firms' investment opportunity set that is only fully realized one period later. Again, we see evidence of a strong instrument, and an economically significant role for peer firm financial policy.

In column (5), we incorporate the lagged and contemporaneous realized (or total) stock return for firm i, and the lagged and contemporaneous expected stock return for the peer group.[11] This specification addresses two related concerns. The first is that the asset pricing model (equation (4)) is misspecified, in which case there may still be common factors in the estimated idiosyncratic component of stock returns. The second is that our results are capturing a sequencing or timing of returns within an industry, so that firm i is responding to its own return shortly after firm j responds to its return.

Including firm i's total return eliminates both of these concerns since only the portion of peer firms equity shocks that is orthogonal to firm i's total return is available for identification. More simply, if peer firm idiosyncratic returns are capturing a common factor shared by firm i, then this factor is better captured by firm i's total return. Likewise, if firm i is simply responding to it's own stock return following the returns of its peers, then including firm i's return should eliminate this alternative. Again, the results are largely unchanged, which is particularly reassuring since there is, by construction, no scope for identifying variation to contain information impounded in firm i's returns or prices (i.e., market-to-book ratio).

Finally, in column (6), we include quadratic and cubic polynomials of each firm-specific factor and peer firm average in our primary specification (i.e., firm size, profitability, tangibility, market-to-book). Again, we see little change in the results. As an

[11] Using the realized return for the peer group would confound our results since the identifying variation would be shared by the instrument and the control variable.

aside, we also mention that our results are robust to a more refined definition of peer groups based on intra-industry size groupings (e.g., Bizjak, Lemmon, and Naveen (2008) and Byrd, Johnson, and Porter (1998)).

Panel C in Table VI presents similar results for the same specifications in first difference form. We note that in columns (4) and (5), the second stage estimate of the direct peer effect is statistically significant only at the 10% level. However, the magnitude of the coefficient estimates is similar and statistically indistinguishable from our primary estimates in Panel A, as well as other robustness tests. This feature implies that the issue in columns (4) and (5) is one of power, as opposed to bias.

In unreported analysis, we employ our empirical model and identification strategy on corporate fixed investment measured by capital expenditures. The motivation behind this analysis is to further address concerns over latent investment opportunity commonalities among peer firms. More specifically, we regress firm i investment on peer firm average investment, firm specific and peer firm averages of cash flow and the market-to-book ratio, and industry and year fixed effects. We instrument for peer firm average investment with their average idiosyncratic equity shock. The results reveal no statistically or economically significant direct (or indirect) peer effect, despite a highly statistically significant positive first stage estimate. Thus, the peer effect found in financial policy seems unlikely to be driven by a corresponding commonality among investment opportunities.

Additionally, we examine the effects of altering the definition of the peer groups, as we did in Panel B of Table II. Two interesting results emerge. First, with randomly assigned industries designed to mimic the average number of firms found in our 3-digit SIC code definition (18 firms), we find a significantly negative first stage estimate and a statistically insignificant second stage estimate indicative of no peer effect. As we move to coarser definitions of the peer group (e.g., 2- and 1-digit SIC codes), both the first and second stage estimates are statistically insignificant. The first stage estimates become insignificant because the distribution of our instrument is collapsing around the unconditional mean of zero. The second stage estimate is insignificant because of a combination of a weak instrument and a noisier definition of the peer group. These findings reinforce the importance of the peer group defintion.

The robustness of the results may at first appear surprising. However, this feature largely reflects the instrument properties highlighted above. The instrument is conditionally orthogonal to firm i's contemporaneous and future accounting measures and stock returns. Therefore, adding additional controls such as firm characteristics, peer firm characteristics, and stock returns has little affect on our coefficient estimates. While no instrument is perfect, we believe that these results minimize the scope for alternative interpretations based on omitted or mismeasured firm i characteristics or asset pricing factors. Firms choose leverage ratios, both levels and changes, in close accord with their peers' choices.

A.2. Robustness Tests - Direct Vs. Indirect Peer Effect Channels

The results above suggest that the peer effect works through financial policy, as opposed to characteristics. The effect of average peer firm capital structure on firm i's leverage ratio is significantly larger than that of a change in any average peer firm characteristic. Further, many of the robustness tests performed above, while motivated by alternative hypotheses based on omitted firm specific characteristics, lend further evidence favoring the importance of the direct channel as opposed to the indirect channel. The inclusion of additional peer characteristics (column (1)), lagged peer firm average leverage ratios (column (3)), contemporaneous peer firm characteristics (column (4)), peer firm expected returns (column (5)), and nonlinear peer characteristics (column (6)) all mitigate contamination of the direct peer effect estimate (β) by omitted indirect peer effects.

As an additional robustness check, we perform a double sort of the data based on quintiles of our instrument, lagged average peer firm idiosyncratic returns, and the endogenous variable, average peer firm leverage changes. Within each quintile combination, we compute the average change in leverage. As before, we perform this analysis on both book and market leverage but present only the book leverage results for brevity. The goal with this analysis is to determine whether firms' financial policies are responding more to the equity shock or more to the subsequent capital structure change. If firms leverage changes are being driven by peer firm leverage changes, then the magnitude of the peer firm equity shock should only be relevant in so far as it is accompanied by a peer firm leverage change. Alternatively, the magnitude firm i's leverage change should be largely independent of the magnitude of the equity shocks, driven primary by the magnitude of peer firms' leverage changes.

The results are presented in Table VII. Presented in parentheses at the top of each column and in the leftmost row are the quintile averages for the sorting variables. We see that peer firm average leverage changes range from a -5% in the first quintile to 8% in the fifth quintile. Likewise, peer firm average equity shocks range from -18% in the first quintile to 18% in the fifth quintile. The inner cells of the table contain the average change in leverage for each quintile combination. For example, the average change in leverage among firms in the lowest peer firm equity shock quintile and the highest peer firm leverage change quintile is 5.7%.

The Table provides the following insights. The average change in leverage by firm i only responds to the shock when peer firms change their leverage in a significant manner. Consider the third quintile of industry average leverage change — column 3. This quintile corresponds to observations in which peer firms did not significantly alter their leverage, either positively or negatively. The average change in leverage for firm i is indistinguishable from zero in all but two case, and in these two cases the economic magnitude of the change is small — less than 1%. In other words, when peer firms do not change their leverage, firms do not change their leverage regardless of the magnitude of the equity shock experienced by peer firms.

More broadly speaking, the average leverage change appears conditionally independent of the magnitude of the equity shock. Holding fixed the magnitude of peer firms' leverage change, the leverage change of firm i is roughly constant. That is, within each column the leverage change is roughly constant across peer firm equity shocks. The last two columns shows that even the difference in leverage changes between the extreme peer firm average leverage change portfolios (columns 1 and 5) and the no change peer firm average leverage change portfolio (column 3), exhibit conditional independence from the size of the equity shock. Thus, firms leverage ratios respond to peer firms' equity shocks *only* when their is an accompanying change in peer firm leverage ratios, suggesting that peer effects work primarily through financial policy as opposed to firm characteristics.

