Do Peer Firms Affect Financing Decisions?*

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Abstract

Using instrumental variables, we show that firms' industry peers play an important role in shaping corporate financial policies. Both the characteristics and financial policies of competitors are important determinants of capital structure. On average, a one standard deviation change in peer firms' leverage ratios is associated with a 9% change in own firm leverage ratios — a marginal effect that is significantly larger than that of any other observable determinant. Driving this leverage effect is a linkage among firms' security (debt and equity) issuance decisions. We also show that these effects are driven largely by the efforts of younger, less successful firms that mimic industry leaders. Our study highlights the interdependent nature of corporate financial policies; firms do not make financing decisions in isolation of one another as often assumed in theories of corporate capital structure.

Most research on corporate capital structure assumes that firms choose their financial policies independently of their peers.[1] However, there are several reasons to believe that firms do not make financing decisions in isolation of one another. Theoretically, interactions in the product markets can generate interactions among financial policies. Alternatively, learning motives may link firms' financial policies, as can herding behavior to avoid any negative consequences associated with a separating equilibrium. Empirically, firms in the same industry tend to have similar capital structures. Median or average industry leverage is an important, if not the most important, observable capital structure determinant. Further, survey evidence indicates that CFOs often consider the financing decisions of other firms in their industry when setting financial policy.[2]

While well motivated and empirically important, peer firm financial policy and its link to corporate capital structure does not have a unique interpretation because of the reflection problem (Manski (1993)). The reflection problem refers to a specific endogeneity problem that arises when trying to infer whether the behavior of a group influences the behavior of the individuals that comprise the group. In our context, this problem is created by using a measure of peer firm financial policy, such as industry average leverage, as an explanatory variable for individual firm financial policy. In particular, any observed similarity in financing behavior among the firms within an industry — or any other peer group — can be attributed to three potential explanations.

The first explanation — which we refer to as a correlated effect — is that firms in the same industry have similar firm characteristics or face similar institutional environments, such as production technologies and investment opportunities. The inability to perfectly measure or observe these determinants generates a role for peer firm financial policy in so far as it proxies for these omitted firm specific characteristics. The second explanation — referred to as a contextual effect — is that firms are responding to the characteristics of other firms in the industry, or the context in which they operate. For example, firms whose competitors are more financially sound may face lower liquidation costs, which

[1]Theoretical examples include traditional tax-bankrupcty cost tradeoff theories, (Scott (1976)), agency-based theories (Jensen and Meckling (1976)), information asymmetry (Myers and Majluf (1984)), optimal contracting (DeMarzo and Fishman (2007)). Empirically, there are no studies of which we are aware that explicitly model the interplay between financing decisions of peer firms.

[2]See studies by Brander and Lewis (1986) and Maksimovic and Zechner (1991) (product market competition), Conlisk (1980) (Learning), and Ross (1977) (Signalling). Studies by Bradley, Jarrell, and Kim (1984), Frank and Goyal (2007), Lemmon, Roberts, and Zender (2008) all show that industry effects have the most economically important impact on leverage among observable leverage determinants. Graham and Harvey (2001) show that almost one quarter of surveyed CFOs identify the behavior of competitors as an important input into their financial decision making.

lead to higher optimal debt ratios (Shleifer and Vishny (1992)). The last explanation — referred to as a peer effect — is that firms' financial policies are responding directly to the financing decisions of their peers.

The goal of this paper is to disentangle these explanations to better understand the role played by firms' peers in determining financial policy. We begin by showing that the importance of peer firm behavior for capital structure does not come solely from common unobserved characteristics or correlated effects. Rather, interactions between a firm and its peers are relevant and important for financial policy.

We then investigate the nature of these interactions – whether firms respond to competitors' characteristics (contextual effects), their financial policies (peer effects), or both. To do so, we employ an instrumental variables approach designed to address the endogeneity of other firms' financing decisions. Our identification strategy uses the lagged idiosyncratic component of *other* firms' stock returns as an instrument for their financing decisions. Intuitively, the identifying assumption is that an idiosyncratic shock to the stock price of firm j in period t has no affect on the financing decision of firm i in period $t+1$ but for its affect on firm j's financing decision in period $t+1$. We take several steps to justify this assumption.

First, we estimate firm-specific, rolling regressions of stock returns on the usual asset-pricing factors and an industry factor. This specification ensures that the estimated residual (i.e., instrument) is orthogonal to industry shocks, while enabling the sensitivity to these shocks to vary by firm and year. Indeed, intra-industry correlation among idiosyncratic stock returns is virtually zero. Nonetheless, we also include as a control variable the own-firm stock return. Doing so alleviates the concern that variation in the instrument which is correlated with the own-firm stock return is being used for identification.

In other words, even if the shock to firm j's stock price is correlated with firm i's stock return, this correlation is absorbed by including firm i's return as a regressor. Therefore, the threat to our identification strategy is isolated to an unobserved variable that is (1) correlated with the *non-systematic* portion of *other* firms' stock returns, and (2) correlated with firm i's financial policy, even after partialing out firm i's stock return, market-to-book ratio, and all other control variables. While such a variable is not immediately apparent, we undertake a number of robustness tests to ensure proper identification of the peer effect and rule out alternative hypotheses.

Our first stage results show that idiosyncratic stock returns are strongly correlated with leverage, primarily through their affect on equity policy. Firms experiencing positive shocks to the stock price are significantly more likely to issue equity, issue relatively more equity, and, consequently, reduce their leverage. These results are similar to previous evidence linking total stock returns to equity policy, but they highlight that the idiosyncratic component of stock returns is the more important determinant of equity policy. Statistically speaking, the first stage F-statistics are well above weak-instrument thresholds, illustrating that the instrument relevance test is easily passed. Economically speaking, this finding shows that managers respond to the firm-specific information or mispricing contained in market equity prices when making financing decisions.

The second stage results show evidence for both peer effects and contextual effects. Firms' capital structure choices are directly influenced by those of their industry peers as well as by the characteristics of their competitors. Moreover, the peer effect plays an even more important role in shaping financial policy than suggested by previous results. OLS regressions indicate that a one standard deviation increase in the industry average leverage ratio is associated with a 7% increase in leverage for each firm in the subsequent period — the largest marginal effect among existing regressors. The two stage least squares estimates indicate that this effect increases to nearly 10% and remains the largest marginal effect among existing regressors. We document this effect for both book and market measures of leverage as well as for individual financing decisions (i.e. the debt-equity choice). Simply put, the financing behavior of firms' peers is the most important observable determinant of corporate capital structure.

Our investigation of the mechanism behind these interactions reveals that younger, less successful firms appear to mimic the capital structures of industry leaders — more mature, successful firms. More precisely, industry entrants and less profitable firms appear very sensitive to the financial policies of industry encumbants and more profitable firms. However, the reverse is not true; industry leaders are not influenced by the policies of newcomers and less successful firms. This finding is consistent with a learning story whereby uncertainty about optimal financial policy in conjunction with costly optimization (Conlisk (1980)) leads some firms to mimic and learn from others.

We find less support for product market competition and signalling based explanations. For example, the impact of peer firms on financial policy shows virtually no variation across industries delineated by the degree of competition (i.e., Herfindahl-Hirschman Index (HHI)). Even the extreme comparison of industries defined by the justice department to be concentrated (HHI > 1800) and unconcentrated (HHI < 1000) reveals almost identical sensitivities of financial policy to peer firm behavior. Similarly, we find little consistent variation in the effect of peer firms across proxies for the cost of external financing. More financial constrained firms, as measured by the Whited and Wu or Kaplan and Zingales index, have capital structures that are more sensitive to the behavior of their peers; yet, smaller, non-dividend paying firms' capital structures are less sensitive to that of their peers. Thus, the degree to which firms are using financial policy as a costly signal to pool with other firms is unclear.

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

Our study is also related to the work of Mackay and Phillips (2005). These authors identify a significant amount of intra-industry variation, while exploring industry equilibrium models such as Maksimovic and Zechner (1991). Our study compliments theirs by showing that intra-industry leverage heterogeneity is also marked by significant interdependencies. That is, while leverage ratios vary widely within industries, a change in the leverage ratio of one firm directly affects those of the other firms in the industry. Thus, within industry leverage distributions tend to "shift" as all firms respond to one another, as opposed "stretching" and "contracting" where each firm acts in isolation.

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

I. Data and Summary Statistics

Corporate accounting data come from Standard & Poor's (S&P) Annual Compustat database. We draw a sample of firm-year observations during the period 1965 to 2006, subject to the following criteria. We exclude all financial firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900 and 4999), government entities (SIC codes greater than or equal to 9000), and any firms that underwent a significant acquisition during the sample period as indicated by Compustat variable *aftnt1* equal to “AB”. These screens are undertaken to ease comparisons with previous capital structure studies and remove regulated firms for which financial policy and leverage ratios have distinctly different meanings. We exclude any observations with missing data for the variables used in the study.[3]

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

Table I presents summary statistics for our sample. The aforementioned screens produce 78,023 firm-year observations corresponding to 9,208 unique firms. There are 172 industries represented in our sample. The typical industry contains approximately 19 firms, though the distribution is highly right skewed as indicated by the median number of firms, 12. To address the large number of firms present in some industries, as well as the documented intra-industry heterogeneity (Mackay and Phillips (2005)), we investigate more refined peer groups in some of our empirical analysis below.

Summary statistics for the financial policy variables and firm characteristics are presented after winsorizing all ratios at the upper and lower one percentiles. All variables are formally defined in Appendix A. Book and market leverage are approximately 25%. The propensities to issue debt and equity in excess of 1% of book assets are 40% and 21%, respectively. The average flow of net debt and net equity relative to start of period assets are 3.0% and 3.3%, respectively. The firm characteristics have sample moments similar to those found in previous studies of capital structure (e.g., Frank and Goyal (2007)).

