Do Peer Firms Affect Corporate Financial Policy?*

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September 6, 2011

*We thank Andy Abel, Ulf Axelson, Daniel Bergstresser, Philip Bond, Murray Frank, Ken French, Itay Goldstein, Robin Greenwood, Richard Kihlstrom, Jiro Kondo, Arvind Krishnamurthy, Camelia Kuhnen, Doron Levit, Ulrike Malmendier, David Matsa, Atif Mian, Mitchell Petersen, Nick Roussanov, and Moto Yogo, conference and seminar participants at the NBER Fall Corporate Finance Meeting, Minnesota Corporate Finance Conference, Western Finance Association Meeting, Cornell University, Harvard Business School, 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: (314) 935-6394, leary@wustl.edu.

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Abstract

We show that the most important observable capital structure determinant for many firms is the capital structure of their peers; firms make financing decisions in large part by responding to the financing decisions of peer firms, as opposed to changes in firm-specific characteristics. Consistent with information-based theories of learning and reputation, we find that smaller, less successful firms are more likely to adjust their capital structures and financial policies in response to the actions of their larger, more successful peers. Additionally, we quantify the externalities engendered by these peer effects, which can amplify the impact of changes in exogenous determinants on leverage by over 70%.

Most research on corporate financial policy assumes that firms choose their capital structures independently from the choices made by their competitors, or peers. In other words, a firm's capital structure is typically assumed to be determined by a function of its marginal tax rate, expected deadweight loss in default, information environment, and incentive structure. As such, the role for peer firm behavior in affecting capital structure is often ignored, or at most an implicit one through its unmeasured impact on firm-specific determinants.

However, peer firms play a central role in shaping a number of other corporate policies.[1] Additionally, existing evidence suggests that the behavior of peer firms may matter for capital structure. Several finance textbooks note that mimicking peer firms' capital structures is not only common, but may also be part of an optimal financial strategy.[2] Indeed, survey evidence indicates that a significant number of CFOs cite the importance of peer firm financing decisions for their own financing decisions (Graham and Harvey (2001)). Finally, existing empirical work has shown that industry average leverage ratios are an economically important determinant of firms' capital structures (Welch (2004) and Frank and Goyal (2007)).

The goal of this paper is to identify whether, how, and why peer firm behavior matters for corporate capital structures. Achieving this goal is important for three reasons. First, it moves us closer to answering a fundamental question in corporate finance; namely, how do firms choose their capital structures? Second, it enables us to examine theories of corporate behavior that have received relatively less attention in the capital structure literature, such as theories of reputational concerns (e.g., Scharfstein and Stein (1990) and Zwiebel (1995)), learning (e.g, Conlisk (1980)), herding (e.g, Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1998)), and strategic interaction (e.g., Brander and Lewis (1986)). Third, it has potentially important implications for future research on capital structure because of the externalities engendered by peer effects.

[1] Examples include product pricing (Bertrand (1883)), product output (Cournot (1838)), non-price product features such as advertising, product durability, and warranties (e.g., Stigler (1968)), labor practices (e.g., Manning (2005) for a historical discussion and Bizjak, Lemmon, and Naveen (2008) for evidence on executive compensation).

[2] For example, Damodaran (2010 p. 442) states "there is no denying the fact that managers look at industry averages and practices on capital structure for guidance. Consequently, it does make sense to check the optimal debt ratios that emerge from the cost of capital and APV approaches against industry averages, and to adjust them towards peer group ratios." Ross, Westerfield and Jaffe (2010 p. 547) note that "many real-world firms simply base their capital structure decisions on industry averages...After all, the existing firms in any industry are the survivors. Therefore we should pay at least some attention to their decisions."

However, identifying peer effects is empirically challenging because of the reflection problem (Manski (1993)). This problem refers to a specific form of endogeneity that arises when trying to infer whether the actions or characteristics of a group influences the actions of the individuals that comprise the group. In the current context, this problem is created by using measures of peer firm financial policy, such as industry average leverage, or peer firm capital structure determinants, such as industry average profitability, as explanatory variables for individual firms' financial policies. In particular, any correlation between firms' financial policies and the actions or characteristics of their peers 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 measures in so far as they proxy for these factors. In essence, the correlation between firms' financial policies and the actions or characteristics 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 operate through two distinct channels. The first channel is via actions, in which firms respond to their peers' financial policies. The second channel is via characteristics, in which firms respond to changes in the characteristics of their peers — profitability, risk, etc. Thus, identifying peer effects poses two identification challenges. The first involves distinguishing between the two explanations for any observed correlation between firms' financial policies and the actions or characteristics of their peers. The second involves distinguishing between the two channels through which peer effects operate: actions versus characteristics.

To address the first challenge, we instrument peer firms' financial policies with the lagged idiosyncratic component of peer firms' stock returns. Motivation for this instrument comes from two sources. First, the instrument must be correlated with capital structure decisions and there is substantial theoretical and empirical evidence linking stock returns to financial policy (e.g. Myers (1977, 1984); Marsh (1980); Loughran and Ritter (1995)). Second, a valid instrument will be firm-specific in that it does not contain information about other firms conditional on observable determinants. The firm-specific nature of idiosyncratic returns and the large asset pricing literature aimed at isolating this component suggest that this measure is a good starting point to address the reflection problem.

To construct the instrument, we estimate firm-specific, rolling regressions of stock returns on the usual asset-pricing factors and an industry factor. This process produces an estimated residual (i.e., instrument) with a number of desirable properties. First, the conditional correlation between firms' idiosyncratic returns and those of their peers is virtually zero, mitigating concerns that our instrument is capturing omitted common factors linking peer firm financial policies. 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. Finally, the shocks are uncorrelated with firm characteristics 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 negatively correlated with both leverage levels and changes, primarily through their effect on debt and equity issuance decisions. 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 ten 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. 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 debt or equity when their peers issue that same security. Importantly, these inferences are extremely robust. We find statistically and economically large peer effects in both book and market measures of leverage, and in both levels and changes in leverage. Further, our results and inferences are unaffected by a number of specification changes and robustness tests examining alternative explanations.

To address the second identification challenge, we show that, conditional on peer firm financial policy, capital structure is largely insensitive to peer firms' idiosyncratic stock returns. In other words, firms' leverage ratios only respond to peer firms' equity shocks when those shocks are accompanied by changes to peer firms' leverage ratios. Further, while peer firm characteristics such as profitability are relevant for financial policy, their marginal effect is significantly smaller than that of peer firm actions and even firm-specific determinants. Thus, our findings suggest that the primary channel through which peer effects in capital structure operate is a response to peers' financial policies, as opposed to changes in peers' characteristics.

In addition to identifying an economically important source of variation in corporate financial policies, our results highlight the presence of externalities in those policies. 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 two channels through which peer effects operate: actions and characteristics. This impact on peer firms' financial policies feeds back onto firm A's financial policy, and so on.

The key implication of this feedback is that the marginal effect of any capital structure determinant can no longer be gleaned solely from that determinant's coefficient, even in linear models. Instead, the marginal effect is a function of an amplification term due to the action channel of peer effects, a spillover term due to the characteristics channel of peer effects, and the size of the peer group. We show that the amplification term varies from a low of 7.5% in large peer groups to a high of 70.3% in small peer groups. In other words, in industries with few firms, the impact of a change in profitability, for example, on leverage is 70.3% larger than implied by the estimated coefficient because of feedback among financial policies. We also show that the spillover effects from changing peer characteristics can either offset or further amplify the effect of changes in exogenous characteristics.

To better understand why peer firms influence financial policy, we examine heterogeneity in the estimated effect by examining which firms and CEOs mimic their peers and which firms are being mimicked. Consistent with models of reputational concerns and learning, we find that smaller, less successful (i.e., lower profitability and stock returns), and more financially constrained firms mimic the financial policies of industry leaders (i.e., larger, more profitable firms with higher stock returns). By contrast, the financial policies of industry leaders are not influenced by those of non-leaders. We also find that lower paid CEOs exhibit more mimicking behavior, though this finding is statistically weak. While helping to shed light on the underlying mechanism behind peer effects, this analysis also reinforces our identification strategy as most alternative hypotheses leave little room for systematic heterogeneity in the peer effect.

Our study is most closely related to those documenting the importance of industry as a capital structure determinant.[3] For example, recent work by Frank and Goyal (2007)

[3] Bradley, Jarrell, and Kim (1984) show that 54% of the cross-sectional variance in firm leverage ratios is explained by industrial classification. Graham and Harvey (2001) show that almost one quarter of

shows that industry median leverage has the single most explanatory power for firm leverage among the 25 firm characteristics and macroeconomic variables they consider. However, past studies have left the interpretation of these industry effects largely unresolved, a point explicitly noted by Frank and Goyal (2007, 2008). 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. Our study is also related to the work of Mackay and Phillips (2005) and Almazan and Molina (2005), both of whom examine intra-industry variation in capital structures. Our study compliments theirs by showing that this variation is accompanied by strong interdependencies in financial policy.[4]

An important by-product of our study is to highlight the salient empirical issues that appear in observational studies of peer effects, as opposed to randomized experiments (e.g., Duflo and Saez (2003) and Lerner and Malmendier (2009)). Ordinary least squares regressions will typically not provide meaningful results because of the reflection problem, and, as such, a clear identification strategy is needed to rule out the null of omitted or mismeasured shared characteristics. Further, feedback and spillover effects arising from the presence of peer effects obscure the marginal effects of exogenous variables. Neither the direction nor magnitude of association between a covariate and the dependent variable can be inferred from that covariate's coefficient, even in linear specifications. We present closed form expressions for the marginal effects of exogenous covariates in a general linear setting.

The paper proceeds as follows. Section I introduces the data and presents summary statistics. Section II develops the empirical model and highlights the identification challenge. Section III discusses our identification strategy, focusing on the construction of our instrument, its economic and statistical properties, and potential identification threats. Section IV presents our estimates of the peer effects and the corresponding feedback effects. Section V examines cross-sectional heterogeneity in the effects to better understand the economic mechanisms behind the peer effects. Section VI concludes.

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surveyed CFOs identify the behavior of competitors as an important input into their financial decision making. Welch (2004) finds that deviations from industry leverage are among the most economically significant determinants of leverage changes.