B. Financial Policy

In Table VIII, we examine net equity and net debt issuing activity to understand whether peers are influencing specific financing decisions, such as net equity and net debt issuances, or whether leverage is changing because of passive changes in the market value of equity or accumulation of retained earnings. This concern is partly mitigated by the inclusion of firm-specific equity shocks and profitability in the regressions. However, we wish to provide more direct evidence on the precise financing channels driving the leverage results.

Column (1) presents results where the dependent variable is an indicator equal to one if the firm performs a net equity issuance in excess of 1% of total assets, and zero otherwise. This regression models the decision by firms to issue equity in a given year. While a logit or probit model may be more appropriate from a forecasting perspective, we present results using the linear model in equation (2) to ease the interpretation and comparison with other findings. Unreported instrumental variables results using a probit model reveal quantitatively similar findings.

The first stage results reveal that the idiosyncratic component of stock returns is strongly correlated with equity issuance decisions. This effect is both economically and statistically significant, again highlighting that the idiosyncratic component of stock returns is as important for financial policy, if not more so, than the systematic component. The second stage results show that the peer effect is also significant. A one standard deviation increase in the probability of issuing equity by peer firms leads to an 9.1% ($\hat{\beta} \times SD = 0.517 \times 0.176$) increase in the probability of firm i issuing equity. In fact, other than firm i's own market-to-book ratio, the peer effect is the most economically important determinant. The other firm-specific factors show similar relations to equity issuance decisions as found in previous studies.[12] None of the peer firm average characteristics are statistically significant.

While the decision to issue equity is closely tied to peers, the relative amount to issue (or repurchase) is only weakly related. Column (2) shows a weak statistcal and economic relation among firms when choosing the amount of net equity issued relative to their assets, despite a highly significant first stage estimate. Thus, firms are more strongly influenced by their peers when it comes to the form of financing, whereas the amount is only weakly related.

Looking at column (3) and the decision to issue debt, the estimated coefficient implies that a one standard deviation increase in peer firms' probability of issuing debt is met with a 9.7% ($\hat{\beta} \times SD = 0.658 \times 0.148$) increase in the probability of firm i issuing debt. This effect dwarfs those of the firm-specific effects, the largest of which is 3.9% (Net PPE / Assets). However, this estimate is highly imprecise, as evidenced by the small t-statistic. Column (4) reveals a similar result for the relative amount of debt issued - a statistically insignificant direct peer effect.

Column (5) presents results from the same equity issuance decision model as column (1) but restricts the sample to firm-year observations in which the firm issues either equity or debt. In columns (1) through (4), there are many firm-year observations in which firms undertake no net equity or net debt issuing activity. As such, the implicit comparison in these models is with the other financing choice *and* no issuance. Column (5) enables us to understand whether peers affect the preference between debt versus equity, conditional on an issuance. The results show that firms exhibit a strong preference for equity *and* debt when their peers exhibit a similar preference. A one standard deviation increase in

[12]See studies by Hovakimian, Opler, and Titman (2001), and Leary and Roberts (2005).

the probability of issuing equity relative to debt by firms' peers leads to a 11.0% (0.627×0.176) increase in the probability of issuing equity. Again, this effect is statistically and economically significant, even larger than the firm-specific market-to-book ratio.

This analysis shows that peer effects impact leverage through their role in shaping individual financing decisions. Firms security choice, debt or equity, is dictated to a large extent on the security choice of their peers. This finding also offers an alternative interpretation as to why financing tends to occur in clusters or waves. Traditional views have been based on "windows of opportunity," in which capital can be raised at favorable terms because of information asymmetry (e.g., Bayless and Chaplinsky (1996)), or variation in market conditions (e.g., Pastor and Veronesi (2004)), in which business cycles generate variation in aggregate risk and the profitability of capital raising acitivities. Our identification strategy and robustness tests ensure that neither of these explanations are behind our results. Finally, the relative unimportance of the peer firm characteristics here further reinforce the previous evidence pointing towards the direct channel of financial policy through which peer effects operate.

C. Amplification Effects

An important implication of the empirical model in equation (2) and the estimated peer effects is the presence of externalities. A simple example will illustrate how these externalities function, using the results in Panel A of Table VI to make things concrete. Assume firm A's profitability increases. This change leads to a decline in firm A's leverage, as suggested by the negative coefficient estimates on firm-specific EBITDA / Assets. The decline in firm A's leverage leads to a decline in leverage for every other firm in firm A's peer group via the direct peer effect — the positive coefficient on peer firm average leverage. Additionally, the decline in firm A's profitability leads to an increase in leverage for every other firm in firm A's peer group via the indirect peer effect, or the positive coefficient on peer firm average EBITDA / Assets. These latter two affects feedback onto firm A's leverage, again via the direct and indirect peer effect channels, and so on, and so on.

We can more easily see and quantify these effects by first focusing on a particular industry j and year t. This focus is of no consequence. It simply eases the presentation and discussion. Rewriting our model, equation (2), in matrix notation produces

$$y = \frac{\beta}{N-1}Qy + X\lambda + \frac{1}{N-1}QX\gamma + Z\delta + \varepsilon. \quad (5)$$

where $y = (y_1, ..., y_N)'$ is a vector of outcomes for the N firms in an arbitrary industry-year combination, Q is an $N \times N$ matrix with zeros on the diagonal and ones everywhere else,

X is an $N \times k_1$ matrix of exogenous variables that appear as both firm specific factors and peer firm averages in our model (e.g., sales, profitability, market-to-book, tangibility), Z is an $N \times k_2$ matrix of exogenous variables that appear only as firm specific factors (e.g., industry and year fixed effects), and ε is an $N \times 1$ vector of residuals.

Solving equation (5) for y yields

$$y = \left(I - \frac{\beta}{N-1}Q\right)^{-1}\left(X\lambda + \frac{1}{N-1}QX\gamma + Z\delta + \varepsilon\right). \tag{6}$$

Of interest is the marginal effect or derivative of the outcome for firm $i = 1, ..., N$, y_i, with respect to the $m = 1, ..., k_1$ exogenous variables for firm $l = 1, ..., N$, x_{lm}. This derivative equals

$$\frac{\partial y_i}{\partial x_{lm}} = \begin{cases} \lambda_m\left(1 + \frac{\beta^2}{(N-1+\beta)(1-\beta)}\right) + \gamma_m\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i = l \\ \lambda_m\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) + \gamma_m\left(\frac{1}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i \neq l \end{cases} \tag{7}$$

(See Appendix C for a derivation.)

In a standard linear model without peer effects, both β and γ are equal to zero and the derivative reduces to $\partial y_i / \partial x_{lm} = \lambda_m$ for all i and l. In other words, changing x_m for observation l only affects observation l's outcome and does so by λ_m. With peer effects, λ_m is no longer a sufficient statistic for the marginal effect of exogenous variables, and externalities create a channel for cross-observation affects.