II. How Important is Industry Leverage to Corporate Capital Structures?

As a first step, we reexamine the empirical link between industry leverage and corporate capital structures using the existing empirical literature as our guide. The goal is twofold. First, we want to highlight the economic significance of this determinant relative to

[3]The specific variables include total assets, net sales, the market-to-book ratio, operating income before depreciation, net PPE, book leverage, market leverage, net equity issuance, net debt issuance, idiosyncratic equity returns. All variables are formally defined in Appendix A.

other determinants. Second, we want to provide results against which we can benchmark subsequent findings.

Table II presents estimated marginal effects, t-statistics (in parentheses), and model statistics for several variations of the following model of leverage,

$$y_{igt} = \alpha + \beta \bar{y}_{-igt} + \lambda' X_{igt-1} + \phi' \nu_t + \delta' \mu_g + \psi' \omega_i + \varepsilon_{igt}. \tag{1}$$

The indices i, g, and t correspond to firm, industry, and time period, respectively. The outcome variable, y_{igt}, is financial leverage. For robustness, we examine both book and market leverage.

The first term, $\bar{y}_{-igt}$, denotes the average leverage for all firms in industry g, excluding firm i, during period t.[4] While we discuss the endogeneity problem in detail below, we note here that previous authors have attempted to mitigate endogeneity concerns by lagging the industry average leverage one period. For consistency, we follow this practice in estimating equation (1). Throughout the paper, we use the notation $\bar{x}$ to denote the sample mean of x, and the "$-i$" subscript to denote all observations other than the i^{th} observation.

The second term, X_{igt-1}, is a K-dimensional vector of firm-specific determinants of financial policy, lagged one period. In Table II, we focus on the most common and robust determinants of capital structure (see, for example, Rajan and Zingales (1995) and Frank and Goyal (2003, 2007)). We incorporate year (ν_t), and industry (μ_g) or firm (ω_i) fixed effects to capture common components of leverage ratios. For identification, in each specification we restrict the firm or industry fixed effects to be zero. The error term, ε_{igt}, is potentially correlated within firms and heteroskedastic. As such, all standard errors and test-statistics are robust to these two concerns (Petersen (2009)).

This model of leverage is frequently found in empirical capital structure studies. Like others, we estimate the model by ordinary least squares (OLS), though generalized least squares (GLS) estimates are qualitatively similar. The marginal effects are computed as the product of the estimated coefficient and the corresponding variable's standard deviation. Thus, the estimates indicate the change in leverage associated with a one standard deviation change in the covariate.

Specifications (1) through (3) show that in a pooled regression, average industry leverage is the most economically important determinant of capital structure. A one standard deviation change in average industry book leverage is associated with a 5.2%

[4]Using the median produces similar results.

change in individual firms' book leverage ratios. This effect is almost 30% larger, in magnitude, than the next most important determinant, profitability. Additionally, a comparison of the adjusted R-squares for specifications (1) and (2) reveals that industry average leverage, by itself, explains more variation in book leverage ratios than the other observable determinants combined.

Specifications (4) and (5) incorporate industry and firm fixed effects to address unobserved heterogeneity concerns (Lemmon, Roberts, and Zender (2008)). While no longer the most important characteristic, changes in average industry leverage still have an economically and statistically large impact on within-industry and within-firm variation in leverage. Interestingly, the change in the economic magnitude of industry effects arising from the inclusion of industry and firm fixed effects highlights that industry leverage is more important for explaining cross-sectional, as opposed to time-series, variation in leverage ratios. This finding is important because cross-sectional, as opposed to time-series, variation in leverages ratios is arguably the larger mystery in the capital structure puzzle (e.g., Myers (1984), Welch (2004), Lemmon, Roberts, and Zender (2008), and Strebulaev and Yang (2008)).

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

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

These results highlight and emphasize what is largely scattered throughout the existing literature. Industry leverage is an economically important and robust determinant of corporate capital structure. We now turn to understanding why.

III. Why Would Firms' Financial Policies Be Related?

There are a variety of reasons why firms' financial policies would affect one another. In this section, we outline three potential mechanisms suggested by existing theories:

costly optimization, interactions between financial policy and product market strategy, and signalling with financial policy. While this list may not be exhaustive, it represents the more popular explanations and serves to motivate the empirical analysis below.

First, an individual firm's financial policy can be directly influenced by that of its peers when there is a high degree of uncertainty with respect to optimal capital structure. Conlisk (1980) shows that when decision making is costly it is optimal for some agents to be optimizers and others imitators. The imitators bear the cost of converging only slowly to optimal behavior, but save the decision cost. Thus, if firms cannot costlessly discern the true optimal financial structure, some firms may simply "follow the crowd" in an effort to learn that structure.

Second, the interaction between financial structure and product market competition can generate peer effects in financing decisions. Prior research offers several theoretical reasons why financial structure might affect product market strategies. For example, in Brander and Lewis (1986) a high debt level commits the firm to aggressive quantity competition; in Bolton and Scharfstein (1990), high leverage invites predatory price competition from less levered rivals; in Chevalier and Scharfstein (1996), firms with high leverage under-invest during an industry downturn and lose market share to more conservatively financed competitors.

Anticipation of these product market effects can lead firms to make similar financing choices as their peers. For example, in the symmetric duopoly of Brander and Lewis (1986), both firms choose high debt levels in equilibrium to protect themselves from the aggressive commitment of the other. Similarly, if the potential cost of price predation (Bolton and Scharfstein (1990)) or under-investment (Chevalier and Scharfstein (1996)) is severe enough, highly levered firms will mimic the capital structures of their less levered rivals.

Note, however, that product market interactions need not lead to commonality in financial structure within industries. As noted by MacKay and Phillips (2005), in models of competitive industries, equilibrium outcomes tend to generate dispersion in financial policy within industry segments. For example, Maksimovic and Zechner (1991) show that a firm's optimal financial structure is a function of the risk of its technology choice relative to that of its rivals. In equilibrium firms choose either a safe technology and low debt or risky technology and high debt. MacKay and Phillips (2005) show empirical support for these models. Whether product market interactions can also lead, in some settings, to clustering of financial policies within peer groups is ultimately an empirical question that we address in more detail below.

Finally, Ross (1977) provides an explanation based on costly signalling. He shows that when insiders have better information about firm value than outside investors, insiders may try to use financial structure to signal this information to the market. However, if the signal is not sufficiently costly, low quality firms will imitate the financial structure of the high quality firms to avoid having their type detected. A pooling equilibrium results in which all firms make the same financing choices.

IV. Empirical Model

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

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

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

Equation (2) is similar to existing models found in the capital structure literature, such as equation (1), but for the addition of the K-dimensional vector, $\bar{X}_{-igt}$. This vector contains average firm-specific characteristics for firm i's industry, excluding firm i. Each term in this vector corresponds to a firm-specific determinant in X_{igt}.

The parameter vector is $(\alpha, \beta, \lambda', \gamma', \delta', \phi')$. We refer to these parameters as structural parameters only to distinguish them from the composite, or reduced form, parameters that appear in the context of instrumental variables. Like the vast majority of the empirical capital structure literature, we leave unspecified the precise optimization problem undertaken by the firm.[5]

The three explanations for industry commonality in financial structures are captured by the parameters β, γ, and δ. The peer effect coefficient, β, captures the direct effect of peer firms' financial policies, $\beta \bar{y}_{-igt}$, on firm i's financial policy, y_{igt}. The contextual effects coefficients, γ, captures the effect of peer firms' *characteristics* on firm i's financial policy. Finally, the industry fixed effect coefficients, δ, captures the possibility that firms in the same industry have similar financial policies because they share common (possibly unobserved) characteristics or operate in the same institutional environment.[6]

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

[6] The implicit assumption is that these common unobserved characteristics are either time-invariant or, at least, slow-changing.

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

A. The Identification Problem

The empirical goal is to disentangle the three effects on financial policy emanating from peer effects, contextual effects, and firm characteristics. Ignoring the period fixed effects for the moment, this goal amounts to identifying the structural parameters, $(\alpha, \beta, \lambda', \gamma', \delta')$. The difficulty arises from the presence of $\bar{y}_{-igt}$ as a regressor in equation (2).

The intuition behind the problem is fairly straightforward. If firms' financing decisions are influenced by one another, then firm i's capital structure is a function of firm j's and vice versa. That is, the explanatory variable encompassing firm j's capital structure is simultaneously determined with the dependent variable representing firm i's capital structure. In the context of equation (2), the average industry leverage $\bar{y}_{-igt}$ is an endogenous regressor because all of its components are simultaneously determined with the dependent variable, y_{igt}.

More formally, Manski (1993) shows that without an instrument, one can not separately identify the structural parameters. Specifically, by invoking the equilibrium condition $E(y_i|\mu_g) = E(y_{-i}|\mu_g)$, we can derive the following reduced form model for the population version of equation (2) using the results in Manski (1993):[7]

$$E(y|X, \mu_g) = \frac{\alpha}{1-\beta} + \left(\frac{\beta\lambda + \gamma}{1-\beta}\right)' E(X|\mu_g) + \left(\frac{\delta}{1-\beta}\right)' \mu_g + \lambda' X. \tag{3}$$

Two features of the coefficients of equation (3) are noteworthy. First, we can only identify composite parameters, not the structural parameters themselves, since we are left with five unknowns and only four equations. Second, with $\lambda \neq 0$ the coefficient on the industry average characteristics (i.e., contextual effects) can only be zero if both β and γ are zero. In other words, non-zero coefficients on the contextual effects indicates that either a peer effect or a contextual effect is present. This finding is informative

[7]See Appendix B for a formal derivation.

because it implies that interactions of some type — peer or contextual — are relevant for financial policy.