[4]More broadly, our study is related to other works examining peer effects in corporate finance including: mutual fund voting (Matvos and Ostrovsky (2009)), governance (John and Kadyrzhanova (2008)), investment decisions (Duflo and Saez (2002)), entrepreneurship (Lerner and Malmendier (2009)), and compensation (Shue (2011)).

I. Data and Summary Statistics

Our primary data comes from the merged CRSP-Compustat database during the period 1965 to 2008. Because of its popularity, we relegate a complete discussion of the data, sample construction, and variable definitions to Appendix A. Table I presents summary statistics for our final sample of 82,644 firm-year observations corresponding to 9,717 unique firms. There are 227 industries, defined by three-digit SIC code, represented in our sample. The typical industry contains approximately 14 firms, though the distribution is right skewed as indicated by the median number of firms, 8. 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 alternative peer group definitions in 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 number of variables, in levels and first differences, used throughout this study are presented after Winsorizing all ratios at the upper and lower one percentiles. We Winsorize to mitigate the influence of extreme observations and eliminate any data coding errors. Winsorizing at the 2.5 or five percentiles has no qualitative affect on any of our results. Similarly, trimming, instead of Winsorizing, observations produces qualitatively similar findings. Variables are grouped into two distinct categories: peer firm averages and firm-specific factors. The former category includes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. The latter group includes variables constructed as firm i's value in year t. All variables are formally defined in Appendix A. At this point, we simply note the similarity of the summary statistics to those found in previous empirical studies of capital structure, such as Frank and Goyal (2007).

II. The Empirical Model

Our empirical model of capital structure is a generalization of that used in many past studies (e.g., Rajan and Zingales (1995) and Frank and Goyal (2007)),

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

where the indices i, j, and t correspond to firm, industry, and year, respectively. We focus on a linear specification to emphasize the intuition and highlight the salient econometric issues. Extensions are discussed below.

The outcome variable, y_{ijt}, is a measure of corporate financial policy, such as leverage. The covariate $\bar{y}_{-ijt}$ denotes peer firm average outcomes. We focus on the average throughout this study, though substituting the median produces similar findings. Previous studies typically lag this variable, 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. For the purposes of our study, which will focus on identification, a contemporaneous measure is more appealing because it limits the amount of time for firms to respond to one another. While this makes it harder to identify mimicking behavior, it mitigates the confounding effects that can occur over longer periods of time.

The K-dimensional vectors $\bar{X}_{-ijt-1}$ and X_{ijt-1} contain peer firm average and firm-specific characteristics, respectively. Industry and year fixed effects are represented by the error components μ_j and ν_t, respectively. Finally, ε_{ijt} is the firm-year specific error term that is assumed to be 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 parameter vector is $(\alpha, \beta, \gamma', \lambda', \delta', \phi')$. 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.[5] The coefficients δ', along with λ' and ϕ' capture the first explanation for common industry behavior: shared characteristics or institutional environments. Peer effects are captured by β and γ', which measure the influence of peer firm actions and characteristics, respectively.

The model is easily extended along a number of dimensions. Each firm may be influenced by multiple peer groups. 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.

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

III. Identification

The empirical goal is to disentangle the various explanations for industry commonality in capital structure by statistically identifying the structural parameters. The primary difficulty arises from the presence of $\bar{y}_{-ijt}$ as a regressor in equation (1). 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. This simultaneity implies that $\bar{y}_{-ijt}$ is an endogenous regressor and that the structural parameters are not identified. This section discusses the identification problem and our strategy for addressing it.

A. The Identification Problem

Ignoring the year fixed effects for notational convenience, consider the population version of equation (1),[6]

$$y = \alpha + \beta E(y|\mu_j) + \gamma' E(X|\mu_j) + \lambda' X + \delta' \mu_j + \varepsilon. \tag{2}$$

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

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

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

$$E(y|\mu_j) = \alpha + \beta E(y|\mu_j) + \lambda' E(X|\mu_j) + \gamma' E(X|\mu_j) + \delta' \mu_j. \tag{4}$$

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

$$E(y|\mu_j) = \frac{\alpha}{1-\beta} + \left(\frac{\gamma + \lambda}{1-\beta}\right)' E(X|\mu_j) + \left(\frac{\delta}{1-\beta}\right)' \mu_j. \tag{5}$$

Plugging the equilibrium solution into equation (3) yields the reduced form model

$$E(y|X, \mu_j) = \alpha^* + \gamma^{*\prime} E(X|\mu_j) + \delta^{*\prime} \mu_j + \lambda^{*\prime} X, \tag{6}$$

where the superscript "*" refers to reduced form or composite parameters that are functions of the underlying structural parameters. Specifically,

$$\alpha^* = \frac{\alpha}{1-\beta}; \quad \gamma^{*\prime} = \left(\frac{\beta\lambda + \gamma}{1-\beta}\right)'; \quad \delta^{*\prime} = \left(\frac{\delta}{1-\beta}\right)'; \quad \lambda^{*\prime} = \lambda'$$

Immediately apparent is that the structural parameters cannot be recovered from the composite parameters since there are fewer equations than unknowns.

[6] The illustration of the identification problem in this section follows closely that in Manski (1993).

B. A Reduced Form Test for Peer Effects

As long as the intercept, the average peer characteristics, the peer 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 (6)) 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 γ' are zero. Thus, a reduced form test for the presence of peer effects is a test of the joint significance of $\gamma^{*'}$.

Table II presents the reduced form estimation results for several different specifications of book and market leverage. The table body presents estimated coefficients scaled by the corresponding variables' standard deviation, t-statistics in parentheses, and model summary statistics. We scale the coefficient estimates by the standard deviation to ease the interpretation and comparison of the estimates — a practice we follow throughout the paper. For example, column (2) shows that a one standard deviation increase in net PPE / Assets is associated with a 5.2% increase in book leverage and is the largest effect among firm-specific factors in that specification. Recovery of the unscaled coefficient estimates can be accomplished by dividing by the standard deviations provided in Table I.

We note two relevant findings. First, the R-squares in Columns (1) and (6) show that average industry characteristics capture 6% and 15% of the variation in book and market leverage ratios, respectively. These estimates are highly statistically significant, though they do fall short of the variation explained by firm-specific factors (columns (2) and (7)). Second, tests of the null hypothesis that the peer firm average coefficients are jointly zero are all rejected at better than the one percent level in every specification (F-stat towards the bottom of the table). The scaled 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 their coefficients are nonlinear combinations of the underlying structural parameters. Unreported results based on a larger set of explanatory variables including: the marginal tax rate, stock returns, earnings volatility, R&D expenditures, SG&A expenditures, and Altman's Z-Score, produce similar inferences.

While these results indicate the presence of peer effects, they cannot identify the channel through which peer effects operate, actions versus characteristics, or the magnitude of the peer effects and associated externalities. For these features, we turn to an instrumental variables approach.

C. 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, a valid instrument is a determinant of capital structure that is unique to a given firm — one not shared by firm i and its peers.

One approach to isolating exogenous variation in peers' capital structures would be to identify shocks to individual firms' capital structures caused by firm-specific random events (e.g. losses due to natural disasters, accidental CEO deaths, etc.). While a valid approach, identifiable random events are rare enough to raise concerns over both statistical power and external validity. Additionally, even if one could identify a sufficient number of such events, these events would have to be purged of any spillover effects that directly influence the behavior of peer firms. In other words, an accidental CEO death, for example, may have a direct effect on peer firm financial behavior through the impact on the CEO labor market or anticipated shift in product market behavior.

An alternative approach that allows us to address these concerns begins with a known capital structure determinant and extracts only that portion of its variation that is idiosyncratic to a firm's peers for use as an instrumental variable. In effect, this strategy isolates the firm-specific impact of capital structure relevant events on a particular determinant. This enables us to estimate peer effects over a large sample similar to those used in prior capital structure studies. However, it also requires greater care to ensure, as much as possible, that the identifying variation from our instrument is truly idiosyncratic, and therefore exogenous to other firms' capital structure decisions.

The determinant that we focus on is lagged stock returns, so that the lagged idiosyncratic component of stock returns of peer firms is our instrument for their financing decisions. Motivation for this choice of instrument comes from several sources. First, stock returns impound many, if not all, value relevant events. Second, there is a vast asset pricing literature focused on estimating the expected and idiosyncratic components of returns. Finally, there is theoretical and empirical precedent for a relationship between lagged stock returns and capital structure choices.[7]

[7] 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

What is unknown is whether or not the idiosyncratic component of lagged stock returns contains information relevant for financial policy. 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, or, equivalently, whether the estimated idiosyncratic component of returns is truly devoid of information about other firms' financial policies beyond its affect on its own firm's financial policy. 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.

D. Construction of The Instrument

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

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{IND}(\bar{R}_{-ijt} - RF_t) + \eta_{ijt}, \tag{7}$$

where R_{ijt} refers to the total return for firm i in industry j over month t, $(RM_t - RF_t)$ is the excess market return, and $(\bar{R}_{-ijt} - RF_t)$ is the excess return on an equal weighted industry portfolio excluding firm i's return. As with our peer groups, industry is defined by three-digit SIC code. 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 peer group.[8]

We estimate equation (7) 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. For example, to obtain expected and idiosyncratic returns for IBM between January 1990 and December 1990, we first estimate equation (7) 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 (7) to compute the expected and idiosyncratic returns as follows:

$$\begin{aligned} \text{Expected Return}_{ijt} \equiv \hat{R}_{ijt} &= \hat{\alpha}_{ijt} + \hat{\beta}_{ijt}^{M}(RM_t - RF_t) + \hat{\beta}_{ijt}^{IND}(\bar{R}_{-ijt} - RF_t) \\ \text{Idiosyncratic Return}_{ijt} \equiv \hat{\eta}_{ijt} &= R_{ijt} - \hat{R}_{ijt} \end{aligned}$$

policy is linked to stock prices because of debt overhang considerations. Empirically, Marsh (1980), Loughran and Ritter (1995), Baker and Wurgler (2002), and Welch (2004) among others have shown a strong correlation between past returns and issuance choice or leverage ratios.

[8]In unreported analysis, we examine an expanded version of equation (7) that includes the small minus big portfolio return (SMB), the high minus low portfolio return (HML), and the momentum portfolio return (MOM). (See Fama and French (1993) and Carhart (1997) for details.) Results obtained using this specification are qualitatively similar.

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, hence the parameter subscripts in equation (7), but constant within a calendar year. Thus, our construction of idiosyncratic returns allows for heterogeneous sensitivities to aggregate shocks.