The direct peer effect, β, amplifies the effect of a change in an exogenous variable on y. This amplification mechanism is represented by the parenthetical expression multiplying λ_m for the case in which $i = l$. For β in the open unit interval and $N > 1$, this expression is strictly greater than 1. Thus, changes in x in the presence of direct peer effects lead to even larger changes in y because of the feedback among peer outcomes. In addition to this amplification effect is an externality represented by the second term in the $i = l$ case. Here, the direct and indirect peer effects interact to either further amplify ($\gamma_m > 0$) or decrease ($\gamma_m < 0$) the marginal effect of a change in x_{im} on y_i.

The direct peer effect also creates a role for cross-observation externalities, as seen by the parenthetical term multiplying λ_m for the case in which $i \neq l$. This product captures the impact of the change in firm l's outcome arising from the exogenous change in x_{lm} on firm i's outcome. This is a spillover effect. Amplifying or decreasing this spillover is the second term in the $i \neq l$ case.

Table IX presents estimates and test statistics of the parameters, derivatives, and multipliers for our model of book leverage found in column (1) of Panel A, Table VI.

t-statistics are in parentheses and chi-square statistics with one degree of freedom are in brackets. The columns labeled λ and γ simply repeat the firm specific and peer firm average characteristic parameter estimates for ease of reference. The third column presents the estimated derivatives for the case in which $i = l$. (The fourth column scales the derivatives by the variable standard deviation to get a sense of economic magnitudes.) We can see that the estimated derivatives are close to the firm specific parameter estimates (λ). This similarity masks two offsetting forces: (1) amplification from the direct peer effect, and (2) contraction from the indirect peer effect.

The estimated amplification effect is indicated at the bottom of the table. The estimate of 1.114 implies that the direct peer effect amplifies exogenous changes in firm characteristics by just over 11%. Using profitability as an example, this implies that feedback among financing choices increases the marginal effect of a unit change from -0.236 to -0.263. However, offsetting this amplification is the indirect peer effect represented by γ and the second term in the $i = l$ expression in equation (7). The positive estimate on the peer firm average profitability ($\lambda = 0.210$) works to dampen the net marginal effect of a change in firm i's profitability on firm i's leverage. The magnitude of the second parenthetical term in the $i = l$ case is given by Spillover Term 1 and is 0.156, though this estimate is statistically noisy. As the effects of these two countervailing forces are similar in magnitude, the net effect given by the third column is close to the gross effect found in the first column.

While the gross and net effects may be similar in magnitude, the interpretation is very different from that provided by traditional models of financial policy without externalities. With peer effects, the impact of an exogenous change in leverage determinants influences capital structure directly and indirectly via feedback and spillover effects. Further, these latter effects, particularly the amplification mechanism, are significant. What is not significant are the spillover effects across observations. In particular, the cross-observation derivatives ($\partial y_i / \partial x_{lm}$ for $i \neq l$) are economically small and statistically insignificant at the 5% level.

In sum, the presence of peer effects alters the interpretation of existing marginal effects by creating amplification and spillover mechanisms. Shocks to one firm impact all other peer firms, which resonate back onto the original firm.

VI. Why do Firms Mimic One Another?

As mentioned in the introduction, there is relatively little capital structure theory rationalizing interactions in financial policy, even less rationalizing the type of interactions identified above. However, prior theoretical literature has suggested several potential motives for why managers might be influenced by other firms' choices in setting financial policy. The first is that by observing the actions of other firms, managers may be able to infer others' private information. As shown by Banerjee (1992) (among others), this can lead managers to rationally put more weight on the decisions of other firms than on their own information. This is especially likely when optimization is costly or time-consuming (Conlisk, 1980) or when individual managers' signals are noisy and other firms in the industry are perceived as having greater expertise (Bikhchandani, Hirshleifer and Welch, 1998). Bikhchandani et al. refer to this as observational learning or social learning.

Additionally, Scharfstein and Stein (1990) and Zwiebel (1995) have shown, in the context of investment choices, how managers' reputational concerns can lead to herd behavior. Specifically, in the model of Scharfstein and Stein (1990), higher quality managers receive correlated signals about investment opportunities, while lower quality managers receive independent signals. Managers therefore mimic the investment choice of others in order to increase their perceived type. In this case, herding is more important than making efficient investment choices, since blame is shared in the event of a bad outcome. In this setting, herding behavior can be mitigated by short-term incentive contracts and relative performance evaluation, or when managers outside opportunities are greater.

In Zwiebel's model, managers' types are inferred from their relative performance. Because managers perceived to be below a cutoff type are fired, they prefer to mimic the investment choices of others in order to minimize the volatility of their relative performance. The exceptions are low-skilled managers for whom volatility increases the likelihood of not being fired. Thus, in contrast to Scharfstein and Stein (1990), relative performance evaluation generates, rather than mitigates, herding behavior.

Mimicking of financial policies can also be understood in the context of signaling models. For example, Ross (1977) shows that when insiders have better information about firm value than outside investors, insiders may try to use financial structure to signal this information to the market. However, if the signal is not sufficiently costly, low quality firms will imitate the financial structure of the high quality firms to avoid having their type detected. A pooling equilibrium results in which all firms make the same financing choices.

Finally, interactions between financial structure and product market competition may also lead to mimicking of financial policies. One motivation is fear of predation. For example, in Bolton and Scharfstein (1990), high leverage invites predatory price competition from less levered rivals; in Chevalier and Scharfstein (1996), firms with high leverage under-invest during an industry downturn and lose market share to more conservatively financed competitors. If the expected cost of this predatory behavior is severe enough, highly levered firms will mimic the capital structures of their less-levered rivals.

An alternative motivation is the effect of financial structure on a firm's own product market strategy. For example, in the symmetric duopoly model of Brander and Lewis (1986), high debt levels commit a firm to compete aggressively. The competitors' best response is to also commit to aggressive competition, so both firms choose the same high debt level. Note, however, that product market interactions need not lead to commonality in financial structure within industries. As noted by MacKay and Phillips (2005), in models of competitive industries (e.g., Maksimovic and Zechner, 1991), equilibrium outcomes tend to generate dispersion in financial policy within industry segments. Whether product market interactions can also lead, in some settings, to clustering of financial policies within peer groups is ultimately an empirical question that we address in more detail below.

A. Empirical implications

To attempt to distinguish among these alternative motivations, we ask: which types of firms are most influenced by the financial policy choices of their peers? If firms mimic their peers in an effort to learn about optimal capital structure, we would expect such behavior to be most pronounced among firms that view their peers as having superior information. Thus, younger firms, new entrants, and those with lower market share should be influenced by peer firm choices more than industry leaders are. Similar predictions are shared by the reputational concerns models. Those managers with greater reputational concerns are likely to be younger CEOs with less tenure, but also those managing younger, less successful firms. However, as discussed by Scharfstein and Stein (1990), if reputational concerns are driving mimicking of financial policies, this tendency should be weaker when managers have better outside opportunities, when compensation is tied to (short-term) firm performance or when they are evaluated relative to their peers.

The pooling explanation based on signaling models relies on the signal (e.g. debt issuance) being relatively low-cost. We would thus expect peer effects to be stronger among firms with low cost access to external capital, i.e. those with lesser financing constraints. If mimicking is driven by a fear of predation, it should be more pronounced among firms for which predation would be more costly: those with higher market share and greater distress costs. Finally, if herding in financial policy is driven by the impact of financial structure on product market strategy, we would expect peer effects to decrease with the competitiveness of the industry.