Table III presents the estimated marginal effects and t-statistics (in parentheses) of the reduced form model. The layout and specifications mimic those found in Table II, but for the replacement of the endogenous peer effect $\bar{y}_{-igt}$ with exogenous lagged contextual effects, $\bar{X}_{-igt-1}$. Two findings are particularly relevant.

First, Columns (1) and (6) show that average industry characteristics capture 6.4% and 16% of the variation in book and market leverage ratios, respectively. These estimates are just over half of the variation captured by the industry average leverage ratios (see the corresponding columns in Table II). The difference in variation is due to some combination of firm-specific effects and peer effects.

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

These findings are important, if ambiguous in their interpretation, because they imply that firms do not pursue similar financial policies solely because they share the same information set, investment opportunities, culture or institutional environment (i.e., correlated effects). Rather, the evidence suggests that firms respond to their peers – either their characteristics or their policies – in making capital structure choices. In order to distinguish between these interactive effects — contextual and peer — we turn to an instrumental variables approach.

V. Disentangling Peer, Contextual, and Correlated Effects

A. The Instrument: Idiosyncratic Equity Shocks

A valid instrument satisfies both the rank (or 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 this subsection, we argue that the idiosyncratic component of *other* firms' equity returns from the previous period satisfies these conditions for instrument validity. We first describe how we construct our instrument. In the following subsection, we discuss why we believe it meets both the relevance and exclusion conditions.

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

$$\begin{aligned} r_{igt} = \alpha \quad &+ \quad \beta_{it}^{m}(rm_t - rf_t) + \beta_{it}^{SMB} SMB_t + \beta_{it}^{HML} HML_t + \beta_{it}^{MOM} MOM_t \\ &+ \quad \beta_{it}^{g}(r_{gt} - rf_t) + \eta_{igt} \end{aligned} \tag{4}$$

The indices are unchanged from above. The first four factors are those typically found in empirical asset pricing studies: the excess market return ($rm_t - rf_t$), the small minus big portfolio return (SMB_t), the high minus low portfolio return (HML_t), and the momentum portfolio return (MOM_t).[8] The fifth factor is the excess return on an equal weighted industry portfolio, ($r_{gt} - rf_t$). While not a priced risk factor, this last factor is included to remove any variation in returns that is common across firms in the same industry. Inclusion of this factor ensures that the estimated residual, our instrument, is orthogonal to industry-wide shocks.

We estimate equation (4) for each firm on a rolling annual basis using historical monthly returns. We require at least 24 months of historical data and use up to 60 months of data in the estimation. For example, to obtain expected and idiosyncratic (i.e., residual) returns for January 1990 through December 1990 for IBM, we first estimate equation (4) using monthly returns from January 1985 through December 1989. Using the estimated coefficients and the factor returns from January 1990 through December 1990, we use equation (4) to compute the expected and idiosyncratic returns as follows:

$$\begin{aligned} \text{Expected Return}_{igt} &= \hat{\alpha} + \hat{\beta}_{it}^{m}(rm_t - rf_t) + \hat{\beta}_{it}^{SMB} SMB_t + \hat{\beta}_{it}^{HML} HML_t \\ &\quad + \hat{\beta}_{it}^{MOM} MOM_t + \hat{\beta}_{it}^{g}(rg_t - rf_t) \\ \text{Idiosyncratic Return}_{igt} &= \hat{\eta}_{igt} \end{aligned}$$

To obtain expected and idiosyncratic returns for 1991, we repeat the process by updating the estimation sample from 1986 through 1990 and using factor returns during 1991. This process generates betas that are firm-specific and time-varying but constant within a calendar year.[9] Thus, our instrument explicitly allows for heterogeneous sensitivities to aggregate shocks.

[8] See Fama and French (1993) and Carhart (1997) for details on the factors. We thank Ken French for kindly providing the data for these factors.

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

Table III presents sample means and medians for the estimated coefficients. On average, each of the rolling regressions has 58 monthly observations, though the majority rely on a full five-year window. Additionally, we see that the average R-square is approximately 30%. Unsurprisingly, the regressions load strongly positively on the industry factor, followed by the market and size factors. The average monthly return is 1.5%. The expected return is slightly larger at 1.6% — a difference exacerbated by rounding — which results in a slight negative average idiosyncratic monthly return. Economically speaking, these differences are negligible.

For consistency with our annual accounting data, we transform the estimated monthly idiosyncratic returns in two ways. First, we annualize the return through compounding. Second, we compute an average monthly return for each calendar year and multiply this average by 12. To ease the discussion we focus on our findings using the first transformation, though our results are qualitatively similar using the second.

Finally, we note that the instrument, average idiosyncratic stock returns, need not be zero for a given observation since the instrument is a conditional average over a subset of firms in a given year. Of course, the average of this average (i.e., the unconditional average) should be and is (bottom of table IV) close to zero.

B. Instrument Validity

Relevance of the instrument is motivated by economic theory suggesting a linkage between stock returns and financial policy. For example, Myers and Majluf (1984) suggest that financial policy is linked to stock prices because of information asymmetry between managers and investors. Likewise, Myers (1977) suggests that financial policy is linked to stock prices because of debt overhang considerations.[10] What is unknown is whether or not the idiosyncratic component of stock returns contains information relevant for financial policy. Fortunately, this condition is empirically testable.

What is untestable is the exclusion condition that disallows any direct link between the instrument and outcome variable. However, there is good reason to believe that this condition is satisfied in our setting. To see why, consider the reduced form version of equation (2), using the idiosyncratic component of other firms' stock returns as instruments for their financing decisions,

$$y_{igt} = \alpha^* + \beta^* \bar{\eta}_{-igt-1} + \lambda^{*'} X_{igt-1} + \gamma^{*'} \bar{X}_{-igt-1} + \rho^{*'} \eta_{igt-1} + \psi^{*'} \omega_i + \delta^{*'} \mu_g + \phi^{*'} \nu_t + \epsilon_{igt}. \quad (5)$$

[10]Indeed, there is a substantial amount of empirical evidence showing that financial policy and stock returns are strongly related (e.g., Loughran and Ritter (1995), Baker and Wurgler (2002), and Welch (2004)).

Idiosyncratic stock returns are denoted by η, and we label the reduced form parameters with " * " to distinguish them from the structural parameters in equation (2). There are two changes to note in equation (5). First, we have replaced the endogenous peer effect variable, $\bar{y}_{-igt}$, with its instrument, lagged average idiosyncratic stock returns, $\bar{\eta}_{-igt-1}$. Second, we have included firm i's lagged idiosyncratic stock return, η_{igt-1} for internal consistency; if other firms' idiosyncratic returns affect their financing decision, so too should firm i's.

Statistically, the concern is that ε_{igt} from equation (2) is correlated with $\bar{\eta}_{-igt-1}$. But recall that any element of ε_{igt} must be both relevant for firm i's financial policy *and* not captured by any of the included capital structure determinants. Likewise, $\bar{\eta}_{-igt-1}$ by definition includes only that portion of other firms returns that is uncorrelated with any of the systematic return factors, including the industry return. Economically, then, any identification threat must come from an omitted variable satisfying the following conditions: (1) it is correlated with the *non-systematic* portion of *other* firms' stock returns, and (2) it is correlated with firm i's financial policy, even after partialing out firm i's idiosyncratic stock return and all other variables included in the model. Broadly speaking, variables relevant to financial policy could be of three types: characteristics of firm i, macroeconomic or market conditions, and characteristics of peer firms (if contextual effects are relevant). Below we consider the plausibility of an identification threat coming through omitted variables of these three types.

Previous empirical work (e.g., Lemmon, Roberts and Zender (2008)) suggests there are a number of firm characteristics that are relevant for capital structure but either poorly measured or omitted from equation (2). However, we argue that it is unlikely that these could satisfy the above conditions of an identification threat. Consider an obvious threat, such as investment opportunities, which are poorly measured and likely correlated with both stock returns and financial policy. In order for an alternative hypothesis based on mismeasured investment opportunities to contaminate our results, one would have to argue that other firms' idiosyncratic returns better capture firm i's investment opportunities than do firm i's idiosyncratic return and all other firm i-specific measures in the regression.

A similar argument could be made for other hard to measure constructs, such as risk and liquidation values. While not impossible, we believe that such an argument is largely implausible since any omitted characteristic of firm i that is relevant to its financial policy should be better captured by firm i's proxy variables (e.g., stock return, market-to-book, size, etc.) than by the idiosyncratic component of firm j's stock return. However, this argument highlights the importance of isolating the idiosyncratic component of stock returns rather than using total returns as an instrument. If the variation in individual total stock returns are dominated by the idiosyncratic component, then the average total return of other firms in an industry may provide a more accurate measure of the investment opportunities facing each individual firm than their own individual stock returns. Effectively, the averaging will net out the noise in each firm's individual stock return. We therefore remove the systematic return components that are likely to to contain information about common investment opportunities and use only on the idiosyncratic portion for our instrument.

It is also unlikely that any omitted market conditions or macroeconomic variables could threaten identification. First, these are likely captured by the year fixed effects in equation (2) or by the systematic return components. Second, any identification threat would have to be reflected in firm j's idiosyncratic return, but not firm i's. This would rule out even sector-specific macro shocks that might not be fully captured by the year fixed effects.