Table III presents summary statistics for the estimated factor regressions. 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 adjusted R-square is approximately 23%. The regressions load positively on both market and industry factors, whose factor loadings sum to approximately one. The average idiosyncratic return is less than 10 basis points in magnitude — an artifact of rounding.

We construct our instrument by first compounding the monthly returns to obtain an annual measure consistent with the periodicity of the accounting data. We then average over peer firms to maintain consistency with the peer effect measures. Before discussing the properties of the instrument, we note that, conditional on a properly specified asset pricing model (equation (7)), 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. Panel A of 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) is zero, as suggested by the approximately zero average idiosyncratic return shown at the bottom of Table III, and the zero balance point in Figure 1.

We also note that there is a link between the asset pricing model (equation (7)) and the structural model for financial policy (equation (1)). Because both models are linear, our ability to control for certain variables in the model for financial policy is partially determined by the specification that we choose for our asset pricing model. For example, within an industry-year, our instrument — peer firm average idiosyncratic returns — is perfectly negatively correlated with firm i's idiosyncratic and total return. This collinearity prevents us from including industry and year fixed effect interactions in our model of financial policy. However, it does permit us include industry and year fixed effects separately. Additionally, because the (conditional) average idiosyncratic shock varies across industry-years, our instrument is not perfectly correlated with firm i's return across industries or within industries over time. This allows us to control for firm i's idiosyncratic and total return in the financial policy model, which, as we discuss in section IV.B. below, helps rule out several identification threats.

Panels B and C show what happens to our instrument as the industry definitions become coarser and the size of the peer group increases. We see that the distribution collapses around zero, and more so for the one-digit (Panel C) industry definition than the two-digit industry definition (Panel B). Thus, we rely on economic theory to impose a restriction on the size of the peer group to ensure sufficient variation in our instrument.

E. Identification Threats

Identification threats come from correlation between our instrument and omitted or mismeasured capital structure determinants that are correlated with our instrument. We refer collectively to these determinants as common factors because, by definition, they affect both firm i's capital structure and firm j's capital structure via correlation with firm j's idiosyncratic stock return. If these factors are present, then our estimates of the structural parameters will contain traces of bias. This subsection takes a first step towards addressing this issue by examining the statistical properties of our instrument and their economic implications. We address specific alternative hypotheses in a series of robustness tests below.

E.1. Distinguishing Peer Effects from Omitted or Mismeasured 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)). The relevant issue in the current context is whether these omitted variables or measurement errors are correlated with our instrument conditional on other observable characteristics. 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 than are the other included firm characteristics, and (2) not capturing a common factor shared among firms within the peer group.

The first consideration highlights the importance of isolating the idiosyncratic component of stock returns rather than using total returns as an instrument. If the idiosyncratic component accounts for a significant portion of the variation in individual stock prices, 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 market-to-book ratios or stock returns. Intuitively, the averaging of returns can net out the noise in each individual stock return.

Table IV examines the extent to which our instrument correlates with firm i characteristics. 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. Note that correlation with the characteristics is not problematic because the characteristics are all included in the regression as control variables. However, economically large associations between the instrument and firm characteristics would raise 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 the asset pricing model (equation (7)).

The results reveal one statistically significant coefficient in each model. However, the economic magnitudes of these partial correlations are tiny. For example, a one standard deviation change in profitability leads to a 10 basis point change in contemporaneous average peer firm idiosyncratic returns. This 10 basis points is less than 0.006 of a standard deviation. Additionally, a joint test of the significance of all of the included firm specific factors fails to reject the null hypothesis that all of the coefficients are zero Indeed, the partial adjusted R-square for the firm-specific factors is less than 5 basis points. Thus, the instrument contains no significant information about firm i's current or near-future observable capital structure determinants.

With regard to an omitted common factor, consideration (2), we note that each specification contains year fixed effects. However, a more salient concern is with regards to an omitted 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 small (approximately 0.05). 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 (7)) purges most all of the intra-industry correlations present in raw returns. 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.[9]

[9]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

E.2. Distinguishing Between Channels: Actions and Characteristics

In addition to identifying a peer effect, we would like to distinguish between the two channels through which peer effects work, actions and 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 coefficient on peer firms' actions, β, captures variation due to peer firms' changing characteristics. However, the fact that firm i's relevant characteristics are hard to observe and measure implies the same for its peers. Thus, another identification concern is that our estimate of the 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 A introduces a new product, which positively impacts the idiosyncratic component of its stock return. In the following period, firm A issues equity to finance increased production, and reduces its leverage ratio towards a new optimum. In response, peer firm B issues equity and reduces its leverage too. The question is, to what is firm B responding: the change in financial policy or the introduction of the new product?

To help distinguish between these alternatives, we need to exploit heterogeneity in the capital structure response by peer firms to their equity shocks. We do so by performing 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 and a t-stat of whether this change is significantly different from zero. We perform this analysis on both book and market measures of leverage, but present only the market leverage results for brevity.

The results are presented in Table V, where quintile "1" represents the lowest 20% of the distribution and quintile "5" the highest. 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 6.3% with a t-statistic of 29.5. We note a near monotonic increase in the average leverage change across each row. In other words, holding fixed the peer firm equity shock, leverage changes are strongly positively correlated with changes in peer firm leverage. The converse is not true. Average leverage changes are

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.

largely uncorrelated with the peer firm equity shock, holding fixed the peer firms' average leverage change. In fact, in column (3), where the average peer firm leverage change is indistinguishable from zero, the cell averages are all economically small. Thus, firms only change their leverage in response to a peer firm equity shock if it is accompanied by a change in peer firm leverage.

These findings suggest that our instrument is more likely capturing a response to peer firm financial policies, as opposed to characteristics.[10] They also speak to the validity of the instrument more generally. We want an instrument that is uncorrelated with firm i's leverage, but through its correlation with peer firms' capital structures. The results in Table V show that conditional on peer firms' capital structures, there is no correlation between the instrument and firm i's leverage change.

IV. The Role and Implications of Peer Effects

A. Leverage

Table VI presents the leverage regression results. The estimation method and dependent variable are indicated at the top of the columns. The body presents coefficient estimates scaled by the corresponding variables' standard deviations, and t-statistics in parentheses. Columns (1) and (2) present ordinary least squares (OLS) estimates of existing models for book and market leverage levels. These results provide a means of comparison with previous studies that have identified industry leverage as a potentially important determinant of capital structure (e.g., Welch (2004), Frank and Goyal (2007) and Lemmon, Roberts, and Zender (2008)).

Columns (3) through (6) present 2SLS estimates for equation (1). We present results for book and market leverage in both levels (columns (3) and (4)) and first differences (columns (5) and (6)). The latter specifications help address concerns over omitted firm i characteristics, since it is similar 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, peer firm average idiosyncratic equity returns, which is the same across all specifications. Thus, we instrument for the endogenous peer firm average outcome

[10] While the results in Table V diminish the scope for our instrument to be picking up a peer effect operating through characteristics, the analysis does not allow us to completely rule it out. It is possible that the only peer firm characteristics that influence firm i's capital structure are those that also impact its peers' capital structures.

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 peer firm equity shock is strongly negatively associated with both the level and first difference in the average peer firm leverage ratio. 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. A one standard deviation increase in peer firm leverage, book or market, leads to an approximately 10% increase in own firm leverage. Compared to traditional firm-specific determinants, peer firm financial policies have a dramatically larger effect. In the market leverage regression, the next most impactful determinant is the market-to-book ratio whose scaled coefficient is -6.2% — almost 40% smaller. For book leverage, the effect of profitability is less than half that of peer firm average leverage.

Columns (5) and (6) 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 peer firm average leverage changes have 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. Also reassuring is that the estimated firm-specific effects in columns (3) and (4) are similar to those found in the OLS results of columns (1) and (2). These similarities reinforce our previous finding that our instrument is largely uncorrelated with firm-specific characteristics (Table IV).

The significant coefficients on peer firm average characteristics 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 and peer firms' financing decisions, the results in column (3) 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 are consistent with the industry equilibrium argument of Shleifer and Vishny (1992). As a firm's competitors become more financially healthy, liquidation values increase. As such, debt becomes less costly allowing firms to increase leverage.

The relevance of peer firm characteristics implies that a firm's position relative to that of its peers is important in forming financial policy, consistent with the implications of Mackay and Phillips (2005). For example, the positive coefficient on firm-specific log(Sales) in column (3) suggests that larger firms on average have higher leverage ratios. However, the negative coefficient on peer firms' log(Sales) implies that a firm of a given size will use more leverage when its competitors are smaller than when its competitors are larger.

Comparing coefficient magnitudes suggests that peer effects work primarily 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. These findings reinforce those of Table V. Thus, while both actions and characteristics of peers are relevant for financial policy, the former appear to be the more economically important channel.

B. Robustness Tests - Peer Effects Vs. Omitted and Mismeasured Common Factors

B.1. Specification Changes

Panel B of Table VI presents a number of robustness checks aimed at mitigating identification concerns stemming from omitted or mismeasured common factors. For brevity, we report only those results with the change in market leverage as the dependent variable. However, we repeat all of the analysis in Panel B using the change in book leverage, as well as the levels of both market and book leverage. Our inferences and conclusions are largely unaffected by these different leverage measures.

All specifications in Panel B include firm-specific factors and peer firm averages for log(sales), the market-to-book ratio, EBITDA / Assets, and Net PPE / Assets. For consistency with the dependent variable, each of these explanatory variables is in first difference form. We also include year fixed effects. Finally, we focus attention on the key variables of interest: the first stage estimate of the instrument parameter, and the second stage estimate of the peer firm leverage parameter.

In column (1), we replace the lagged firm-specific equity shock with the lagged and contemporaneous firm-specific realized (or total) stock return. The first stage instrument estimate is unaffected and we note an attenuation in second stage peer effect estimate; however, the coefficient is still economically larger than any other observable determinant (not reported) and highly statistically significant. This specification change ensures that the identifying variation from peer firm's idiosyncratic returns is orthogonal to firm i's stock returns - lagged and contemporaneous. In other words, alternative hypotheses must now rely on lagged idiosyncratic stock returns of peer firms containing information about firm i's capital structure that is not contained in firm i's stock returns, as well as any of the other control variables. This fact allays a number of identification concerns related to correlated returns.