B. Heterogeneity in peer effects

In light of the predictions discussed above, in this section we examine heterogeneity in the strength of the estimated peer effect across both firm and CEO characteristics. ***To be completed...***

VII. Conclusions

This study has shown that firms do not make financing decisions in isolation. Rather, the financing decisions of firms' peers are an important determinant of corporate capital structures and financial policies. We find that not only are peer effects statistically significant, they are economically large. Marginal effects of peer decisions on the level and change in book and market leverage are or greater than other observable capital structure determinants. Underlying these leverage effects are peer effects among security (debt and equity) choices.

We also find a significant role for peer firm characteristics in shaping capital structure. While more difficult to interpret, the results suggest that a firm's position relative to its industry is relevant for its capital structure choice, consistent with the findings of MacKay and Phillips (2005). Thus, while direct peer effects drive firms in the same industry to similar capital structures, indirect peer effects help explain the distribution of capital structures *within* industries.

An interesting by-product of these peer effects is the presence of amplification and spillover effects. Changes affecting one firms capital structure affect peer firms' capital structures, which feedback onto the original firms capital structure, and so on, and so on. Thus, the marginal effect of capital structure determinants has a very different interpretation in the presence of interactive effects, as there are multiple channels through which changes to one determinant influence the capital structure decision.

Given the economic importance of peer effects documented here, we hope that future research, both theoretical and empirical, will explore more closely the implications for this feedback and the mechanisms behind this capital structure determinant.

Appendix A: Variable Definitions

Compustat variable names denoted by "dataXXX." Time periods are denoted by (t) or (t-1) suffixes. We screen firm-year observations based on nonmissing data for the levels and first differences of the following variables: net equity issuances, net debt issuances, book leverage, market leverage, sales, market-to-book ratio, profitability, tangibility, and idiosyncratic component of stock returns.

Total Book Assets = data6.

Total Debt = Short-Term Debt + Long-Term Debt = data9 + data34.

Book Leverage = Total Debt / Total Book Assets.

Market Value of Assets (MVA) = data199 * data54 + data34 + data9 + data10 - data35.

Market Leverage = Total Debt / MVA.

Net Debt Issuances = [(data9(t) + data34(t)) - (data9(t-1) + data34(t-1))] / data6(t-1).

Debt Issuance Indicator = 1 if Net Debt Issuances > 1%; 0 otherwise.

Net Equity Issuances = (data108 - data115(t) / data6(t-1).

Equity Issuance Indicator = 1 if Net Equity Issuances > 1%; 0 otherwise.

Firm Size = Log(Sales) = Log(data12).

Tangibility = Net PPE / Assets = data8 / data6.

Profitability = EBITDA / Assets = data13 / data6.

Market-to-Book Ratio = MVA / Total Book Assets.

Common Dividends = data21.

Common Dividend Indicator = 1 if data21 > 0; 0 otherwise.

Sales, General, and Administrative Expenses = data189 / Firm Size.

Research and Development Expenses = data46 / Firm Size.

Capital Expenditures = data128.

Capital Investment = Capital Expenditures(t) / Net PPE(t-1).

Altman's Z-Score = (3.3 * data170 + data12 + 1.4 * data36 + 1.2 * (data4 - data5)) / data6

Earnings Volatility is computed each year as the historical standard deviation of EBITDA / Assets. We require at least three years of nonmissing data.

Marginal Tax Rates were downloaded from John Graham's website.

Appendix B: The Identification Problem

This appendix provides a formal derivation of the identification problem discussed in section IV B. Ignoring the time fixed effects for notational convenience, consider the population version of equation (2),

$$y = \alpha + \beta E(y|\mu_j) + \lambda' X + \gamma' E(X|\mu_j) + \delta' \mu_j + \varepsilon. \tag{8}$$

The two conditional expectations on the right hand side of equation (8) are peer group means, such as industry averages, and correspond to the direct and indirect peer effects.

The corresponding mean regression of y on X and μ_j (the conditional expectations are functions of μ_j) is therefore

$$E(y|X, \mu_j) = \alpha + \beta E(y|\mu_j) + \lambda' X + \gamma' E(X|\mu_j) + \delta' \mu_j. \tag{9}$$

Taking expectations of this equation with respect to the firm characteristics, X, conditional on μ_j yields the equilibrium condition

$$E(y|\mu_j) = \alpha + \beta E(y|\mu_j) + \lambda' E(X|\mu_j) + \gamma' E(X|\mu_j) + \delta' \mu_j. \tag{10}$$

Assuming that $\beta \neq 1$, this equilibrium has a unique solution

$$E(y|\mu_j) = \frac{\alpha}{1-\beta} + \left(\frac{\gamma+\lambda}{1-\beta}\right)' E(X|\mu_j) + \left(\frac{\delta}{1-\beta}\right)' \mu_j. \tag{11}$$

Equation (11) is the mean regression of y on μ_j ($E(X|\mu_j)$ is by definition a function of μ_j). Assuming the intercept, conditional expectation of X, and the group fixed effects are linearly independent, the composite parameters, $\alpha/(1-\beta)$, $[(\gamma+\lambda)/(1-\beta)]'$, and $[\delta/(1-\beta)]'$ are identified. However, the structural parameters $(\alpha, \beta, \gamma', \lambda')$ are not identified since we have fewer equations than unknowns. Therefore, without further information or parameter restrictions, one cannot distinguish direct peer effects from indirect peer effects from firm-specific effects.

Appendix C: Exogenous Variable Derivatives

For ease of reference, we repeat equation (6) here:

$$y = \left(I - \frac{\beta}{N-1}Q\right)^{-1}\left(X\lambda + \frac{1}{N-1}QX\gamma + Z\delta + \varepsilon\right),$$

where $y = (y_1, ..., y_N)'$ is a vector of outcomes for the N firms in an arbitrary industry-year combination, Q is an $N \times N$ matrix with zeros on the diagonal and ones everywhere else, X is an $N \times k_1$ matrix of exogenous variables that appear as both firm specific factors and peer firm averages in our model (e.g., sales, profitability, market-to-book, tangibility), Z is an $N \times k_2$ matrix of exogenous variables that appear only as firm specific factors (e.g., industry and year fixed effects), and ε is an $N \times 1$ vector of residuals. and ones everywhere else.