A more subtle threat to identification of the peer effect could come from an omitted contextual variable. That is, it is possible that firm j's idiosyncratic return captures an element of firm j's investment opportunities, risk, etc. that are not captured by the firm j characteristics included in $\bar{X}_{-igt-1}$. If this omitted characteristic of firm j is also relevant for firm i's capital structure, then our instrument could be correlated with the error in equation (2).

While possible, we note that for this to be a concern, several tenuous conditions must hold. First the omitted variable must be specific to a firm's competitors but not shared by the firm itself. Any industry shocks, for example, would be captured by the industry return in equation (4) or by firm i's characteristics and returns. Second, the omitted factor would have to be important enough to affect the competitor's characteristics and the financing choices of both the competitor and firm i, but at the same time not be reflected in firm i's return. For example, suppose a competitor receives a firm-specific shock to investment opportunities that is expected to reduce future profitability. This may increase expected liquidation costs and thereby affect firm i's financing choice. However, it also affects the competitive landscape facing firm i and is therefore likely to be reflected in firm i's stock price and return. Overall, while we can not definitively rule it out, it is difficult to conceive of an economically plausible omitted characteristic that would meet all of the necessary conditions of an identification threat.

One identification threat not adequately addressed is a nonlinear relation between leverage and its determinants. In other words, it may be possible that firm j's idiosyncratic stock return captures an misspecification of functional form. We investigate this possibility in robustness tests below.

Finally, while the exclusion restriction is, strictly speaking, untestable, we can examine the extent to which our instrument correlates with firm characteristics. Note that correlation with the characteristics is not problematic per se, since the characteristics are all included in the regression as control variables. In other words, identification of the peer effect cannot come from variation in the instrument that is correlated with any observable firm characteristics. However, economically large associations between the instrument and firm characteristics raises potential concerns about the extent to which we have removed common variation among firms' returns by estimating equation (4). Recall, the key assumption is that the average idiosyncratic stock return of *other* firms is not a better proxy for the investment opportunities, risk, etc. than the firm i-specific characteristics.

In unreported analysis, we find that there are no statistically significant correlations between our instrument ($\bar{\eta}_{-igt}$) and any of the firm characteristics (X_{igt}). In addition, the correlation between ($\bar{\eta}_{-igt}$) and (η_{igt}) is economically tiny (less than 0.05). Ultimately, the average equity shock of other firms in an industry bears little relation to the characteristics of firm i. This result is reassuring in that there does not appear to be an obvious omitted common factor for which our instrument may be a better proxy than firm i's own characteristics.

C. Leverage

Panel A of Table V presents the estimated marginal effects, t-statistics (in parentheses) and model statistics from two-stage least squares (2SLS) regressions of equation (2). We present results for book and market leverage in both levels and first differences. We instrument for the endogenous peer effect in each specification with the average idiosyncratic stock returns of the peer firms.

The first stage results reveal that the average equity shock is strongly negatively associated with both the level and first difference in average industry leverage ratios. Economically, the sign of the estimate makes sense and is consistent with previous findings relating total returns to leverage. The marginal effects are economically significant as well, stronger than some determinants and weaker than others (unreported). Statistically speaking, the instrument easily passes weak instrument tests (e.g., Stock and Yogo (2005)).

The second stage results build on the results of the reduced form model by showing evidence that — with the exception of changes in book leverage — *both* peer effects and contextual effects play a role in leverage policy. We first note that the estimated firm-specific effects are similar to those found in Table II, and similar to that found in the existing literature. For example, comparing column (9) from Table II with column (2) in Table IV, we note that the coefficients on each firm specific characteristic are all within one percentage point of one another. Similarly, column (4) from Table II reveals marginal effects that are quantitatively close to those in column (1) of Table IV. These similarities are not surprising in light of the fact that the variation from our instrument used to identify the peer effect is uncorrelated with the firm-specific characteristics.

Of more interest, the positive coefficients on the (instrumented) industry average leverage indicate that a firm's capital structure choice is directly influenced by the choices of its industry peers. Even after instrumenting and controlling for own firm characteristics, contextual effects, and industry fixed effects, these peer effects are statistically and economically significant. In fact, the economic magnitude of the peer effect is slightly larger in the 2SLS estimation relative to the OLS estimation. For example, specification (2) of Table V shows that the marginal effect of peers' market leverage ratios is 9.7% using 2SLS. When we estimate this same model by OLS, the estimated marginal effect is 7.0%, almost identical to that found in specification (8) of Table II.

Columns (3) and (4) in Table V reinforce these findings by showing similar results for changes in leverage ratios. In particular, peers have significant influence over both the level and changes to leverage ratios. This finding is reassuring because it shows that the unobserved firm specific heterogeneity found by Lemmon, Roberts, and Zender (2007) is not responsible for our findings.

The significant coefficients on the industry averages suggest that capital structure decisions are affected not only by the leverage choices of a firm's competitors, but also by their competitors' characteristics (i.e., contextual effects). That is, controlling for firm i's characteristics, column (2) implies that firms whose competitors are smaller, more profitable or have higher market-to-book ratios tend to have higher leverage ratios. These latter two results appear consistent with the industry equilibrium argument of Shleifer and Vishny (1992), for example. As a firm's competitors become more financially healthy, liquidation values likely increase. As such, debt becomes less costly, firms can take on more debt, and leverage rises.

More generally, the contextual effects findings suggest that firms consider not only their own characteristics in forming financial policy, but their characteristics relative to their competitors. For example, the positive coefficient on firm i's log(Sales) in column (2) suggests that larger firms on average have higher leverage ratios. However, the negative coefficient on *other* firms' size implies that a firm of a given size will use more leverage when its competitors are smaller than when its competitors are larger. This pattern of opposite signs between firm-specific and contextual effects also holds for the other included and significant characteristics. These results are consistent with the findings of MacKay and Phillips (2005), who suggest that a firm's relative position within its industry is an important determinant of capital structure.

Unfortunately, it is difficult to place a precise interpretation on the contextual effects. There is little theory beyond that explicitly mentioned that speaks directly to these findings, and the proxies are relatively coarse. However, the main implication is that competitor characteristics represents an additional channel through which interactions between a firm and its industry peers can influence its financing choice.

Ultimately, this analysis makes two points. First, the financial policy of peer firms plays an important role in capital structure. In fact, the second most economically important determinant of market leverage, behind industry leverage, is a firm's market-to-book ratio, whose marginal effect is less than 70% that of the peer effect. Second, the characteristics of firms' peers also play a role in shaping financial policy, albeit a seemingly smaller one than that played by their financial decisions.

C.1. Robustness Tests

In Panel B of Table V we present a number of robustness checks to mitigate concerns about the potential identification threats discussed above. Recall that the general concern is that there is an omitted variable relevant to firm i's capital structure that is correlated with our instrument. While the specification in Panel A of Table V includes the most robust empirical capital structure determinants, we explore a number of relevant alternative hypotheses in this subsection by expanding the basic leverage specification along a number of dimensions. In light of the similarity in results across market and book leverage measures, we focus our attention here on market leverage for brevity.

Column (1) presents a linear model of market leverage estimated using 2SLS. This is the same model as in equation (2) but for the inclusion of several additional firm-specific effects and contextual effects in order to mitigate omitted variable concerns. These include the expected stock return, Altman's Z-Score, Graham's marginal tax rate, cash flow volatility, capital expenditures, R & D expense, S,G & A expense and the intra-industry standard deviation of leverage. The estimated peer effect is virtually unchanged from that reported in column (2) of Table V. The inclusion of intra-industry leverage dispersion reinforces the distinction between interactive (i.e., peer or contextual) effects and correlated effects. That is, while peer effects or contextual effects may lead to similar leverage ratios within an industry, our estimates of these effects are not simply capturing the fact that firms in the same industry have similar capital structures (perhaps due to some common omitted factor). Even controlling for the degree of industry commonality, we find that peer firms' policies influence capital structure decisions.

In Column (2) we add underwriter fixed effects to equation (2). That is, we first gather information from the SDC new issues data base on the lead underwriter for every covered issue of public equity, public debt and syndicated loans. For each underwriter, we then create an indicator variable equal to one in a given firm-year if the firm has used that underwriter for any issuance prior to year t. We include these indicators to control for the possibility that firms make similar financing decisions because they receive similar advice from their investment banks. If firm-bank relationships change over time, our instrument could be picking up common bank influence rather than an interactive effect. We note two features of the results. First, inclusion of the bank fixed effects increases the adjusted R^2 by nearly 10 percentage points, suggesting that bank relationships do influence capital structure decisions. However, we also find that the estimated peer effect is virtually unchanged, suggesting that common behavior is not simply a manifestation of common underwriter relationships.

Column (3) adds lagged market leverage to the model of equation (2) as an additional explanatory variable. The results are again similar to those found in column (2) of Table V. This similarity suggests that mean reversion in leverage is not responsible for our findings.

In column (4) we address the concern that other firms' idiosyncratic returns may capture a nonlinear relationship between leverage and the included determinants. Here, the same model as in equation (2) is used but for the inclusion of polynomial terms in all of the exogenous variables. Specifically, we include second and third order polynomial terms for all firm-specific characteristics (X_{igt-1}), contextual effects ($\bar{X}_{-igt-1}$), and firm i's abnormal return. Again, the results mimic those found in column (2) of Table VI, suggesting that identification is not coming through a nonlinear association.

Finally, in column (5), we include contemporaneous, rather than lagged, industry average characteristics. This helps to address the concern that other firms' idiosyncratic returns are picking up a shock to their firm characteristics. If this is the case, these shocks should be reflected in the firms' characteristics at time t. The results show that the estimated peer effect is unaffected, reinforcing again our identification assumption.