One such concern is that the asset pricing model (equation (7)) is misspecified. In this case, common factors may remain in the estimated idiosyncratic component of stock returns. By including firm i's total return, we mitigate this concern because any common component in stock returns that is relevant for capital structure is, arguably, better captured by firm i's stock returns, as opposed to firm j's lagged idiosyncratic return.

Another concern is that firms receive industry-wide shocks to their equity valuations and that these shocks are asynchronous, so that the year fixed effects are inadequate controls. For example, industries may experience "hot" and "cold" equity markets due to shifting investor demands, which cause equity valuations for all firms in an industry to move in the same direction (e.g., the tech sector in the late 1990s). Because these shifts in investor demand are reflected in prices, this concern is largely eliminated by including firm i's stock returns in the specification. Further, by including both the contemporaneous and lagged stock return, we eliminate concerns regarding the timing of equity price shocks whereby some firms in an industry get shocked earlier than their peers.[11]

Ultimately, by including the stock returns we rule out any alternative hypotheses that are based on correlated stock returns, or correlated fundamentals that are reflected in stock returns. The robustness of our findings in column (1), in addition to the other properties of our instrument discussed in section III.E, imply that any alternative explanation for our results must be based on an omitted variable or measurement error containing variation that satisfies the following criteria: (1) it is important for firm i's capital structure, (2) it is correlated with lagged peer firm idiosyncratic returns, (3) it is uncorrelated with firm i's idiosyncratic and total return, (4) it is uncorrelated with the industry stock return, and (5) it is uncorrelated with all of firm i's capital structure determinants. While we cannot definitively rule out the existence of such variation, we

[11]Likewise, this specification alleviates concerns over common movements in credit prices. If stock returns contain information about the cost of debt, then an alternative based on shifts in investor demand for credit would require a demand shock that (1) affects the whole industry, yet is not captured by the industry return in the asset pricing model, and (2) is reflected in the peer firms' idiosyncratic returns, but is not reflected in firm i's total return. Coupled with the further evidence discussed below, this alternative seems unlikely.

see no obvious alternative hypothesis based on it.

This claim is further supported by the remaining columns in Panel B. Each column illustrates the robustness of our results - both first and second stage estimates - to a variety of specification changes. Of course, in light of the previous paragraph, this robustness is unsurprising. And, because of the similarity of the results, we only briefly discuss the specific changes to the model and their motivation.

Column (2) examines a "kitchen sink" model of capital structure including additional explanatory variables previously identified as relevant for capital structure. Specifically, we include lagged firm-specific and peer firm averages for: 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.

Column (3) incorporates bank fixed effects, and bank fixed effects interacted with the CRSP value weighted market return.[12] (See Appendix A for details on the construction of these bank fixed effects.) This specification addresses the concern that commonality among firms' capital structures is due to the use of common banks, commercial or investment, within the industry, and that the financial advice from these banks varies over the business cycle. This change has little effect on our results, despite the sharp decline in observations due to the additional data requirements. However, the adjusted R-square — not reported — is 9% higher relative to that from a comparable model without the bank effects estimated on the same sample. 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.[13]

Column (4) incorporates firm i's lagged leverage ratio to capture any targeting behavior or dynamic feedback from the explanatory variables onto leverage ratios. This specification addresses the concern that the instrument is correlated with a change in firm i's leverage target, or with a perturbation away from that target, in a way not captured by the other included variables. It also allows for dynamic targeting behavior in leverage (e.g., Flannery and Rangan (2006) and Kayhan and Titman (2007)).

[12] In unreported results we interact the bank effects with the yield spread on Baa over Aaa corporate bonds as an alternate measure of market conditions. The results are qualitatively similar.

[13] Related, we believe that common institutional ownership is unlikely responsible for our findings. The large majority of institutional investors are passive and unlikely dictating financial policy. Brav et al. (2008) estimate that the activist share of total institutional equity ownership ranges from 0.7% to 2.3% from 2000 to 2007.

Column (5) replaces the lagged control variables with contemporaneous controls to address the concern that capital structure relevant shocks affect our firm-specific and peer firm characteristics with a lag. Unreported results including both lagged and contemporaneous controls in the specification show that our results are again robust to this change.

Finally, Column (6) includes quadratic and cubic polynomials of each firm-specific factor and peer firm average characteristic in our primary specification (i.e., firm size, profitability, tangibility, market-to-book). Again, we see little change in the results, suggesting that functional form misspecification is unlikely behind our results.

B.2. Peer Effects in Investment and Dividend Policies

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 peer effect, despite a highly statistically significant positive first stage estimate.

We perform a similar exercise on corporate dividends, with modification to the included control variables, and again fail to find significant peer effects. These results suggest that our empirical method is unlikely producing spurious results due to latent commonalities among investment opportunities. However, they do not necessarily imply that there are no peer effects in corporate investment or dividend policy. A more thorough investigation of these issues is beyond the scope of the current study, though a potentially fruitful area for future research.

B.3. Alternative Peer Group Definitions

We examine the effects of altering the definition of the peer groups on our results. For example, we find 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)). Specifically, we segment each industry into three equal-size groups: small, medium, and large. The standard deviation scaled 2SLS coefficient estimate for peer firm market leverage is approximately 13%, even larger than the estimate of 9.6% in column (3) of Table VI.

We also examine the effect on our 2SLS estimate of the coefficient on peer firm leverage when using peer groups based on: random assignment, one-digit SIC code, and two-digit SIC code. First, as we move to coarser definitions of the peer group, two- and one-digit SIC codes, both the first and second stage estimates become statistically insignificant. The first stage estimates become insignificant because the distribution of our instrument is collapsing around the unconditional mean of zero (Panels B and C of Figure 1). The second stage estimate is insignificant because of a combination of a weak instrument and a noisier definition of the peer group. 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. These findings reinforce the importance of the peer group definition, and further suggest that any noise in our definition works to attenuate the estimated effect.

C. Financial Policy

In Table VII, we examine net equity and net debt issuing activity to understand whether peers are influencing specific financing decisions. While a logit or probit model may be more appropriate from a forecasting perspective, we present results using a linear probability model (equation (1)) to ease the interpretation and comparison with other findings. Unreported instrumental variables results using a probit model reveal quantitatively similar findings.

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 probability that firms will issue equity relative to not issuing equity, which includes debt issuances, debt retirements, stock repurchases, and no financing activity. The first stage results reveal that the idiosyncratic component of stock returns is strongly positively correlated with equity issuance decisions. This effect is both economically and statistically significant, again highlighting that the idiosyncratic component of stock returns is important for financial policy. 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 8.0% 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 (e.g., Hovakimian, Opler, and Titman (2001) and Leary and Roberts (2005)).

Column (2) presents analogous results for the decision to issue debt. The first stage estimate shows that firms are less likely to issue debt in response to a positive equity shock when they would prefer to issue equity. However, the second-stage results show that firms are significantly more likely to issue debt when their peers do so. Column (3) reinforces the findings in columns (1) and (2) by restricting attention to the subsample of observations in which either a stock or debt issuance occurred. In other words, we exclude observations in which there was no issuing activity. Again, we see a highly significant first stage estimate suggesting that firms are less (more) likely to issue debt (equity) following a positive equity shock. And, firms are more likely to issue debt or equity when their peers do the same.

In sum, the peer effect in leverage is being driven by peer effects in financing choices. These effects are economically large, significantly larger than almost any other estimated effect. Further, they do not appear to be driven by common shocks working through stock returns because we are able to control for firm i's own return. Thus, when firms raise external capital, their choice between debt and equity is dictated to a large extent by the security choices of their peers.

D. *Amplification, Spillover, and Marginal Effects*

An important implication of the empirical model in equation (1) and the estimated peer effects is the presence of externalities. To illustrate, assume that firm A's profitability increases. This change leads to a decline in firm A's leverage, as suggested by the negative scaled coefficient estimate for firm-specific EBITDA / Assets (see Table VI). 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 positive coefficient on peer firm average leverage. Additionally, the increase in firm A's profitability leads to an increase in leverage for every other firm in firm A's peer group via the positive coefficient on peer firm average EBITDA / Assets. These latter two effects feedback onto firm A's leverage, again via the coefficient on peer firm average leverage, and so on.

The presence of these externalities implies that the total derivative is no longer equal to the partial derivative, even in a linear model, because of the presence of the outcome variable on the right hand side of the equation. Since the total derivative is the economic quantity of interest, the effect of a change in any exogenous capital structure determinant cannot be inferred solely from its coefficient. Rather, the derivatives of interest are:

$$\frac{dy_i}{dx_{lm}} = \begin{cases} \lambda_m \left(1 + \frac{\beta^2}{(N-1+\beta)(1-\beta)}\right) + \gamma_m \left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i = l \\ \lambda_m \left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right) + \gamma_m \left(\frac{1}{(N-1+\beta)(1-\beta)}\right) & \text{for} \quad i \neq l \end{cases} \tag{8}$$

where i and l denote firm-year observations and m denotes the regressor. Thus, dy_i/dx_{lm} measures the change in y for observation i given a one unit change in x_m for observation l. (See Appendix B for a derivation.)

In the typical 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. With peer effects, there are several distinctions. When $i = l$, the peer firm average leverage coefficient, 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 β in the open unit interval and $N > 1$, this expression is strictly greater than 1.[14] Because of the presence of peer firm characteristics, this amplification may either be further amplified or offset depending on the correlation between the outcome variable and the peer firm characteristics, γ_m. (The second term in the case $i = l$.) When $i \neq l$, the derivative is no longer zero. Instead, cross-observations effects are determined by the relative importance of peer firm actions (β) and characteristics (γ).

Using the estimated market leverage model in column (3) of Panel A in Table VI, we estimate the derivatives in equation (8). Table VIII presents these estimates, scaled by their corresponding variable standard deviation, and the corresponding chi-square test statistics in brackets. We also present estimates of the amplification term (the first parenthetical expression in the case $i = l$), spillover term 1 (the second parenthetical expression in the case $i = l$), spillover term 2 (the second parenthetical expression in the case $i \neq l$), and their corresponding chi-square test statistics in brackets.[15] Because the size of the industry, N, plays a central role in the derivative expressions, we present estimates for three different size industries based on the 10^{th} (3 firms), 50^{th} (8 firms), and 90^{th} (26 firms) percentiles of the industry size distribution. For ease of reference, the columns labeled ($\lambda \times \sigma_x$) and ($\gamma \times \sigma_x$) repeat the firm specific and peer firm average characteristic scaled parameter estimates from column (3) of Panel A in Table VI. We also present the unscaled peer firm average leverage coefficient (β).