The goal is to derive a closed form solution for the derivative of an arbitrary element y_i in the vector y with respect to an arbitrary element x_{lm} in the matrix X. To accomplish this, we need expressions for the two $N \times N$ matrices multiplying X:

$$\left(I - \frac{\beta}{N-1}Q\right)^{-1} \quad \text{and} \quad \left(I - \frac{\beta}{N-1}Q\right)^{-1}\frac{1}{N-1}Q.$$

Induction and matrix algebra shows that the first matrix is symmetric and has two distinct elements on and off the main diagonal.

$$\begin{array}{ll} \text{On-Diagonal:} & \frac{N-1-\beta(N-2)}{(N-1+\beta)(1-\beta)} \\ \text{Off-Diagonal:} & \frac{\beta}{(N-1+\beta)(1-\beta)} \end{array}$$

Using this result and the definition of Q, the second matrix is also symmetric and has two distinct elements on and off the main diagonal.

$$\begin{array}{ll} \text{On-Diagonal:} & \frac{\beta}{(N-1+\beta)(1-\beta)} \\ \text{Off-Diagonal:} & \frac{1}{(N-1+\beta)(1-\beta)} \end{array}$$

Therefore, the derivative of an arbitrary element y_i in the vector y with respect to an arbitrary element x_{lm} in the matrix X is therefore equal to

$$\frac{\partial y_i}{\partial x_{lm}} = \begin{cases} \lambda_m\left(1 + \frac{\beta^2}{(N-1+\beta)(1-\beta)}\right) + \gamma_m\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i = l \\ \lambda_m\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) + \gamma_m\left(\frac{1}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i \neq l \end{cases}$$

where we used the equality

$$\frac{N-1-\beta(N-2)}{(N-1+\beta)(1-\beta)} = \left(1 + \frac{\beta^2}{(N-1+\beta)(1-\beta)}\right)$$

to rewrite the amplification term multiplying λ_m in the case $i = l$.

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Figure 1

Industry Average Idiosyncratic Stock Returns Distribution

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all analysis variables. The figure presents the empirical distribution of our instrument, industry average idiosyncratic annual equity returns, excluding the i^{th} observation's return.

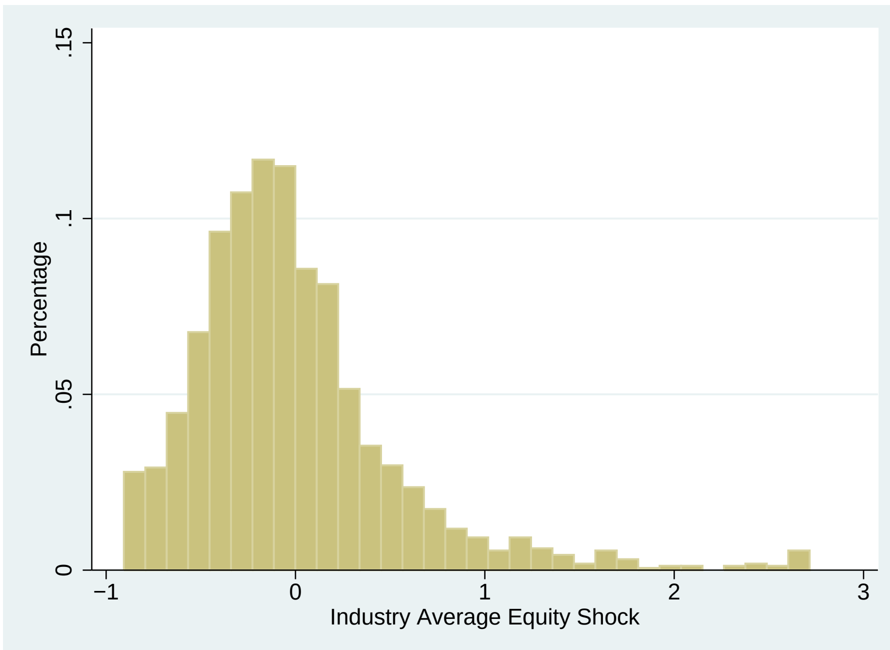

Table I

Summary Statistics

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all analysis variables. The table presents means, standard deviations (SD), and medians. All variables are formally defined in Appendix A. Peer firm averages are defined as the 3-digit SIC code average excluding the i^{th} observation.

	Levels			First Differences		
	Mean	Median	SD	Mean	Median	SD
Financial Policy Variables						
Book Leverage (Total Debt / Book Assets)	0.241	0.218	0.199	0.004	-0.000	0.095
Market Leverage (Total Debt / Market Assets)	0.277	0.220	0.247	0.004	0.000	0.116
$I(NetEquityIssuance/BookAssets > 0.1)$	0.211	0.000	0.408	-0.006	0.000	0.461
Net Equity Issuance / Book Assets	0.032	0.000	0.210	-0.010	0.000	0.235
$I(NetDebtIssuance/BookAssets > 0.1)$	0.397	0.000	0.489	-0.007	0.000	0.635
Net Debt Issuance / Book Assets	0.029	0.000	0.159	-0.003	0.000	0.223
Indirect Peer Effects (Peer Firm Avgs)						
Log(Sales)	4.592	4.446	1.311	0.118	0.120	0.108
Market-to-Book	1.540	1.345	0.775	-0.053	-0.026	0.356
EBITDA / Assets	0.080	0.102	0.089	-0.005	-0.003	0.030
Net PPE / Assets	0.312	0.263	0.172	0.001	0.000	0.015
Firm Specific Factors						
Log(Sales)	4.986	4.921	2.158	0.096	0.091	0.288
Market-to-Book	1.382	0.961	1.355	-0.035	-0.005	0.878
EBITDA / Assets	0.105	0.128	0.161	-0.003	0.000	0.103
Net PPE / Assets	0.322	0.272	0.221	-0.001	-0.002	0.054
Industry Characteristics						
# of Firms per Industry-Year	17.988	12.000	22.211			
Total # of Industries	178					
Sample Characteristics						
Observations	76,501					
Firms	9,293					

Table II

Peer Firm Capital Structure: OLS Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated coefficients and t-statistics in parentheses from various leverage regressions. Peer firm averages are defined as the 3-digit SIC code average excluding the i^{th} observation. All models are estimated by OLS. All variables are in levels and all right hand side variables are lagged one year relative to the dependent variable, either book or market leverage as indicated above the columns, with the exception of peer firm averge leverage which is contemporaneous with the dependent variable. Panel B presents results for four different definitions of industry: randomly assigned, 1-digit SIC, and 2-digit SIC. The randomly assigned industries are constructed to mimic the size of 3-digit SIC codes. The estimates for the randomly assigned industries are constructed by an iterative procedure that (1) randomly assigns observations to industries and (2) estimates the model. This procedure is repeated 100 times. The displayed coefficients, t-statistics, and R-squared are averages over the 100 iterations. The adjusted R-squared for the firm fixed effect specification measures the explained variation after partially out the firm fixed effects. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Panel A: Different Leverage Specifications

	Book Leverage					Market Leverage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer Firm Avg Leverage	0.780**		0.622**	0.238**	0.250**	0.802**		0.579**	0.295**	0.408**
	(37.847)		(28.005)	(8.753)	(11.125)	(45.225)		(32.219)	(13.199)	(21.308)
Log(Sales)		0.010**	0.008**	0.009**	0.018**		0.015**	0.010**	0.011**	0.037**
		(11.722)	(9.340)	(9.923)	(7.303)		(14.933)	(9.824)	(9.768)	(14.318)
Market-to-Book		-0.017**	-0.012**	-0.013**	-0.003**		-0.058**	-0.047**	-0.048**	-0.021**
		(-16.554)	(-11.517)	(-11.709)	(-2.690)		(-46.943)	(-41.163)	(-40.800)	(-23.343)
EBITDA / Assets		-0.220**	-0.221**	-0.229**	-0.196**		-0.303**	-0.290**	-0.295**	-0.266**
		(-20.753)	(-21.213)	(-21.974)	(-18.253)		(-29.499)	(-29.415)	(-29.478)	(-25.554)
Net PPE / Assets		0.219**	0.137**	0.198**	0.163**		0.211**	0.125**	0.178**	0.186**
		(24.675)	(15.363)	(16.652)	(11.954)		(21.597)	(13.015)	(13.563)	(12.452)
Firm Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
Industry Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501
Adj. R^2	0.123	0.112	0.170	0.192	0.062	0.213	0.247	0.307	0.322	0.154