D. Financial Policy

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

Column (1) presents results where the dependent variable is an indicator equal to one if the firm performs a net equity issuance in excess of 1% of total assets, and zero otherwise. This regression models the decision by firms to issue equity in a given year. While a logit or probit model may be more appropriate from a forecasting perspective, we present results using the linear model in equation (2) to ease the interpretation and comparison with other findings. Instrumental variables results using a probit model reveal similar findings and are not reported for brevity.

The first stage results reveal that the idiosyncratic component of stock returns is strongly correlated with their equity issuance decisions. This effect is both economically and statistically significant, again highlighting that the idiosyncratic component of stock returns is as important for financial policy if not more so than the systematic component. The second stage results show that the peer effect is also significant. A one standard deviation increase in the probability of issuing equity by peer firms leads to a 6.6% 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.[11] None of the contextual effects are statistically significant.

While the decision to issue equity is closely tied to peers, the relative amount to issue (or repurchase) is unrelated. Column (2) shows no significant relation among firms when choosing the amount of net equity issued relative to their assets. Likewise, debt policy appears to be statistically unrelated to firms' peers under our identification strategy. We say statistically unrelated because the magnitudes of the marginal effects are quite large.

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

Looking at column (3) and the decision to issue debt, the estimated marginal effect suggests that a one standard deviation increase in peer firms' probability of issuing debt is met with an 7.0% increase in the probability of firm i issuing debt. This effect dwarfs those of the firm-specific effects, the largest of which is 3.8% (Net PPE / Assets). However, this estimate is highly imprecise and the first stage estimate only marginally significant. Column (4) reveals analogous results for the relative amount of debt issued - an insignificant peer effect and somewhat weak first-stage estimate.

Column (5) presents results from the same equity issuance decision model as column (1) but restricts the sample to firm-year observations in which the firm issues either equity or debt. In columns (1) through (4), there are many firm-year observations in which firms undertake no net equity or net debt issuing activity. As such, the comparison was with the other financing choice *and* do nothing. Column (5) enables us to understand whether peers affect the preference between debt versus equity. The results show that firms exhibit a strong preference for equity *and* debt when their peers exhibit a similar preference. A one standard deviation increase in the probability of issuing equity relative to debt by firms' peers leads to a 8.9% increase in the probability of issuing equity. Again, this effect is statistically and economically significant, on par with the firm-specific market-to-book ratio. Thus, peer effects impact leverage through the their role in shaping individual financing decisions.

E. Industry-Size Group Peer Effects

A number of studies suggest that corporate peer groups are often segmented within industries according size (e.g., Bizjak, Lemmon, and Naveen (2008) and Byrd, Johnson, and Porter (1998)). Additionally, Table I shows that more half of our industries contain more than 30 firms, which may cloud the estimates by including firms that are not actual peers in the peer group. These facts motivate us to examine peer groups defined not by industry but by within industry size-groups. Specifically, we sort firms within each industry-year by sales, though using assets or market capitalization produces very similar results. We then define three intra-industry groups based on the lower, middle, and upper third of the size distribution.

Table VII presents estimated marginal effects, t-statistics (in parentheses), and model statistics from 2SLS regressions of equation (2). The model specification in column 1 is identical to that found in column 2 in Panel A of Table V. The specification in columns 2 through 5 mimic those of columns 1 through 4 of Table VI. The key differences are, first, peer groups are defined by an industry-size group, as described above, Second, the corresponding instrument is the average idiosyncratic component of stock returns from equation (4), where we replace the equal-weighted industry excess return with an equal-weighted industry-size group excess return. We want to ensure that the instrument is orthogonal to any shock that is isolated to a particular size segment within an industry.

The first stage instrument and second stage peer effect estimates are broadly similar to those found in Table V. A one standard deviation increase in the market leverage of a firms' peers is associated with a 13.0% increase in leverage — a slightly larger effect when compared to broad industry groups (9.6% from Table V panel A). This increase in economic magnitude lends additional support to our identifying assumptions. If we are indeed capturing a peer effect, its strength should increase as we refine the reference group to those firms more likely to be considered by managers as peer firms. In fact, in unreported analysis, when we use coarser definitions of industry groups (e.g., one or two digit SIC groups), we find the peer effect weakens.

Returning to Table VII, the propensity to issue equity, relative to any other action or relative to issuing debt, is likewise strongly positively related to peer firm decisions. One noticeable change relative to Table VI is that the relative amount of equity issued is now significantly positively related to peer firms' decisions. We also see negative associations between firms decisions to issue debt and how much debt to issue. However, inspection of the first-stage estimates reveals that there is no significant association, statistical or economic, between the average idiosyncratic component of stock returns and debt policy. In other words, the identifying variation from the instrument has no explanatory power for debt policy relative to all other financing decisions. Thus, the second stage estimate in this case represents nothing more than noise.

VI. What is the Mechanism Behind the Peer Effect?

Given the importance of peer firm behavior for firms' capital structures, the question that remains is: Why is it so important? In other words, which of the mechanisms discussed earlier in Section III are responsible for the interactions between firms' corporate financial policies?

Unfortunately, answering this question is complicated by the fact that the theories motivating our analysis are not mutually exclusive and, in some cases, do not provide unique hypotheses. However, as we discuss below, they do offer some guidance with respect to the firms and industries in which peer effects should be most prevalent. Thus, while the testable hypotheses are not sharp enough to definitively identify the underlying mechanism, the goal of this section is to shed some light on this question by examining heterogeneity in the peer effect.

A. Learning

Following our discussion in section III, the first mechanism we examine is whether firms learn from one another when optimal capital structure is difficult to discern. In particular, if this is what generates peer effects in the data, one would expect to see differences in behavior between industry leaders and followers: followers' capital structure decisions should be influenced by those of the leaders, but not vice versa. Because there is no formal criteria with which to define an industry leader, we examine several definitions to determine whether some firms within an industry mimic the behavior of other firms within the same industry. Specifically, we hypothesize that industry leaders in market share, experience, and performance will also be viewed as leaders in financial policy.

Market share leaders are defined as those firms with sales falling in the top third of the sales distribution for each industry-year combination. Similarly, firms in the upper third of the within industry-year age distribution are defined as industry leaders or incumbents. Finally, performance leaders are defined as firms in the upper third of the within industry-year return on assets (i.e., profitability) distribution. Firms not defined as leaders are defined as followers.

To test the learning hypothesis, we first estimate the following model of market leverage on the subsample of followers,

$$y_{igt} = \alpha + \beta \bar{y}_{igt}^{Leader} + \lambda' X_{igt-1} + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt}.$$

where $\bar{y}_{igt}^{Leader}$ is the average market leverage for the leaders in the industry. As before, we instrument for this variable using the idiosyncratic stock return of the leaders in period $t-1$. All other notation is unchanged from before. Estimating this specification on the subsample of followers enables us to examine whether followers' financial policies are sensitive to those of industry leaders.

Panel A of Table VIII presents the estimation results. Under each industry leader definition, we see that the first stage results are highly statistically significant, mitigating any weak instrument concerns. We also note that the peer effects are all positive (though not significant in the case of market share), implying that industry leaders do affect follower firm financial policy. The effects are largest when leaders are defined in terms of industry experience and success, as opposed to market share. A one standard deviation change in incumbent firms' or the most profitable firms' leverage ratios are associated with a 7.6% and 10.4% change in follower firm leverage ratios, respectively. These effects are of similar magnitude to those found in the industry as a whole (Table V).

In panel B, we repeat the estimation of panel A, but replace $\bar{y}_{igt}^{Leader}$ with $\bar{y}_{igt}^{Follower}$, the average market leverage for the *followers* in the industry, and estimate the model on the subsample of industry leaders. Interestingly, we find that not only are the estimated peer effects much smaller in magnitude, but none of them are statistically significant. In other words, while non-leaders mimic industry leaders' financial policies (panel A), leaders do not appear to consider follower decisions when setting financial policy (panel B).

We also note that this evidence further supports our identification strategy. That is, the asymmetric response between industry leaders and non-leaders is what one would expect if the coefficient on the instrumented average leverage were in fact measuring a peer effect (and if learning was the mechanism behind such a peer effect). On the other hand, if our instrument were picking up an omitted variable correlated with firm i's capital structure, one would not expect this asymmetry.

Before turning to the next mechanism, we consider an alternative explanation for these results, that of leverage rebalancing (Leary and Roberts (2005)). For example, firms with low profitability may have leverage ratios that are too high relative to their optimum. Consequently, they issue equity to delever, which coincidentally moves their leverage closer to that of their more successful peers. To control for this alternative, we incorporate firm i's lagged leverage ratio to absorb any rebalancing or mean reversion (e.g., Flannery and Rangan (2007) and Kayhan and Titman (2008)) in leverage. The results (not shown) reveal that the marginal effect of leader firm leverage on follower firm leverage remains statistically and economically significant (coefficient of 10.8% with a t-statistic of 4.25).

B. Product Market Competition

In section III we discussed several ways in which the interaction between financial policy and product market competition can lead to peer effects in financing choice. If this is in fact the mechanism behind the peer effects documented in section V, we would expect variation in the strength of this effect across industries on several dimensions.

First, as noted earlier, models of perfectly competitive industries tend to predict intra-industry dispersion in financial policy, while oligopoly models lead to similar financing choices in equilibrium. Therefore, we would expect peer effects to be strongest in less competitive industries and weakest (or perhaps negative) in the most competitive industries.

Second, if firms mimic their peers' financing choices out of a fear of predation, we would expect this effect to be strongest among those firms for which such behavior would be most costly. As noted by Grinblatt and Titman (1998), "The predatory policy of the conservatively financed firm is especially effective in industries where customers and other stakeholders are concerned about the long-term viability of the firms with which they do business." (p. 590) Therefore, we would expect predation to be a larger concern for firms making specialized and unique products than for firms producing standardized or commodity products.