There are several findings of particular interest. First, the amplification term, though noisily estimated, varies dramatically across industry size categories and is economically large. Changes in capital structure determinants are magnified by 70% in small industries,

[14]Stationarity requires that β lie within $[0, 1)$. Empirically, this is true as β is statistically indistinguishable from 1 in all of our models. For example, the 2SLS coefficient estimates of β in the market leverage models in Table VI is 0.73.

[15]For the derivatives and spillover terms, the null hypothesis is that the these terms are equal to 0. For the amplification terms, the null hypothesis is that the these terms are equal to 1. Standard errors are computed using the delta method.

and 8% in large industries. Intuitively, each firm has a smaller effect on its peers, the larger is the peer group.

Second, for some determinants, the true marginal effect differs significantly from that implied by the firm-specific coefficient. For example, the marginal effect of asset tangibility is 30% smaller in large industries relative to small industries. The opposite is true of firm size, which plays a more important role in larger industries than smaller industries. These differences are driven by differences in signs and magnitudes between the firm-specific (λ) and peer firm average coefficients (γ). We hope that future theory will help to shed some light on the economic mechanism behind these relations.

We also note that the cross-observation derivatives are all statistically insignificant. This is consistent with the smaller impact of peer firm characteristics on capital structure relative to firm-specific characteristics and peer firm actions. In other words, a change in firm A's profitability, for example, has a larger impact on firm A than on firm B. However, caution must be taken when interpreting these derivatives. They isolate the impact of only one firm on another. If the industry as a whole receives a profitability shock, affecting all or many of the firms, then the spillover can be substantial.

V. Why do Firms Mimic One Another?

Given the importance of peer firm behavior for firms' capital structures, we now turn to *why* firms mimic one another. We begin with a brief discussion of the potential mechanisms behind the estimated peer effects, which we use to guide the subsequent empirical analysis.

A. Theoretical Motivation

Peer effects in capital structure can arise for a variety of reasons. For example, interactions between financial structure and product market competition can lead to financial policy mimicking. Bolton and Scharfstein (1990) present a model in which high leverage invites predatory price competition from less-levered rivals. If the expected cost of this predatory behavior is severe enough, highly levered firms will mimic the capital structures of their less-levered rivals. Similarly, Chevalier and Scharfstein (1996) present a model in which firms with high leverage under-invest during an industry downturn and lose market share to more conservatively financed competitors. This loss can motivate firms to mimic the more conservative leverage policies of their peers.[16]

[16] Another related model is the duopoly market model of Brander and Lewis (1986) in which feedback between product markets and financial policy leads to capital structure mimicking among competitors.

Signalling provides another motivation for mimicking behavior. Ross (1977) shows how financial policy can be used to influence the perceived quality of the firm. Specifically, 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.

Additional motivation for mimicking behavior in capital structure comes from rational herding models (Devenow and Welch (1996)).[17] Zeckhauser, Patel and Hendricks (1991) suggest that free-riding in information acquisition or relative performance evaluation for managers may lead to herd behavior in capital structure policies. Both of these explanations have theoretical precedent in the finance literature. As shown by Banerjee (1992) and others, when a firm's own signal is noisy and optimization is costly or time-consuming (Conlisk, 1980), managers may rationally put more weight on the decisions of others than on their own information. This is especially likely when other firms in the industry are perceived as having greater expertise (Bikhchandani, Hirshleifer and Welch, 1998).

Indeed, Devenow and Welch (1996) note that informational cascades may explain the decisions of managers to assume debt because without a good model of why firms do so, managers may infer the best choice from peer companies. Additionally, managers need not completely ignore their own information, as occurs in the limit in sequential informational cascade models. Rather, it is sufficient that they update their priors in a Bayesian manner based on the observed actions of other firms (e.g., Romer (1993) and Tueman (1994)). As a result, their decisions will be pulled toward that of their peers, relative to what it would be if they relied solely on their own information.[18]

Maksimovic and Zender (1991) also examine the interaction between product markets and financial policy. However, the implications of this study are geared more towards differential positioning within the industry, as opposed to mimicking behavior. See Mackay and Phillips (2005) for a careful examination of these implications.

[17]As Devenow and Welch (1996) discuss, there also exist models of irrational herding in which agents blindly follow one another and forgo rational analysis. We believe that such theories are less relevant in the current setting. Rather, the underlying mechanism behind any herd-like behavior among corporate managers is more likely due to information or incentive distortions, or limited cognitive abilities of managers.

[18]Because our source of identifying variation is firm-specific one must acknowledge an additional assumption for a learning mechanism to be behind our results. Specifically, one must assume that managers cannot disentangle the variation in peer firms actions that come from common and idiosyncratic variation in peer firms' stock returns. If they could, then they would rationally only respond to the

Managers may also mimic other firms' policies to influence their perceived relative quality in the labor market. In the model of Scharfstein and Stein (1990), higher quality investment 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 environment, herding is more important than making efficient investment choices because blame is shared in the event of a bad outcome. Zwiebel (1995) shows that corporate 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.

B. Empirical Results

To shed light on the potential mechanisms behind peer effects in financial policy, we examine heterogeneity in the coefficient on peer firm actions, β. This analysis enables us to answer four questions to help distinguish among the potential economic mechanisms. In which type of industries does mimicking occur? What types of firms mimic? What types of managers mimic? And, who is mimicking whom?

To avoid redundancy, we focus our attention on the change in market leverage as the outcome variable of interest. Specifically, we interact the average change in peer firm leverage and our instrument with indicator variables identifying the lower and upper thirds of each interaction variable's distribution. For binary interaction variables the interaction is directly with the binary variable. Our inferences come from any differences in the estimated scaled (by standard deviation) coefficients across these areas of the distribution.

To maintain consistency with our empirical strategy above, we estimate all of the models using two stage least squares, where now we have two instruments corresponding to the two endogenous variables, both of which are created by the interactions. While this strategy preserves proper identification, it comes at the price of statistical power. The interactions not only "split" the identifying variation, they also create a significant amount of multicollinearity. As such, we will focus our discussion on economically significant differences, acknowledging that many of these differences are statistically noisy.

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variation that contains information about their own firm. We believe that it is unlikely that nonfinancial corporate managers are performing such a decomposition. This belief is akin to that found in the literature on price informativeness for corporate decision, where managers respond to stock price changes despite these change containing both information and noise (e.g., Chen, Goldstein, and Jiang (2006)).

Regardless, we believe that this analysis is still suggestive of the underlying mechanism, and useful for its descriptive value and impetus for future research.

The results in Table IX address the first question by examining whether the peer effect coefficient, β, varies with average industry characteristics. We rank industry average characteristics into three groups and focus on only the lowest and highest of these groups to minimize measurement error (Greene (2008)). We note that the propensity to mimic is fairly similar across different types of industries. However, of particular interest is the third column, which shows that firms have a similar propensity to mimic one another regardless of the industry stock return. This result speaks further to the previously addressed concern that our results may be an artifact of hot equity markets. We also find little difference in the magnitude of peer effects across levels of industry concentration, suggesting that product market interactions are unlikely the primary mechanism behind our results.

Table X reveals that the similarity across industries masks significant heterogeneity within industries. In Panel A of Table X, we ask which firms mimic by examining whether the peer effect coefficient, β, varies with firm characteristics. For each industry-year combination, we rank firms into tertiales based on firm-specific characteristics and again focus on the low and high thirds of distribution of the interaction variable. The results show that smaller (market share), non-dividend paying, unrated firms tend to mimic their peers more strongly than their counterparts. Similarly, more financially constrained (Whited-Wu) firms tend to mimic more. These findings suggest that firms for whom the cost of external capital is relatively costly are more likely to mimic. This conclusion runs counter to the implications provided by signaling models, in which we would expect mimicking to be more pronounced among firms for whom the cost of the signal is lower.

Panel B of Table X looks at how mimicking behavior varies with CEO characteristics. To perform this analysis, we merge Execucomp data onto our Compustat sample. This merge reduces our sample size by 85%. As such, we adjust our empirical approach by ranking the CEO characteristics into only two groups based on their position relative to the median. Acknowledging the decrease in statistical power, the results are mixed in terms of their implications. On the one hand, lower paid CEOs experiencing lower growth in pay are more likely to mimic their peers. This finding appears consistent with the reputational concerns models of Scharfstein and Stein (1990) and Zwiebel (1995), as well as learning models more generally. On the other hand, CEOs with a longer tenure as CEO are more likely to mimic, and we find no difference in mimicking behavior between older and younger CEOs.

Finally, Table XI examines which firms are mimicking and which firms are being mimicked. To answer this, we examine whether one group of firms, which we denote followers, more strongly mimic another group of firms, which we denote leaders. We define leaders and followers by sorting firms within each industry-year into tertiales based on various measures of success – profitability, market share, incumbency, stock returns, and earnings growth. Followers are those firms in the bottom two thirds and leaders are those firms in the top third of the distribution.

For the purpose of estimation, we exclude the top third of the distribution (i.e., the leaders) from the sample so that the estimation is performed using only the subsample of follower firms. We also replace the peer firm average leverage change of the followers with that of the leaders. In essence, we are estimating the extent to which follower firms are sensitive to the financial policies of leader firms.

The results in Table XI show that the financial policies of younger, smaller (market share), less profitable firms with low stock returns and lower earnings growth are very sensitive to the financial policies of their more successful counterparts. All of these models exhibit a strong first stage estimate, and statistically significant second stage estimate. Additionally, the peer effect estimates are economically large.

As a robustness check on these findings, we perform a falsification test by rerunning the analysis using the sample of leaders and the peer firm leverage change of the followers. This analysis asks whether leaders mimic followers. Unreported results show that, despite statistically significant first stage estimates, the second stage estimates are all insignificant or marginally significantly negative. In other words, leader firms' financial policies are insensitive to the financial policies of follower firms.

This evidence on who mimics whom is consistent with the motivation for capital structure peer effects offered by Damodaran (2010): "[F]irms in a business tend to follow the leader... When this firm chooses a financing mix, presumably based upon its fundamentals, other firms in that sector then imitate the leader, hoping to imitate its success." Ross, Westerfield, and Jaffe (2010) echo a similar explanation: "After all, the existing firms in any industry are the survivors. Therefore we should pay at least some attention to their decisions."