Panel B: Different Industry Definitions

	Book Leverage			
	Random Industry	1-Digit SIC Industry	2-Digit SIC Industry	3-Digit SIC Industry
Peer Firm Avg Leverage	-0.013	0.020**	0.047**	0.622**
	(-0.137)	(8.410)	(22.281)	(28.005)
Log(Sales)	0.010**	0.021**	0.018**	0.008**
	(11.725)	(11.041)	(9.844)	(9.340)
Market-to-Book	-0.017**	-0.023**	-0.019**	-0.012**
	(-16.531)	(-16.361)	(-13.781)	(-11.517)
EBITDA / Assets	-0.220**	-0.035**	-0.034**	-0.221**
	(-20.753)	(-20.274)	(-20.204)	(-21.213)
Net PPE / Assets	0.219**	0.041**	0.030**	0.137**
	(24.693)	(19.045)	(14.545)	(15.363)
Firm Fixed Effects	No	No	No	No
Industry Fixed Effects	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Obs	76,407	76,323	76,323	76,501
Adj. R^2	0.112	0.120	0.157	0.170

Table III

Reduced Form OLS Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated coefficients and t-statistics in parentheses from various leverage regressions. All models are estimated by OLS. All variables are in levels and all right hand side variables are lagged one year relative to the dependent variable, either book or market leverage as indicated above the columns. Indirect Effects refer to peer firm averages, defined as th. 3-digit SIC code average excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. F-stat is the test statistic of the null hypothesis that all of the indirect effects' coefficients equal zero. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Book Leverage						Market Leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Indirect Effects (Peer Firm Avgs)										
Log(Sales)	0.002		-0.006**	-0.016**	-0.011**	0.017**		0.007**	-0.009*	-0.009**
	(1.229)		(-2.783)	(-4.711)	(-4.017)	(6.569)		(2.736)	(-2.367)	(-2.920)
Market-to-Book	-0.026**		-0.017**	0.004	-0.004	-0.074**		-0.041**	0.003	-0.012**
	(-9.047)		(-6.011)	(1.541)	(-1.621)	(-21.364)		(-12.712)	(1.124)	(-5.129)
EBITDA / Assets	-0.011		0.126**	0.195**	0.038	-0.165**		-0.011	0.086**	-0.020
	(-0.445)		(5.146)	(7.359)	(1.728)	(-5.670)		(-0.393)	(2.841)	(-0.824)
Net PPE / Assets	0.206**		0.012	0.048	0.055*	0.190**		0.019	0.133**	0.113**
	(15.894)		(0.709)	(1.485)	(2.244)	(12.502)		(1.032)	(3.583)	(4.039)
Firm Specific Factors										
Log(Sales)		0.010**	0.010**	0.009**	0.019**		0.015**	0.012**	0.010**	0.039**
		(11.722)	(10.770)	(9.863)	(7.669)		(14.933)	(10.353)	(9.717)	(14.800)
Market-to-Book		-0.017**	-0.014**	-0.013**	-0.003**		-0.058**	-0.050**	-0.049**	-0.021**
		(-16.554)	(-12.333)	(-12.033)	(-2.714)		(-46.943)	(-41.414)	(-40.818)	(-23.329)
EBITDA / Assets		-0.220**	-0.237**	-0.233**	-0.197**		-0.303**	-0.306**	-0.299**	-0.269**
		(-20.753)	(-22.047)	(-22.168)	(-18.272)		(-29.499)	(-29.690)	(-29.598)	(-25.418)
Net PPE / Assets		0.219**	0.200**	0.199**	0.164**		0.211**	0.177**	0.179**	0.190**
		(24.675)	(16.316)	(16.555)	(12.030)		(21.597)	(13.133)	(13.549)	(12.814)
Firm Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
Industry Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	146.636**		22.144**	15.833**	5.511**	350.862**		81.229**	5.670**	15.477**
Obs	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501	76,501
Adj. R^2	0.064	0.112	0.117	0.191	0.056	0.160	0.247	0.261	0.318	0.134

Table IV

Stock Return Factor Regression Results

The table presents mean factor loadings and adjusted R-squares from the regression

$$\begin{aligned} r_{ijt} = \alpha \quad &+ \quad \beta_{it}^{m}(rm_t - rf_t) + \beta_{it}^{SMB} SMB_t + \beta_{it}^{HML} HML_t + \beta_{it}^{MOM} MOM_t \\ &+ \quad \beta_{it}^{j}(rj_t - rf_t) + \eta_{ijt}, \end{aligned}$$

where r_{ijt} is the return to firm i in industry j during period t, $(rm_t - rf_t)$ is the excess return on the market, SMB_t is the small minus big portfolio return, and HML_t is the high minus low portfolio return, MOM_t is the momentum portfolio return, $(rj_t - rf_t)$ is the excess return on an equal-weighted portfolio of stocks in the same industry as defined by three-digit SIC code. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data from the CRSP database. We require at least 24 months of historical data and use up to 60 months of data in the estimation. Expected returns are computed using the estimated factor loadings and realized factor returns. Idiosyncratic returns are computed as the difference between realized and expected returns.

	Mean	Median	SD
α_{it}	0.766	0.683	1.552
β_{it}^{M}	0.215	0.288	0.812
β_{it}^{SMB}	0.120	0.107	0.935
β_{it}^{HML}	0.002	0.022	0.838
β_{it}^{IND}	0.801	0.700	0.680
β_{it}^{MOM}	-0.014	-0.016	0.570
Obs Per Regression	58	60	5
Adjusted R^2	0.296	0.287	0.177
Avg Monthly Return	0.014	0.000	0.181
Expected Monthly Return	0.015	0.013	0.118
Idiosyncratic Monthly Return	-0.001	-0.007	0.175