Related, predatory behavior is most costly for firms with significant market share, as they have the most to lose. For example, Opler and Titman (1994) show that the tendency for highly levered firms to lose market share in an industry downturn is most pronounced in industries with fewer competitors. If predation fears are generating peer effects, then we would expect these effects to be strongest in less competitive industries. Note that this prediction is consistent with the more general prediction that financial structure interdependence is more likely to result from models of imperfect competition.

Third, if fear of predation drives interdependence in financing decisions, we would expect peer effects to vary with industry leverage. The direction, however, depends on the form of competition. When firms compete by quantity as in Brander and Lewis (1986), higher debt leads to more aggressive competition and firms cluster at high leverage in equilibrium. In this case, we would expect to find the strongest peer effects in high debt industries. On the other hand, in Bolton and Scharfstein (1990) low leverage facilitates aggressive price competition. Conservatively financed competitors may then induce firms with high debt to de-lever. In this case, peer effects would be strongest in industries with low leverage.

Based on these predictions, we evaluate the potential role of product market competition by studying how peer effects vary with proxies for industry competitiveness, product uniqueness and leverage. We use the Herfindahl-Hirschman Index (HHI) to measure industry competitiveness, and the level of research and development (R&D) spending and sales, general, and administrative (SG&A) expenses to proxy for product uniqueness. For R&D, SG&A and leverage, we first construct an industry-level measure by averaging across firms in an industry each year (HHI is by definition measured at the industry level). We then stratify each proxy's distribution into thirds with group 1 corresponding to the lowest third, group 2 the middle third, and group 3 the upper third. In other words, the most concentrated industries, industries with the highest levels of R&D or SG&A spending and with the highest average leverage all fall in group 3; the most competitive, least R&D or SG&A intensive and least levered all fall in group 1.

We then estimate the following model of market leverage:

$$\begin{aligned} y_{igt} &= \alpha + \beta\bar{y}_{-igt}I_{igt-1}(Group1) + \beta\bar{y}_{-igt}I_{igt-1}(Group2) + \beta\bar{y}_{-igt}I_{igt-1}(Group3) \\ &+ \lambda' X_{igt-1} + \delta'\mu_g + \phi'\nu_t + \varepsilon_{igt}, \end{aligned} \tag{6}$$

where $I_{igt-1}(GroupZ)$ is an indicator function equal to one if firm i is in group $Z \in \{1, 2, 3\}$ during period $t-1$. For example, if Transportation Equipment Manufacturing is among the most concentrated industries during 1990 (highest third of HHI distribution), then the group 3 indicator for all firms in that industry would equal 1 in 1991 because of the one period lag and the other two indicators would equal 0.

The results are presented in Table IX. Because of the interactions, we have three endogenous variables corresponding to the three interactions. As such, we instrument each interaction by interacting the average idiosyncratic stock return of firm i's peers with the corresponding indicator variables identifying in which group firm i falls. In other words,

$$[\bar{\eta}_{-igt-1}I_{igt-1}(Group1)] \text{ instruments for } [\bar{y}_{-igt}I_{igt-1}(Group1)]$$
$$[\bar{\eta}_{-igt-1}I_{igt-1}(Group2)] \text{ instruments for } [\bar{y}_{-igt}I_{igt-1}(Group2)]$$
$$[\bar{\eta}_{-igt-1}I_{igt-1}(Group3)] \text{ instruments for } [\bar{y}_{-igt}I_{igt-1}(Group3)]$$

The first stage F-statistics all reveal highly statistically significant instruments. The second stage results in the first column show little, if any variation in peer effects between competitive and concentrated industries. Peer effects are statistically and economically significant in both concentrated and competitive industries. Further, the coefficient estimate for firms in the lowest HHI group is statistically indistinguishable from that for firms in the highest HHI group. While the significant peer effect in concentrated industries is consistent with a role for product market interactions, the equally strong effect in competitive industries suggest that, at a minimum, this is not the only mechanism at work.

The second and third columns examine how peer effects vary with our proxies for product uniqueness. We find large and significant peer effects for industries with both high and low levels of R&D and SG&A. However, we also find that the magnitude of the peer effect declines significantly as the level of R&D and SG&A spending increases. This is opposite of what we would expect under the predation explanation, as discussed above. For example, a one standard deviation increase in peer firm leverage is associated with a 6.3% increase in leverage in industries with little R&D spending, but only a 4.5% increase in R&D intensive industries. The letters B and C indicate that the pairwise differences between Group 2 and Group 3, and Group 3 and Group 1 are both statistically significantly different from zero at the 5% level.

The fourth column shows that peer effects are more pronounced in industries marked by high leverage and in fact are not statistically significant in low leverage industries. This is again inconsistent with the predictions of a price-based predation story. It could be consistent with a quantity-based competition story as in Brander and Lewis (1986). However, some caution is needed in interpreting this result, as prior empirical evidence (e.g. Opler and Titman (1994)) shows more support for the idea that highly levered firms are at risk for market share loss than that they compete more aggressively.

While perhaps not conclusive, the evidence is overall not supportive of a role for product market interactions in generating peer effects in financing decisions. Peer effects are as strong in competitive industries as in concentrated ones, they become weaker as product uniqueness increases, and they are found primarily in high leverage industries. Note that this does *not* imply that product market interactions are unimportant for capital structure decisions more generally, simply that it is not manifested in a peer effect.

C. Signalling

The third mechanism is based on costly signalling, in which firms pursue similar financial policies as their peers in order to avoid any costs from a separating equilibrium. Under this explanation, the similarity of firms' financial policies should vary with cost of signalling, that is the cost of mimicking one's peers. Inherently unobservable, we proxy for the cost of signalling with proxies for financial constraints. The motivation for this choice is that more constrained firms face a higher cost of capital — due to an underlying market friction such as information or incentive problems — and therefore cannot as easily mimic the behavior of their industry peers.

We use several proxies suggested by prior literature for the degree of financial constraints: whether a firm has a credit rating (Whited (1992), Calomiris, Himmelberg and Wachtel (1995)); whether a firm pays a dividend (Fazzari, Hubbard and Petersen (1988)); firm size (Gilchrist and Himmelberg (1995)); and two indexes of financial constraints: the Whited-Wu index (Whited and Wu (2006)) and K-Z index of Kaplan and Zingales (1997). To examine the sensitivity of peer effects to these financial constraint measures, we follow a similar procedure as in Table IX. The only difference here is that we sort firms (rather than industries) into thirds within each year-industry combination according to the cross-sectional distribution of each proxy. Group 1 again corresponds to the lowest third, group 2 the middle third, and group 3 the upper third of each proxy's distribution. This specification allows the sensitivity of firm i's financial policy to peer firms' policies to vary as a function of i's degree of financial constraint — it's cost of mimicking peers.

Results from estimating equation 6 with the financial constraint based group indicators are shown in Table X. The first stage F-statistics again reveal highly statistically significant instruments. The second stage results reveal mixed evidence. If firms follow their peers' financing choices in an effort to prevent signaling, we would expect to see the strongest evidence of peer effects among the least constrained firms. In support of this prediction, we find that peer effects are larger for firms with a credit rating than for those without. We also see that the sensitivity to peer effects increases monotonically as we move from small (Group 1) to large (Group 3) firms. For small firms, a one standard deviation increase in peer firm leverage is associated with a 5.5% increase in leverage, compared to a highly significant 13.3% increase in leverage for big firms. The results from columns 2 and 3 of Table IX also provide some support for the pooling explanation. If firms with more unique products lose more value in financial distress, then their cost of raising leverage to mimic peers is greater. We would thus expect pooling to be more prevalent among firms with low levels of R & D or SG & A, consistent with the results in Table IX.

However, these conclusions are not robust to other measures of financing constraints. We find peer effects to be weaker for dividend paying firms than for non-payers. We also find that firms with higher values of the Whited-Wu or K-Z indexes (i.e. more constrained) have stronger peer effects. So while there is some suggestive evidence, ultimately the data do not speak clearly on the relation between financing constraints and peer effects.

In sum, we find strong support for a learning story in which costly optimization encourages new entrants or poor performers follow the policies of industry leaders. We find scant evidence to support the role of interactions between financing and product market strategies in generating peer effects. Of course, this finding is not to be misconstrued as evidence against product market competition playing a role in shaping financial policy. Rather, our results here show only that product market competition does not appear to generate a linkage among peer firms' financial policies. The evidence on the role of pooling incentives and financial constraints is unfortunately inconclusive.

VII. Conclusions

This study has shown that firms do not make financing decisions in isolation. Rather, the financing decisions of firms' peers are important determinants of capital structures. Ours is the first study, to our knowledge, to empirically distinguish this peer effect from other explanations for industry commonality in financial structure. We find that not only are peer effects statistically significant, they are economically large. Marginal effects of peer decisions on book leverage, market leverage and the debt-equity choice are on par with or greater than any traditional capital structure determinant.

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

Finally, we find that firms respond strongly to the financial policies of industry leaders, but not vice versa. In other words, industry entrants and poor performers appear to take their financing cues from better performing and more mature firms in the same industry. Given the economic importance of peer effects documented here, we hope that future research will explore more closely the implications for this feedback and the mechanisms behind this capital structure determinant.

Appendix A: Variable Definitions

Compustat variable names denoted by "dataXXX." Time periods are denoted by (t) or (t-1) suffixes.

Book Leverage = (data9 + data34) / data6.

Market Leverage = (data9 + data34) / (data199 * data54 + data34 + data9).

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

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

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

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

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

Tangibility = Net PPE / Assets = data8 / data6.