In sum, while mostly descriptive, these findings are broadly consistent with the implications from models of observational learning and reputation. That is, those firms that mimic are the ones whose managers are likely to perceive that they have the most to learn and who have the greatest reputational concerns. At the same time, the firms being mimicked are the ones most likely to be perceived as having greater expertise. We hope future research will provide additional, and more powerful, evidence on the precise mechanism behind the peer effects.

VI. Conclusions

This study has shown that firms do not make financing decisions in isolation. Rather, the financing decisions and, to a lesser extent, the characteristics of peer firms are important determinants of corporate capital structures and financial policies. Interdependencies among debt and equity issuances drive interdependencies among leverage ratios. Indeed, peer firm behavior has a remarkably robust and large impact on corporate capital structure, larger than any other observable determinant, on average.

An interesting implication of these findings is the presence of externalities, which we show can significantly amplify or dampen the impact of changes in capital structure determinants. While somewhat suggestive, our evidence points to learning and reputational concerns as motives for these peer effects. Mimicking behavior is concentrated among smaller, more financially constrained firms with lower paid and less experienced managers. By contrast, industry leaders are not influenced by the financial policy choices of their less successful peers.

Our hope is that this study inspires future work on better understanding the mechanisms driving the strong interdependencies among financial policies. Further, an open empirical question is whether or not this mimicking behavior is optimal in a value enhancing sense. Finally, we hope that the findings of this study shift the direction of capital structure research towards models, both theory and empirical, that explicitly recognize the interactions among firms.

Appendix A: Variable Definitions

Corporate accounting data come from the merged CRSP-Compustat database available on the Wharton Research Data Services server. We draw a sample of firm-year observations during the period 1965 to 2008. We choose 1965 as the start year to mitigate the selection bias toward large, successful firms that exist in the early part of the Compustat sample. To maintain consistency with previous empirical studies and to avoid capital structures dictated by regulatory considerations, we exclude 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).[19] Stock return data for our sample of firms come from the Center for Research in Security Prices (CRSP) monthly stock price database.

To ensure consistency throughout our primary analysis, we require each firm-year observation to have 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 the idiosyncratic component of stock returns.

Variable definitions are below. Compustat variable names are denoted by their Xpressfeed pneumonic in bold. Time periods are denoted by (t) or (t-1) suffixes.

Total Book Assets = **at**.

Total Debt = Short-Term Debt + Long-Term Debt = **dltt** + **dlc**.

Book Leverage = Total Debt / Total Book Assets.

Market Value of Assets (MVA) = **prcc_f** * **cshpri** + **dlc** + **dltt** + **pstkl** - **txditc**.

Market Leverage = Total Debt / MVA.

Net Debt Issuances = [(**dltt**(t) + **dlc**(t)) - (**dltt**(t-1) + **dlc**(t-1))] / **at**(t-1).

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

Net Equity Issuances = (**sstk** - **prstkc**(t) / **at**(t-1).

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

Firm Size = Log(Sales) = Log(**sale**).

[19] We include 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 their exclusion, which affects less than 3% of the sample frame's observations.

Tangibility = Net PPE / Assets = **ppent** / **at**.

Profitability = EBITDA / Assets = **oibdp** / **at**.

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

Common Dividends = **dvc**.

Common Dividend Indicator = 1 if **dvc** > 0; 0 otherwise.

Sales, General, and Administrative Expenses = **xsga** / Firm Size.

Research and Development Expenses = **xrd** / Firm Size.

Capital Expenditures = **capx**.

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

Altman's Z-Score = (3.3 * **pi** + **sale** + 1.4 * **re** + 1.2 * (**act** - **lct**)) / **at**

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 obtained from John Graham's website.

We construct bank fixed effects are created for each firm with available issuance data by assuming 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. Results obtained by 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 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. 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. Matching SDC to Compustat was accomplished by matching cusips and dates of issuance to cusips and dates in the Compustat historical company information file. Matching Dealscan to Compustat was accomplished with the link file from Chava and Roberts (2008).

Appendix B: Exogenous Variable Derivatives

To ease the presentation, consider a particular industry j and year t. Rewriting our model, equation (1), in matrix notation produces

$$y = \frac{\beta}{N-1} Qy + X\lambda + \frac{1}{N-1} QX\gamma + Z\delta + \varepsilon. \tag{9}$$

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 (i.e., sales, profitability, market-to-book, and tangibility), Z is an $N \times k_2$ matrix of all other exogenous variables (e.g., industry and year fixed effects), and ε is an $N \times 1$ vector of residuals.

Solving equation (9) for y yields

$$y = \left(I - \frac{\beta}{N-1} Q\right)^{-1} \left(X\lambda + \frac{1}{N-1} QX\gamma + Z\delta + \varepsilon\right). \tag{10}$$

Of interest is the marginal effect or derivative of the outcome for firm $i = 1, ..., N$, y_i, with respect to a change in each $m = 1, ..., k_1$ exogenous variables for all firms $l = 1, ..., N$, x_{lm}. To derive a closed form solution for these derivatives, we need expressions for the two $N \times N$ matrices multiplying X:

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

Induction and matrix algebra shows that the first matrix is symmetric and has two distinct elements. The diagonal elements equal $\frac{N-1-\beta(N-2)}{(N-1+\beta)(1-\beta)}$, and the off-diagonal elements equal $\frac{\beta}{(N-1+\beta)(1-\beta)}$. The second matrix is also symmetric with two distinct elements. The diagonal elements equal $\frac{\beta}{(N-1+\beta)(1-\beta)}$, and the off-diagonal elements equal $\frac{1}{(N-1+\beta)(1-\beta)}$. 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

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

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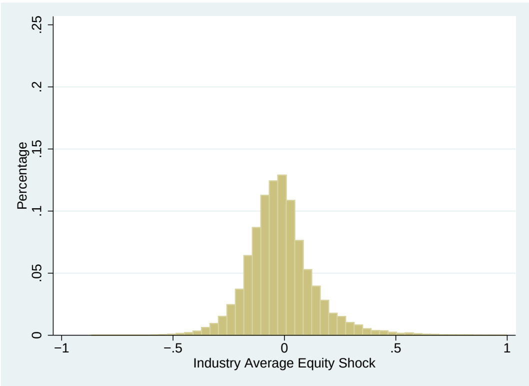
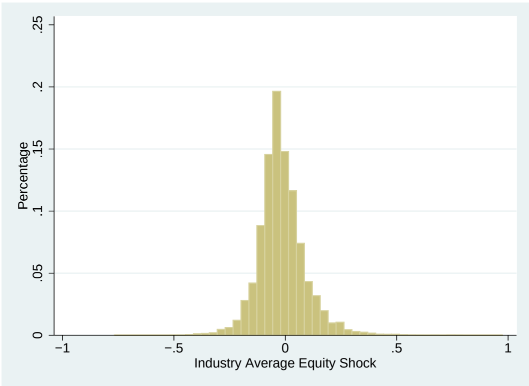
Figure 1
Industry Average Idiosyncratic Stock Returns Distribution

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables. The figure presents the empirical distribution of our instrument, peer firm average idiosyncratic annual equity returns, for three definitions of peer groups based on three-digit SIC code (Panel A), two-digit SIC code (Panel B), and one-digit SIC code (Panel C). Peer firm averages are defined as the peer group average excluding the i^{th} observation. The data has been truncated at -1 and +1 to ease the presentation. The peer firm average for the firm i, year t observation is defined as the sample mean of all firms in the peer group excluding the it observation.

Panel A: Three-Digit SIC Code Peer Groups



Panel B: Two-Digit SIC Code Peer Groups



Panel C: One-Digit SIC Code Peer Groups

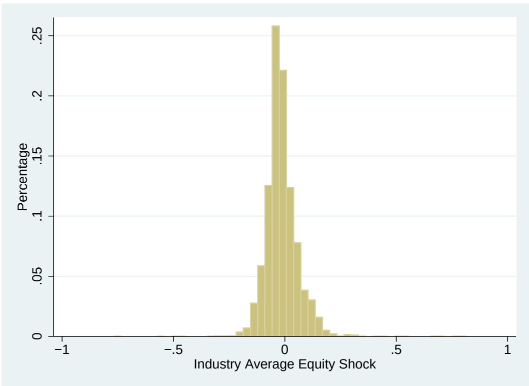


Table I
Summary Statistics

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents means, standard deviations (SD), and medians for variables in level and first-difference form. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t.

	Levels			First Differences		
	Mean	Median	SD	Mean	Median	SD
Peer Firm Averages						
Book Leverage (Total Debt / Book Assets)	0.271	0.259	0.089	0.000	0.001	0.037
Market Leverage (Total Debt / Market Assets)	0.274	0.263	0.132	0.011	0.008	0.057
Log(Sales)	4.431	4.289	1.436	0.129	0.128	0.137
Market-to-Book	1.652	1.432	0.889	-0.048	-0.026	0.430
EBITDA / Assets	0.047	0.085	0.129	-0.001	-0.001	0.044
Net PPE / Assets	0.303	0.258	0.166	-0.002	-0.002	0.019
Firm-Specific Factors						
Book Leverage (Total Debt / Book Assets)	0.245	0.218	0.217	0.006	0.000	0.117
Market Leverage (Total Debt / Market Assets)	0.277	0.217	0.251	0.007	0.000	0.129
Log(Sales)	5.003	4.941	2.206	0.091	0.089	0.380
Market-to-Book	1.404	0.974	1.441	-0.043	-0.007	1.054
EBITDA / Assets	0.097	0.126	0.188	-0.004	-0.000	0.129
Net PPE / Assets	0.315	0.268	0.219	-0.001	-0.002	0.062
Industry Characteristics						
# of Firms per Industry-Year	13.852	8.000	20.424			
Total # of Industries	227					
Sample Characteristics						
Observations	82,644					
Firms	9,717					

Table II

Reduced Form Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents OLS estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. 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. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. F-stat is the test statistic of the null hypothesis that all of the peer firm average coefficients equal zero. The adjusted R-square is a within firm measure for the firm fixed effect specification. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