Table V

Instrument Properties

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for a subset of variables defined in Appendix A. The table presents estimated coefficients and t-statistics in parentheses from OLS regressions. Peer firm averages are defined as the 3-digit SIC code average excluding the i^{th} observation. The dependent variable is our instrument, peer firm average idiosyncratic equity returns. All independent variables are in levels and are either contemporaneous with or a one-period lead relative to the dependent variable. Firm Specific Factors refer to the i^{th} observation's characteristic. Indirect Effects refer to peer firm averages of each firm specific factor. The F-stat P-value is the P-value for F-statistic testing the null hypothesis that the firm-specific factor coefficients are jointly equal to zero. The partial adjusted R-squared is the variation in the dependent variable explained by all of the firm-specific factors and indirect effects after orthogonalizing all varibles with respect to the fixed effects. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Peer Firm Average Equity Shock	
	Contemporaneous Independent Vars	1-Period Lead Independent Vars.
Firm Specific Factors		
Log(Sales)	-0.000	-0.000
	(-1.016)	(-0.030)
Market-to-Book	-0.000	0.000
	(-0.166)	(0.823)
EBITDA / Assets	-0.002	-0.003
	(-0.607)	(-0.958)
Net PPE / Assets	0.001	0.001
	(0.191)	(0.295)
Indirect Effects (Peer Firm Avgs)	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Obs	76,501	76,300
F-Stat P-value	0.599	0.788
Adj. R^2	0.095	0.097
Partial Adj. R^2	-0.000	-0.000

Table VI

Two Stage Least Squares Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated coefficients and t-statistics in parentheses from various leverage regressions. Peer firm averages are defined as the 3-digit SIC code average excluding the i^{th} observation. All models are estimated by linear two stage least squares (2SLS) where the endogenous variable is the peer firm average leverage ratio, and the instrument is the one period lagged peer firm average idiosyncratic component of stock returns. All variables are in levels or first differences as indicated at the top of the columns. All right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable, book leverage (columns (1) and (3)) or market leverage (columns (2) - (4)). Indirect Effects refer to peer firm averages. Firm Specific Factors refer to the i^{th} observation's characteristic. In Panel B, all specifications include firm-specific and indirect effects for firm size, profitability, tangibility, and the market-to-book ratio and are estimated by 2SLS using the same instrumenting procedure as in Panel A. Investment Bank Indicators refer to indicator variables for the primary or lead underwriter for the firm's past security issuances, debt or equity. Additional Control Variables include lagged firm specific and indirect effects for cash flow volatility, a dividend payer indicator, Altman's Z-score, Graham's marginal tax rate, capital expenditures divided by the capital stock as of the previous period, R&D expenditures divided by sales, and SG&A expenditures divided by sales as well as the intra-industry standard deviation of leverage. Stock Return Controls includes firm i's lagged and contemporaneous total stock return, and the industry average expected stock return. Polynomials of Control Variables (Vars) include quadratic and cubic terms of all right hand side variables other than industry average leverage. Contemporaneous indirect Effects (I.E.s) adds contemporaneous indirect effects to the specification in addition to the lagged indirect effects. Panel C is identical to Panel B but for the use of first differences for all variables other than equity returns. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Panel A: Leverage Regressions

	Levels		1^{st} Differences	
	Book Leverage	Market Leverage	Book Leverage	Market Leverage
	(1)	(2)	(3)	(4)
Direct Effect				
Peer Firm Avg Leverage	0.734**	0.658**	0.870*	1.302**
	(3.322)	(4.094)	(2.419)	(3.780)
Indirect Effects (Peer Firm Avgs)				
Log(Sales)	-0.013**	-0.013**	-0.022	-0.061*
	(-3.916)	(-3.279)	(-1.231)	(-2.060)
Market-to-Book	0.016**	0.036**	0.002	0.002
	(3.448)	(4.105)	(0.859)	(0.657)
EBITDA / Assets	0.210**	0.220**	0.042	0.070*
	(7.715)	(4.764)	(1.256)	(2.482)
Net PPE / Assets	-0.117	-0.042	-0.035	-0.098
	(-1.949)	(-0.732)	(-0.745)	(-1.680)
Firm Specific Factors				
Log(Sales)	0.009**	0.010**	0.008**	0.023**
	(9.552)	(9.503)	(3.927)	(11.575)
Market-to-Book	-0.013**	-0.048**	-0.002**	0.000
	(-11.550)	(-40.202)	(-2.696)	(0.708)
EBITDA / Assets	-0.236**	-0.297**	-0.029**	-0.038**
	(-22.141)	(-29.073)	(-4.622)	(-6.860)
Net PPE / Assets	0.197**	0.175**	0.064**	0.087**
	(16.264)	(13.139)	(7.326)	(9.586)
Equity Shock	-0.003*	-0.006**	-0.002*	0.006**
	(-2.078)	(-4.458)	(-2.063)	(6.152)
First Stage Instrument				
Peer Firm Avg Equity Shock	-0.021**	-0.032**	-0.008**	-0.010**
	(-15.243)	(-18.335)	(-9.117)	(-8.094)
Industry Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Obs	76,501	76,501	76,501	76,501
Adj. R^2	0.184	0.319	0.031	0.051

Panel B: Leverage Levels Robustness Tests

	Book Leverage - Level					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect						
Peer Firm Avg Leverage	0.737**	0.978**	0.734**	0.711*	0.706**	0.783**
	(3.079)	(3.590)	(3.599)	(2.523)	(3.243)	(3.604)
First Stage Instrument						
Peer Firm Avg Equity Shock	-0.019**	-0.023**	-0.016**	-0.016**	-0.021**	-0.021**
	(-13.903)	(-10.717)	(-14.842)	(-12.092)	(-15.355)	(-15.486)
Indirect Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional Control Variables	Yes	No	No	No	No	No
Bank Fixed Effects	No	Yes	No	No	No	No
Lagged Dependent Variable	No	No	Yes	No	No	No
Contemporarneous Controls	No	No	No	Yes	No	No
Stock Return Controls	No	No	No	No	Yes	No
Polynomials of Controls	No	No	No	No	No	Yes
Obs	72,537	33,321	76,501	76,300	75,316	76,501
Adj. R^2	0.252	0.263	0.711	0.198	0.194	0.208

Panel C: Leverage First Differences Robustness Tests

	Book Leverage - First Difference					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect						
Peer Firm Avg Leverage	0.811*	1.130	0.851*	0.812	0.785*	0.817
	(2.117)	(1.591)	(2.421)	(1.859)	(2.158)	(1.844)
First Stage Instrument						
Peer Firm Avg Equity Shock	-0.008**	-0.006**	-0.008**	-0.007**	-0.008**	-0.007**
	(-8.954)	(-4.598)	(-9.332)	(-7.641)	(-9.138)	(-7.555)
Indirect Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional Control Variables	Yes	No	No	No	No	No
Bank Fixed Effects	No	Yes	No	No	No	No
Lagged Dependent Variable	No	No	Yes	No	No	No
Contemporarneous Controls	No	No	No	Yes	No	No
Stock Return Controls	No	No	No	No	Yes	No
Polynomials of Controls	No	No	No	No	No	Yes
Obs	68,619	33,321	76,501	76,300	75,316	76,501
Adj. R^2	0.024	-0.010	0.001	0.047	0.022	0.001

Table VII
Average Leverage Changes by Peer Firm Shock and Peer Firm Leverage Changes