Profitability = EBITDA / Assets = data13 / data6.

Market-to-Book Ratio = (data199 * data54 + data34 + data9 + data10 + data35) / data6.

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

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

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

Appendix B: The Identification Problem

This appendix derives more formally the identification problem discussed in section IV B. To better understand this problem, consider the population version of equation (2),

$$y = \alpha + \beta E(y|\mu_g) + \lambda' X + \gamma' E(X|\mu_g) + \delta' \mu_g + \varepsilon. \tag{7}$$

The two conditional expectations on the right hand side of equation (7) are peer group means, such as industry averages, and correspond to the peer effects and contextual effects.

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

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

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

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

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

$$E(y|\mu_g) = \frac{\alpha}{1-\beta} + \left(\frac{\gamma+\lambda}{1-\beta}\right)' E(X|\mu_g) + \left(\frac{\delta}{1-\beta}\right)' \mu_g. \tag{10}$$

Equation (10) is the mean regression of y on μ_g. Assuming the intercept, conditional expectation of X, and the group fixed effects are linearly independent, the composite parameters, $\alpha/(1-\beta)$, $[(\gamma+\lambda)/(1-\beta)]'$, and $[\delta/(1-\beta)]'$ are identified. However, the structural parameters $(\alpha, \beta, \gamma', \lambda')$ are not identified since we have fewer equations than unknowns. Therefore, without further information or parameter restrictions, one cannot distinguish peer effects from contextual effects or firm-specific effects.

What is identified can be deduced from the reduced form equation obtained by substituting equation (10) into equation (8).

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

As long as the intercept, the contextual effects, the group fixed effects, and the firm- specific factors are linearly independent, one can identify the reduced-form parameters and λ. More specifically, the coefficients on the average industry characteristics in equation (11) can indicate the presence of either peer effects or contextual effects since either $\beta\lambda$ or γ must be nonzero for the composite coefficient to be nonzero. However, we can not separately identify β without a valid instrument.

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Table I
Summary Statistics

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all analysis variables. The table presents means, standard deviations (SD), and medians. All variables are formally defined in Appendix A.

	Mean	Median	SD
Financial Policy Variables			
Total Debt / Book Assets	0.241	0.218	0.200
Total Debt / Market Assets	0.277	0.219	0.248
$I(NetEquityIssuance/BookAssets > 0.1)$	0.214	0.000	0.410
Net Equity Issuance / Book Assets	0.033	0.000	0.214
$I(NetDebtIssuance/BookAssets > 0.1)$	0.396	0.000	0.489
Net Debt Issuance / Book Assets	0.029	0.000	0.159
Firm Characteristics			
Log(Sales)	4.924	4.865	2.150
Market-to-Book	1.394	0.967	1.374
EBITDA / Assets	0.103	0.127	0.163
Net PPE / Assets	0.320	0.270	0.221
Equity Return	0.188	0.072	0.653
Industry Characteristics			
# of Firms per Industry-Year	18.873	12.000	24.427
Total # of Industries	172		
Sample Characteristics			
Observations	78,023		
Firms	9,208		

Table II

Industry Leverage and Capital Structure: OLS Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from various leverage regressions. All models are estimated by OLS. All variables are in levels and all right hand side variables are lagged one year relative to the dependent variable, book leverage (columns (1) - (5)) or market leverage (columns (6) - (10)). All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Book Leverage					Market Leverage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Industry Avg. Leverage	0.067**		0.052**	0.018**	0.020**	0.102**		0.071**	0.020**	0.039**
	(35.129)		(25.477)	(7.103)	(8.935)	(42.518)		(29.177)	(6.427)	(14.359)
Log(Sales)		0.022**	0.017**	0.018**	0.041**		0.033**	0.022**	0.021**	0.083**
		(11.910)	(9.044)	(9.084)	(7.933)		(14.739)	(9.886)	(9.099)	(15.189)
Market-to-Book		-0.024**	-0.017**	-0.018**	-0.004*		-0.079**	-0.066**	-0.066**	-0.028**
		(-17.004)	(-12.048)	(-12.361)	(-2.541)		(-46.828)	(-41.475)	(-41.013)	(-22.709)
EBITDA / Assets		-0.035**	-0.035**	-0.036**	-0.033**		-0.048**	-0.046**	-0.046**	-0.043**
		(-20.581)	(-20.555)	(-20.825)	(-18.768)		(-29.106)	(-28.459)	(-28.194)	(-24.507)
Net PPE / Assets		0.049**	0.032**	0.045**	0.032**		0.047**	0.030**	0.041**	0.039**
		(24.681)	(15.708)	(16.527)	(10.526)		(21.501)	(13.726)	(13.958)	(11.899)
Firm Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
Industry Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	77,099	78,023	77,099	77,099	77,099	77,098	78,023	77,098	77,098	77,098
Adj. R^2	0.118	0.112	0.165	0.186	0.059	0.200	0.245	0.295	0.314	0.141

Table III

Reduced Form OLS Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from various leverage regressions. All models are estimated by OLS. All variables are in levels and all right hand side variables are lagged one year relative to the dependent variable, book leverage (columns (1) - (5)) or market leverage (columns (6) - (10)). Contextual Effects refer to industry averages excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. F-stat is the test statistics of the null hypothesis that all of the contextual effects' coefficients equal zero. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Book Leverage					Market Leverage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Contextual Effects (Industry Avg.)										
Log(Sales)	0.007**		-0.002	-0.015**	-0.013**	0.026**		0.015**	-0.009	-0.014**
	(2.576)		(-0.640)	(-3.325)	(-3.123)	(7.386)		(4.460)	(-1.780)	(-2.819)
Market-to-Book	-0.020**		-0.013**	0.001	-0.004*	-0.056**		-0.031**	0.001	-0.010**
	(-9.017)		(-6.021)	(0.354)	(-2.535)	(-20.666)		(-12.354)	(0.604)	(-5.233)
EBITDA / Assets	-0.002		0.010**	0.018**	0.006**	-0.015**		-0.002	0.009**	0.001
	(-0.833)		(4.178)	(7.326)	(2.791)	(-5.584)		(-0.914)	(3.231)	(0.497)
Net PPE / Assets	0.034**		0.001	0.006	0.012*	0.031**		0.002	0.019**	0.023**
	(15.208)		(0.375)	(1.056)	(2.238)	(11.854)		(0.503)	(3.024)	(3.714)
Firm Specific Factors										
Log(Sales)		0.022**	0.020**	0.018**	0.041**		0.033**	0.023**	0.021**	0.083**
		(11.915)	(10.083)	(9.087)	(8.061)		(14.745)	(9.905)	(9.163)	(15.246)
Market-to-Book		-0.024**	-0.019**	-0.018**	-0.004*		-0.079**	-0.069**	-0.067**	-0.029**
		(-17.000)	(-12.725)	(-12.595)	(-2.416)		(-46.827)	(-41.780)	(-41.281)	(-22.788)
EBITDA / Assets		-0.035**	-0.037**	-0.037**	-0.033**		-0.048**	-0.048**	-0.047**	-0.044**
		(-20.586)	(-21.459)	(-21.204)	(-18.903)		(-29.112)	(-28.907)	(-28.559)	(-24.845)
Net PPE / Assets		0.049**	0.045**	0.045**	0.032**		0.047**	0.041**	0.041**	0.039**
		(24.682)	(16.299)	(16.538)	(10.543)		(21.502)	(13.365)	(13.844)	(11.940)
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	146.388**		23.453**	14.151**	5.593**	351.506**		91.117**	5.105**	14.863**
Obs	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023
Adj. R^2	0.064	0.112	0.118	0.186	0.056	0.160	0.245	0.261	0.314	0.135

Table IV

Stock Return Factor Regression Results

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

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

where r_{igt} is the return to firm i in industry g during period t, $(rm_t - rf_t)$ is the excess return on the market, SMB_t is the small minus big portfoio return, and HML_t is the high minus low portfolio return, $(rg_t - rf_t)$ is the excess return on an equal-weighted portfolio of stocks in the same industry as defined by three-digit SIC code. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data from the CRSP database. We require at least 24 months of historical data and use up to 60 months of data in the estimation. For example, the factor loadings for January 1990 through December 1990 for IBM are obtained by estimating the regression using monthly returns from January 1985 through December 1989.