	Book Leverage						Market Leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer Firm Avgs										
Log(Sales)	-0.001		-0.010**	-0.017**	-0.010**	0.019**		0.008*	-0.002	-0.004
	(-0.191)		(-3.575)	(-3.990)	(-2.743)	(5.797)		(2.543)	(-0.345)	(-1.220)
Market-to-Book	-0.021**		-0.015**	0.004	-0.004*	-0.058**		-0.034**	0.001	-0.012**
	(-9.123)		(-6.330)	(1.887)	(-2.040)	(-20.762)		(-13.187)	(0.336)	(-6.604)
EBITDA / Assets	-0.002		0.013**	0.016**	0.001	-0.016**		-0.001	0.003	-0.007**
	(-0.792)		(5.181)	(6.485)	(0.429)	(-5.746)		(-0.588)	(1.324)	(-3.569)
Net PPE / Assets	0.039**		0.005	0.010	0.012**	0.032**		0.006*	0.023**	0.021**
	(17.124)		(1.748)	(1.662)	(2.723)	(12.754)		(1.989)	(3.625)	(4.377)
Firm Specific Factors										
Log(Sales)		0.021**	0.021**	0.019**	0.034**		0.029**	0.020**	0.018**	0.074**
		(10.657)	(9.974)	(9.052)	(5.646)		(12.760)	(8.201)	(7.783)	(14.599)
Market-to-Book		-0.020**	-0.015**	-0.014**	-0.003		-0.076**	-0.066**	-0.063**	-0.029**
		(-11.412)	(-8.341)	(-7.661)	(-1.832)		(-42.052)	(-38.045)	(-37.630)	(-23.715)
EBITDA / Assets		-0.043**	-0.046**	-0.045**	-0.036**		-0.048**	-0.049**	-0.048**	-0.043**
		(-18.836)	(-19.782)	(-19.810)	(-14.510)		(-27.259)	(-27.457)	(-27.644)	(-23.590)
Net PPE / Assets		0.052**	0.045**	0.045**	0.035**		0.044**	0.034**	0.035**	0.035**
		(25.596)	(15.424)	(16.016)	(11.002)		(20.452)	(11.294)	(12.029)	(10.927)
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	146.161**		25.784**	12.130**	4.769**	329.653**		92.003**	3.826**	21.011**
Obs	82,644	82,644	82,644	82,644	82,644	82,644	82,644	82,644	82,644	82,644
Adj. R^2	0.057	0.103	0.109	0.176	0.052	0.150	0.223	0.238	0.296	0.137

Table III
Stock Return Factor Regression Results

The sample consists of monthly returns for all nonfinancial, nonutility firms in the intersection of the annual Compustat and monthly CRSP databases between 1965 and 2008. The table presents mean factor loadings and adjusted R-squares from the regression

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{IND}(\bar{R}_{-ijt} - RF_t) + \eta_{ijt},$$

where R_{ijt} is the return to firm i in industry j during month t, $(RM_t - RF_t)$ is the excess return on the market and $(\bar{R}_{-ijt} - RF_t)$ is the excess return on an equal weighted industry portfolio excluding firm i's return, where industry is 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 one year hence. Idiosyncratic returns are computed as the difference between realized and expected returns.

	Mean	Median	SD
α_{it}	0.801	0.726	1.480
β_{it}^{M}	0.408	0.429	0.701
β_{it}^{IND}	0.624	0.547	0.523
Obs Per Regression	58	60	5
Adjusted R^2	0.225	0.207	0.161
Avg Monthly Return	0.014	0.000	0.181
Expected Monthly Return	0.015	0.014	0.090
Idiosyncratic Monthly Return	-0.001	-0.010	0.174

Table IV
Instrument Properties

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents OLS estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. 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. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. Firm specific factors and peer firm averages include: firm size, profitability, tangibility, and the market-to-book ratio. The F-stat tests the null hypothesis that the firm specific factor coefficients are jointly equal to zero. Partial Adj. R^2 is the adjusted R-square for a regression of the peer firm average equity shock on the firm specific factors after partialling out the effects of peer firm average characteristics, industry fixed effects, and year fixed effects. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

	Peer Firm Average Equity Shock	
	Contemporaneous Independent Vars	1-Period Lead Independent Vars.
Firm Specific Factors		
Log(Sales)	-0.001	0.000
	(-1.262)	(0.078)
Market-to-Book	0.001	0.002*
	(1.402)	(2.325)
EBITDA / Assets	0.001*	0.001
	(2.201)	(1.454)
Net PPE / Assets	-0.000	-0.001
	(-0.296)	(-0.588)
Peer Firm Average Characteristics	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Obs	82,644	82,438
Adj. R^2	0.122	0.125
Joint Significance of Firm Specific Factors		
F-Stat	2.264	2.290
Partial Adj. R^2	0.000	0.000

Table V
Leverage Changes by Peer Firm Equity Shock and Peer Firm Leverage Change

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents average market leverage changes for 25 groups of observations. The groups are formed by the intersection of quintiles based on: (1) one period lagged peer firm average idiosyncratic component of stock returns, and (2) peer firm average change in market leverage, excluding firm i. The column labeled "5 - 1" presents the difference in means between columns 5 and 1. The row labeled "5 - 1" presents the difference in means between rows 5 and 1. 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.

Lagged Peer Firm	Peer Firm Avg Leverage Change Quantiles					
Avg Equity Shock	1	2	3	4	5 (High)	5 - 1
1 (Low)	-0.035**	-0.010**	0.007**	0.021**	0.063**	0.098**
	(-15.461)	(-4.425)	(3.259)	(9.783)	(29.524)	
2	-0.045**	-0.014**	0.004*	0.024**	0.068**	0.113**
	(-19.506)	(-6.826)	(2.056)	(11.836)	(28.307)	
3	-0.044**	-0.006**	0.007**	0.023**	0.070**	0.114**
	(-19.460)	(-3.523)	(4.209)	(10.948)	(25.556)	
4	-0.053**	-0.016**	0.004*	0.025**	0.068**	0.121**
	(-23.266)	(-8.140)	(2.133)	(11.703)	(28.775)	
5 (High)	-0.051**	-0.014**	0.001	0.016**	0.064**	0.115**
	(-28.066)	(-7.181)	(0.496)	(7.310)	(25.278)	
5 - 1	-0.016**	-0.005	-0.006	-0.006	0.001	

Table VI
Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. The method of estimation and dependent variable are indicated at the top of columns. The endogenous variable is the peer firm average leverage ratio, and, for the 2SLS estimations, the instrument is the one period lagged peer firm average idiosyncratic component of stock returns. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. 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 unless otherwise specified. In Panel B, the first difference in market leverage is the dependent variable for all specifications, which include first differences of firm specific and peer firm averages 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. Bank $\times$ Market Return effects include fixed effects for the primary or lead underwriter for the firm's past security issuances, debt or equity, and these same fixed effects interacted with the market equity return. Additional control variables include first differences of lagged firm specific and peer firm averages 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. Polynomials of control variables (Vars) include quadratic and cubic terms of all right hand side variables other than industry average leverage. Contemporaneous controls replace the lagged firm specific and peer firm averages control variables with contemporaneous values. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Panel A: Leverage Regressions

	OLS		2SLS			
	Market Leverage	Book Leverage	Market Leverage	Book Leverage	Δ Market Leverage	Δ Book Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Firm Averages						
Leverage	0.077**	0.052**	0.096**	0.106**	0.065**	0.036**
	(33.806)	(26.012)	(6.438)	(4.602)	(5.543)	(3.888)
Log(Sales)			-0.011*	-0.014**	-0.004**	0.001
			(-2.140)	(-3.037)	(-2.610)	(0.978)
Market-to-Book			0.030**	0.012**	0.001	0.004**
			(5.720)	(4.058)	(1.361)	(2.755)
EBITDA / Assets			0.020**	0.029**	0.002**	0.002*
			(5.275)	(7.336)	(3.110)	(2.228)
Net PPE / Assets			-0.007	-0.039**	-0.001	-0.002*
			(-0.908)	(-3.178)	(-1.429)	(-2.526)
Firm Specific Factors						
Log(Sales)	0.017**	0.018**	0.018**	0.018**	0.005**	0.002
	(7.979)	(9.466)	(7.469)	(8.628)	(7.162)	(1.960)
Market-to-Book	-0.063**	-0.015**	-0.062**	-0.012**	-0.002**	-0.002*
	(-38.193)	(-8.493)	(-36.657)	(-6.565)	(-3.805)	(-2.157)
EBITDA / Assets	-0.047**	-0.043**	-0.047**	-0.045**	-0.003**	-0.004**
	(-27.556)	(-19.216)	(-26.781)	(-19.720)	(-5.027)	(-3.727)
Net PPE / Assets	0.026**	0.036**	0.034**	0.043**	0.004**	0.003**
	(12.195)	(17.789)	(11.432)	(14.912)	(5.970)	(4.364)
Equity Shock			-0.007**	-0.004**	0.002**	-0.001
			(-9.008)	(-4.722)	(2.650)	(-1.766)
First Stage Instrument						
Peer Firm Avg Equity Shock			-0.040**	-0.017**	-0.016**	-0.012**
			(-21.999)	(-10.049)	(-12.326)	(-9.715)
Industry Fixed Effects	No	No	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	82,644	82,644	82,644	82,644	82,644	82,644

Panel B: Δ Market Leverage Robustness Tests

	Δ Market Leverage					
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage Estimate						
Peer Firm Avg Leverage Change	0.030**	0.060**	0.060**	0.076**	0.047**	0.063**
	(2.732)	(5.597)	(3.519)	(6.212)	(4.733)	(5.395)
First Stage Instrument						
Peer Firm Avg Equity Shock	-0.014**	-0.017**	-0.014**	-0.015**	-0.016**	-0.016**
	(-10.921)	(-13.517)	(-7.404)	(-12.171)	(-14.294)	(-12.425)
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Return Controls	Yes	No	No	No	No	No
Additional Control Variables	No	Yes	No	No	No	No
Bank $\times$ Market Return Effects	No	No	Yes	No	No	No
Lagged Dependent Variable	No	No	No	Yes	No	No
Contemporaneous Controls	No	No	No	No	Yes	No
Polynomials of Controls	No	No	No	No	No	Yes
Obs	80,416	74,520	34,709	82,587	82,438	82,644

Table VII

2SLS Security Issuance Decision Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. All models are estimated by linear 2SLS where the endogenous variables is the peer firm average of the dependent variable, 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. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. 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 (3) isolates the subsample of observations in which either an equity or debt issuance, but not both, occurred. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