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents average book leverage changes for 25 groups of observations. The groups are formed by the intersection of two quintiles: (1) one period lagged peer firm average idiosyncratic component of stock returns, and (2) peer firm average change in book leverage, excluding firm i. Group averages are presented in brackets next to the quantile number. For example, the average peer firm average leverage change in quantile 2 is -0.01, and the average lagged peer firm average equity shock for quantile 4 is 0.04. The columns labeled "1 - 3" and "5 - 3" present the difference in means for columns 1 and 3 and 5 and 3, respectively. t-statistics robust to heteroskedasticity and within firm dependence are in parentheses. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Lagged Peer Firm	Peer Firm Avg Leverage Change Quantile						
Avg Equity Shock	1 (-0.05)	2 (-0.01)	3 (0.01)	4 (0.03)	5 (0.08)	1 - 3	6 - 3
1 (-0.18)	-0.036**	-0.009**	-0.002	0.018**	0.053**	-0.034**	0.055**
	(-17.955)	(-4.328)	(-1.056)	(8.741)	(23.836)	(3.000)	(3.000)
2 (-0.08)	-0.041**	-0.008**	0.004*	0.018**	0.050**	-0.045**	0.046**
	(-18.606)	(-3.520)	(2.394)	(10.190)	(20.935)	(3.000)	(3.000)
3 (-0.02)	-0.041**	-0.013**	0.001	0.016**	0.055**	-0.042**	0.055**
	(-20.818)	(-7.073)	(0.461)	(7.598)	(25.874)	(3.000)	(3.000)
4 (0.04)	-0.044**	-0.013**	0.008**	0.015**	0.060**	-0.052**	0.052**
	(-20.418)	(-7.778)	(4.765)	(7.364)	(24.913)	(3.000)	(3.000)
5 (0.18)	-0.044**	-0.010**	-0.004	0.012**	0.057**	-0.040**	0.061**
	(-22.208)	(-5.007)	(-1.678)	(5.893)	(25.297)	(3.000)	(3.000)

Table VIII

2SLS Security Issuance Decision Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated coefficients and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. Peer firm averages are defined as the 3-digit SIC code average excluding the i^{th} observation. All models are estimated by linear 2SLS where the endogenous variables is the peer firm average leverage ratio, and the instrument is the one period lagged peer firm average idiosyncratic component of stock returns. The dependent variable is indicated at the top of the columns in both panels. All right hand side variables are lagged one period. Indirect Effects refer to peer firm averages. Firm Specific Factors refer to the i^{th} observation's characteristic. Issue Stock (Debt) is an indicator variable equal to one if Net Stock (Debt) Issuances normalized by lagged book assets is greater than 1%. Column (5) isolates the subsample of observations in which either an equity or debt issuance occurred. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Issue Stock	Net Stock Issuances	Issue Debt	Net Debt Issuances	Issue Stock*
	(1)	(2)	(3)	(4)	(5)
Direct Effect					
Peer Firm Avg	0.517**	0.120	0.658	0.936	0.627**
	(4.627)	(1.749)	(1.265)	(1.260)	(3.622)
Indirect Effects (Peer Firm Avgs)					
Log(Sales)	0.000	-0.003	-0.005	0.006	0.003
	(0.038)	(-1.391)	(-0.850)	(0.877)	(0.363)
Market-to-Book	-0.026	-0.006	0.013	-0.010	-0.058**
	(-1.914)	(-0.645)	(0.857)	(-0.612)	(-2.924)
EBITDA / Assets	0.076	0.074**	0.176	-0.036	-0.317**
	(1.623)	(3.166)	(0.856)	(-0.346)	(-4.632)
Net PPE / Assets	0.039	0.042*	-0.111	-0.007	-0.036
	(0.771)	(2.499)	(-1.500)	(-0.351)	(-0.518)
Firm Specific Factors					
Log(Sales)	-0.012**	-0.006**	0.014**	-0.003**	-0.023**
	(-9.019)	(-10.670)	(10.446)	(-7.164)	(-12.406)
Market-to-Book	0.071**	0.046**	0.004*	0.010**	0.062**
	(33.713)	(20.903)	(2.090)	(12.867)	(27.704)
EBITDA / Assets	-0.227**	-0.393**	-0.047**	0.030**	-0.139**
	(-15.305)	(-22.264)	(-2.823)	(4.242)	(-6.946)
Net PPE / Assets	0.035*	0.050**	0.175**	-0.000	-0.105**
	(2.454)	(7.319)	(11.509)	(-0.032)	(-5.202)
Equity Shock	0.052**	0.025**	0.018**	0.008**	0.041**
	(18.300)	(11.459)	(5.455)	(5.648)	(10.202)
First Stage Instrument					
Peer Firm Avg Equity Shock	0.088**	0.060**	-0.026**	-0.006**	0.097**
	(26.268)	(16.006)	(-7.016)	(-3.882)	(18.988)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	76,501	76,501	76,501	76,501	34,005
Adj. R^2	0.163	0.227	0.042		0.268

Table IX

Exogenous Variable Derivatives, Marginal Effects, and Leverage Multipliers

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated coefficients, derivatives, marginal effects (i.e., derivatives times the standard deviation of the underlying variable), and multipliers for the exogenous X variables in our book leverage level regression model. The column labeled λ present the estimated coefficients on the firm-specific factors. The column labeled γ present the estimated coefficients on the peer average characteristics. The column labeled $\partial y_i/\partial x_{im}$ present the estimated derivative showing the change to the outcome of ovservation i (y_i) following a one unit change to variable x_m for observation i (x_{im}). The column labeled $\partial y_i/\partial x_{km}$ present the estimated derivative showing the change to the outcome of ovservation i (y_i) following a one unit change to variable x_m for observation k (x_{km}). Amplification Term is equal to $(N-1\beta(N-2))/(N-1+\beta)(1-\beta)$. Spillover 1 is equal to $\beta/(N-1+\beta)(1-\beta)$. Spillover 2 is equal to $1/(N-1+\beta)(1-\beta)$. β is the estimated coefficient on the direct peer effect, peer firm book leverage. t-statistics robust to heteroskedasticity and within firm dependence are in parentheses. chi-square statistics robust to heteroskedasticity and within firm dependence are in brackets. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Variable	Firm-Specific Factors λ	Peer Firm Avgs γ	$\frac{\partial y_i}{\partial x_{im}}$	$\frac{\partial y_i}{\partial x_{im}} \times SD(x_{im})$	$\frac{\partial y_i}{\partial x_{km}}$	$\frac{\partial y_i}{\partial x_{im}} \times SD(x_{km})$
Log(Sales)	0.009**	-0.013**	0.008**	0.017**	-0.001	-0.003
	(9.552)	(2.603)	[31.505]	[31.505]	[2.292]	[2.292]
Market-to-Book	-0.013**	0.016**	-0.012**	-0.016**	0.001	0.002
	(-11.550)	(-2.678)	[37.558]	[37.558]	[0.904]	[0.904]
EBITDA / Assets	-0.236**	0.210**	-0.230**	-0.037**	0.008	0.001
	(-22.141)	(-8.636)	[360.023]	[360.023]	[1.459]	[1.459]
Net PPE / Assets	0.197**	-0.117**	0.201**	0.044**	0.006	0.001
	(16.264)	(3.280)	[212.507]	[212.507]	[0.603]	[0.603]
Amplification Term	1.114					
	[2.758]					
Spillover 1	0.156					
	[0.798]					
Spillover 2	0.212					
	[1.492]					