	Issue Stock	Issue Debt	Subsample of Issuances: Issue Debt
	(1)	(2)	(3)
Peer Firm Averages			
Dependent Variable	0.079**	0.176*	0.104**
	(4.869)	(1.961)	(2.610)
Log(Sales)	0.006	-0.011	-0.001
	(0.867)	(-1.503)	(-0.136)
Market-to-Book	-0.013	-0.005	0.013
	(-1.694)	(-0.262)	(1.885)
EBITDA / Assets	-0.002	0.001	0.021*
	(-0.466)	(0.030)	(2.402)
Net PPE / Assets	0.005	-0.021*	-0.000
	(0.622)	(-2.100)	(-0.014)
Firm Specific Factors			
Log(Sales)	-0.031**	0.028**	0.056**
	(-10.772)	(9.577)	(13.622)
Market-to-Book	0.088**	0.004	-0.086**
	(31.862)	(1.610)	(-25.123)
EBITDA / Assets	-0.030**	-0.011**	0.014**
	(-12.246)	(-3.658)	(4.017)
Net PPE / Assets	0.006*	0.042**	0.024**
	(2.136)	(12.495)	(5.416)
Equity Shock	0.031**	0.012**	-0.027**
	(20.016)	(6.234)	(-11.960)
First Stage Instrument			
Peer Firm Avg Equity Shock	0.082**	-0.019**	-0.097**
	(28.397)	(-5.294)	(-10.626)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	82,644	82,644	35,625

Table VIII

Exogenous Variable Derivatives, Marginal Effects, and Leverage Multipliers

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients and derivatives, both scaled by the corresponding variable standard deviation, from a regression of market leverage on peer firm leverage, peer firm characteristics, and firm specific factors. All variables are in levels. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. Derivatives are computed for three peer groups differing in their size: small (3 firms), medium (8 firms), and large (26 firms). The derivative $\partial y_i/\partial x_{im}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation i (x_{im}). The derivative $\partial y_i/\partial x_{km}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation k (x_{km}). Both derivatives are scaled by the standard deviation of the corresponding x variable, (σ_x). Amplification term is the multiplicative factor due to the peer effect action variable and is equal to $\left(1+\frac{\beta^2}{(N-1+\beta)(1-\beta)}\right)$. The terms Spillover 1 and Spillover 2 are the additive factors due to both the peer firm actions and characteristics, and are equal to $\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right)$ and $\left(\frac{1}{(N-1+\beta)(1-\beta)}\right)$, respectively. In parentheses are t-statistics robust to heteroskedasticity and within firm dependence. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Variable	Firm-Specific Factor	Peer Firm Average	Peer Group Size - Small		Peer Group Size - Medium		Peer Group Size - Large	
	Scaled Coefs ($\lambda \times \sigma_x$)	Scaled Coefs ($\gamma \times \sigma_x$)	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$
Log(Sales)	0.018**	-0.011*	0.014	-0.005	0.016**	-0.002	0.017**	-0.001
	(7.469)	(-2.140)	(1.750)	(-0.486)	(4.396)	(-0.485)	(6.710)	(-0.484)
Market-to-Book	-0.062**	0.030**	-0.058**	0.005	-0.060**	0.002	-0.061**	0.000
	(-36.657)	(5.720)	(-12.418)	(0.862)	(-25.404)	(0.852)	(-34.196)	(0.848)
EBITDA / Assets	-0.047**	0.020**	-0.052**	-0.007	-0.048**	-0.002	-0.047**	-0.001
	(-26.781)	(5.275)	(-8.927)	(-1.005)	(-17.608)	(-0.988)	(-24.688)	(-0.982)
Net PPE / Assets	0.034**	-0.007	0.049**	0.020	0.039**	0.007	0.035**	0.002
	(11.432)	(-0.908)	(4.866)	(1.751)	(8.502)	(1.722)	(11.163)	(1.710)
Peer Firm Avg. Leverage (β)	0.725**							
	(6.438)							
Amplification Term			1.703		1.248		1.075	
			(1.471)		(1.415)		(1.395)	
Spillover 1			0.970		0.342		0.103	
			(1.907)		(1.814)		(1.781)	
Spillover 2			1.336**		0.471*		0.142*	
			(2.709)		(2.526)		(2.463)	

Table IX

In Which Industries Does Mimicking Occur?

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimates for the peer firm average market leverage change interacted with indicator variables identifying the lower and upper third of the within-year distribution of lagged values for average industry profitability, market-to-book ratio, equal-weighted stock return, firm age, R&D / Sales, tangibility, and industry concentration. We exclude the middle third of the distribution for each of these regressions. The coefficient estimates are scaled by the corresponding variable standard deviation. The dependent variable is the change in market leverage ratio. All models are estimated by linear 2SLS where the endogenous variables are the peer firm average leverage ratio changes interacted with indicator variables, and the instruments are the one period lagged peer firm average idiosyncratic component of stock returns interacted with the same indicator variables. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments (First Stage Multivariate F-stat). Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All variables are in first differences except the instrument. All right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable. All test 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. F-stat statistical significance implying less than 15% or 10% size distortion is denoted by "*" and "**", respectively.

	Profitability (3=High)	Market-to-Book (3=High)	Stock Return (3=High)	Firm Age (3=Old)	R& D / Sales (3=High)	Asset Tangibility (3=High)	Indusry Concentration (3=Conc)	Leverage Volatility (3=High)
Peer Firm Avg Leverage Change × Group 1	0.046**	0.052**	0.050**	0.044**	0.049**	0.038**	0.040**	0.048**
	(3.777)	(5.558)	(5.116)	(3.546)	(4.910)	(3.912)	(4.023)	(4.186)
Peer Firm Avg Leverage Change × Group 3	0.052**	0.059**	0.041**	0.042**	0.040*	0.059**	0.046**	0.049**
	(5.432)	(3.157)	(3.393)	(3.399)	(2.562)	(3.019)	(3.993)	(4.939)
First Stage Multivariate F-stat	47.872**	12.266**	36.589**	39.715**	29.412**	18.392**	47.319**	35.347**
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	54,226	52,949	53,246	50,406	51,732	54,410	55,917	54,166

Table X
Which Firms and CEOs Mimic?

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). We also use a subsample conditional on data from Execucomp in Panel B. Panel A presents estimates for the peer firm average market leverage change interacted with indicator variables identifying the lower and upper third of the within industry-year distribution of lagged values for firm specific measures of whether the firm has a credit rating, whether the firm paid a dividend in year $t-1$, market share, profitability, market-to-book ratio, and the Whited-Wu Index of financial constraints. We exclude the middle third of the distribution for each of these regressions. Panel B presents estimates for the peer firm average market leverage change interacted with indicator variables identifying the lower and upper halves of the within industry-year distribution of lagged values for CEO characteristics: age, total pay, growth in total pay, tenure as CEO, and tenure at current company The coefficient estimates are scaled by the corresponding variable standard deviation. The dependent variable is the change in market leverage ratio. All models are estimated by linear 2SLS where the endogenous variables are the peer firm average leverage ratio changes interacted with indicator variables, and the instruments are the one period lagged peer firm average idiosyncratic component of stock returns interacted with the same indicator variables. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments (First Stage Multivariate F-stat). Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All variables are in first differences except the instrument. All right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable unless otherwise specified. All test 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. F-stat statistical significance implying less than 15% or 10% size distortion is denoted by "*" and "**", respectively.

Panel A: Interactions with Firm Characteristics

	Credit Rating (2=Yes)	Dividend Payer (2=Yes)	Market Share (2=Large)	Profitability (2=High)	Market-to-Book (2=High)	Whited-Wu Index (2=Cnstrd)
Peer Firm Avg Leverage Change × Group 1	0.059**	0.049**	0.047**	0.043**	0.050**	0.057**
	(5.305)	(5.074)	(4.489)	(3.682)	(3.845)	(4.494)
Peer Firm Avg Leverage Change × Group 2	0.029**	0.043**	0.039**	0.044**	0.042**	0.065**
	(3.454)	(5.529)	(3.344)	(3.422)	(4.051)	(4.834)
First Stage Multivariate F-stat	47.701**	77.599**	52.581**	34.321**	46.367**	39.974**
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific 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
Obs	82,644	82,644	54,814	53,523	54,912	55,050

Panel B: Interactions with CEO Characteristics

	CEO Age (2=Old)	CEO Total Pay (2=High)	CEO Total Pay Growth (2=High)	CEO Tenure (2=Long)	Company Tenure (2=High)
Peer Firm Avg Leverage Change × Group 1	0.037*	0.047**	0.053	0.010	0.015
	(2.036)	(2.814)	(1.930)	(0.617)	(0.535)
Peer Firm Avg Leverage Change × Group 2	0.037*	0.031	0.032	0.031*	0.015
	(2.137)	(1.512)	(1.882)	(2.017)	(1.248)
First Stage Multivariate F-stat	10.979**	5.548	5.287	12.485**	2.601
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	11,277	10,333	9,367	12,193	6,892

Table XI
Which Firms are Mimicked?

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. All models are estimated by linear 2SLS where the endogenous variable is the industry average leverage change and the instrument is the one period lagged industry average idiosyncratic component of stock returns. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All specifications include one-period lagged peer firm averages and firm specific effects for the following characteristics: firm size, profitability, tangibility, and the market-to-book ratio. Firms are classified as either "Leaders" or "Followers" based on their within industry-year ranking by: age, profitability, market share (sales as a fraction of industry sales), stock returns, and earnings growth. The table restricts attention to the subsample of firms in the middle and lower thirds of the within industry-year distribution (i.e., Followers) of each classification variable and regresses their change in market leverage ratio on the average change in market leverage of firms in the upper third (i.e., Leaders), as well as the control variables indicated towards the bottom of the table. F-stat statistical significance implying less than 10% or 15% size distortion is denoted by "*" and "**", respectively.

	Change in Market Leverage				
	Age	Profitability	Market Share	Stock Return	Earnings Growth
Peer Firm Average					
Leader Firm Avg Leverage Change	0.111**	0.067**	0.054**	0.071**	0.059**
	(3.801)	(6.152)	(5.281)	(3.358)	(3.018)
First Stage Univariate F-stat	36.025**	164.827**	159.948**	46.462**	45.349**
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes
Industry Effects	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	39,264	51,189	45,369	53,157	55,849