	Mean	Median	SD
α_{it}	0.764	0.681	1.567
β_{it}^{M}	0.208	0.281	0.819
β_{it}^{SMB}	0.123	0.112	0.940
β_{it}^{HML}	-0.000	0.020	0.846
β_{it}^{IND}	0.810	0.709	0.684
β_{it}^{MOM}	-0.013	-0.013	0.575
Obs Per Regression	58	60	5
Adjusted R^2	0.298	0.291	0.179
Avg. Monthly Return	0.015	0.000	0.180
Expected Monthly Return	0.016	0.013	0.116
Idiosyncratic Monthly Return	-0.001	-0.007	0.174

Table V
2SLS Leverage Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from various leverage regressions. All models are estimated by linear 2SLS where the endogeneous variable is the Peer Effect, Industry Avg., and the instrument is the industry average idiosyncratic component of stock returns (i.e., Avg. Equity Shock). All variables are in levels, unless otherwise indicated atop the columns, and all right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable, book leverage (columns (1) - (5)) or market leverage (columns (6) - (10)). Contextual Effects refer to industry averages excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. In Panel B, Investment Bank Indicators refer to indicator variables for the primary or lead underwriter for the firm's past security issuances, debt or equity. Additional Control Variables include firms specific and contextual effects for expected stock returns, 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. Polynomials of Exogenous Variables include quadratic and cubic terms of all right hand side variables. Contemporaneous Contextual Effects replaces the lagged contextual effects with contemporaneous measures. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Panel A: Leverage Regressions

	Levels		1^{st} Differences	
	Book Leverage	Market Leverage	Book Leverage	Market Leverage
	(1)	(2)	(3)	(4)
Peer Effect				
Industry Avg.	0.057**	0.096**	0.019**	0.057**
	(2.687)	(4.351)	(3.350)	(6.541)
Contextual Effects (Industry Avg.)				
Log(Sales)	-0.013**	-0.014**	-0.002	-0.006**
	(-2.812)	(-2.637)	(-1.253)	(-3.225)
Market-to-Book	0.009*	0.030**	0.001	0.001
	(2.368)	(4.172)	(0.910)	(0.929)
EBITDA / Assets	0.017**	0.021**	0.001	0.002**
	(7.044)	(5.250)	(1.891)	(3.253)
Net PPE / Assets	-0.019	-0.013	-0.000	-0.002*
	(-1.690)	(-1.262)	(-0.903)	(-2.318)
Firm Specific Factors				
Log(Sales)	0.017**	0.021**	0.002**	0.007**
	(8.770)	(8.991)	(4.474)	(13.746)
Market-to-Book	-0.018**	-0.066**	-0.002**	0.001
	(-12.233)	(-40.716)	(-3.095)	(1.738)
EBITDA / Assets	-0.037**	-0.047**	-0.003**	-0.004**
	(-21.197)	(-28.195)	(-5.107)	(-6.660)
Net PPE / Assets	0.044**	0.040**	0.003**	0.005**
	(16.312)	(13.441)	(7.450)	(9.798)
Equity Shock	-0.002*	-0.003**	-0.000	0.002**
	(-2.350)	(-4.369)	(-0.742)	(4.186)
First Stage Instrument				
Avg. Equity Shock	-0.016**	-0.026**	-0.016**	-0.026**
	(-15.986)	(-19.883)	(-16.024)	(-19.761)
Industry Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Obs	78,016	78,016	77,236	77,235
Adj. R^2	0.182	0.312	0.001	0.060

Panel B: Robustness Tests

	Market Leverage				
	(1)	(2)	(3)	(4)	(5)
Peer Effect					
Industry Avg.	0.094**	0.098**	0.093**	0.095**	0.090**
	(6.206)	(3.342)	(6.394)	(4.769)	(2.718)
First Stage Instrument					
Avg. Equity Shock	-0.041**	-0.027**	-0.026**	-0.028**	-0.018**
	(-26.592)	(-13.398)	(-19.887)	(-21.472)	(-14.100)
Contextual Effects	Yes	Yes	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Additional Control Variables	Yes	No	No	No	No
Investment Bank Indicators	No	Yes	No	No	No
Lagged Dependent Variable	No	No	Yes	No	No
Polynomials of Exogenous Variables	No	No	No	Yes	No
Contemporarneous Contextual Effects	No	No	No	No	Yes
Obs	73,533	33,516	78,015	78,016	77,805
Adj. R^2	0.354	0.404	0.771	0.377	0.311

Table VI

2SLS Financing Decision Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. The dependent variable is indicated at the top of the columns in both panels. All right hand side variables are lagged one period, and all estimation is via linear two stage least squares. Issue Stock (Debt) is an indicator variable equal to one if Net Stock (Debt) Issuances — which is normalized by book assets — is greater than 1%. Column (5) isolates the subsample of observations in which either an equity or debt issuance occurred. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Issue Stock	Net Stock Issuances	Issue Debt	Net Debt Issuances	Issue Stock*
	(1)	(2)	(3)	(4)	(5)
Peer Effects					
Industry Avg.	0.066*	0.004	0.070	0.006	0.089*
	(2.522)	(0.223)	(0.487)	(0.249)	(2.048)
Contextual Effects (Industry Avg.)					
Log(Sales)	-0.005	-0.009**	-0.001	-0.001	0.001
	(-0.656)	(-3.301)	(-0.130)	(-0.236)	(0.093)
Market-to-Book	-0.007	0.003	0.015	0.005	-0.035
	(-0.516)	(0.271)	(0.798)	(0.655)	(-1.624)
EBITDA / Assets	0.005	0.009**	0.021	0.006	-0.032**
	(1.176)	(3.485)	(0.561)	(0.918)	(-4.953)
Net PPE / Assets	0.012	0.009**	-0.010	-0.001	-0.004
	(1.394)	(3.127)	(-0.550)	(-0.420)	(-0.361)
Firm Specific Factors					
Log(Sales)	-0.028**	-0.014**	0.027**	-0.006**	-0.051**
	(-9.886)	(-11.066)	(9.713)	(-7.987)	(-12.592)
Market-to-Book	0.097**	0.065**	0.006*	0.014**	0.094**
	(34.709)	(21.447)	(2.275)	(13.971)	(28.191)
EBITDA / Assets	-0.035**	-0.064**	-0.006*	0.006**	-0.023**
	(-14.498)	(-22.379)	(-1.988)	(5.556)	(-6.525)
Net PPE / Assets	0.010**	0.011**	0.038**	0.000	-0.021**
	(3.149)	(8.043)	(11.530)	(0.260)	(-4.908)
Equity Shock	0.025**	0.013**	0.007**	0.004**	0.019**
	(15.880)	(10.020)	(3.956)	(4.986)	(8.416)
First Stage Instrument					
Avg. Equity Shock	0.056**	0.035**	-0.011**	-0.007**	0.056**
	(20.117)	(10.571)	(-3.752)	(-5.587)	(13.417)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	78,016	78,016	78,016	78,016	34,686
Adj. R^2	0.165	0.228	0.046	0.031	0.267

Table VII
2SLS Regressions: Industry-Size Groups

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from variations of the following model of leverage

$$y_{igt} = \alpha + \beta \bar{y}_{-igt-1} + \gamma \bar{X}_{-igt-1} + \lambda' X_{igt-1} + \psi' \omega_i + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt},$$

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt-1}$ is the lagged average industry-size category leverage excluding firm i's outcome and is the endogenous regressor. The term X_{igt-1} is a vector of lagged firm specific characteristics. The term $\bar{X}_{-igt-1}$ is a vector of contextual effects computed as the lagged average industry-size category firm characteristics excluding firm i's outcome. Firm, industry, and year fixed effects are denoted by ω_i, μ_g, and ν_t, respectively. The table also presents the estimated marginal effect and t-statistic for the instrument from the first stage regression. There are three size categories per industry defined by the lower, middle, and upper third of the within industry size-distribution. All models are estimated using two stage least squares. Specification (6) estimates the model on a subsample consisting of firms that either issued debt or equity but not both in a given year. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Market Leverage	Issue Stock	Net Stock Issuances	Issue Debt	Net Debt Issuances
	(1)	(2)	(3)	(4)	(5)
Peer Effects					
Industry-Size Group Avg.	0.130**	0.065*	0.053**	0.135	-0.155
	(3.162)	(2.399)	(2.673)	(0.554)	(-0.436)
Contextual Effects (Group Avg.)					
Log(Sales)	-0.021**	0.019**	0.014**	-0.006	-0.022
	(-4.480)	(3.244)	(5.182)	(-0.528)	(-0.377)
Market-to-Book	0.037**	-0.009	-0.016*	-0.001	0.032
	(2.590)	(-0.933)	(-2.011)	(-0.055)	(0.472)
EBITDA / Assets	0.038**	0.008*	0.015	0.006	0.028
	(6.843)	(2.127)	(1.563)	(0.354)	(0.521)
Net PPE / Assets	-0.026*	0.005	-0.002	-0.014	-0.003
	(-2.552)	(0.902)	(-0.779)	(-0.430)	(-0.421)
Firm Specific Factors					
Log(Sales)	0.019**	-0.037**	-0.016**	0.022**	-0.010**
	(5.510)	(-7.378)	(-6.835)	(4.620)	(-5.564)
Market-to-Book	-0.064**	0.098**	0.064**	0.007*	0.015**
	(-39.393)	(34.510)	(21.186)	(2.202)	(4.984)
EBITDA / Assets	-0.055**	-0.035**	-0.059**	-0.007*	0.007
	(-26.781)	(-13.832)	(-20.476)	(-2.139)	(1.856)
Net PPE / Assets	0.040**	0.010**	0.011**	0.037**	-0.000
	(13.684)	(3.354)	(7.980)	(9.580)	(-0.077)
Equity Shock	-0.003**	0.025**	0.012**	0.007**	0.003*
	(-3.404)	(15.675)	(9.515)	(3.843)	(2.139)
First Stage Instrument					
Avg. Equity Shock	-0.010**	0.036**	0.014**	0.005	0.001
	(-7.815)	(14.479)	(9.766)	(1.820)	(0.581)
Fixed Effects					
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Obs	77,399	77,374	77,374	77,402	77,402
Adj. R^2	0.276	0.161	0.230	0.006	

Table VIII

2SLS Regressions: Do Firms Mimic Industry Leaders?

The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from variations of the following model of leverage

$$y_{igt} = \alpha + \beta \bar{y}_{igt-1}^{Leader} + \gamma \bar{X}_{-igt-1} + \lambda' X_{igt-1} + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt},$$

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt}$ is the average leverage of leader firms in i's industry. and is the endogenous regressor. Leader (follower) firms are defined by the top (bottom and middle) tertiale of the within industry-year distribution of sales, years spent within an industry, and profitability. Panel A restricts attention to the sample of followers and includes the average leverage of the leader firms as the endogenous peer effect. Panel B restricts attention to the sample of leaders and includes the average leverage of the follower firms as the endogenous peer effect. The term X_{igt-1} is a vector of lagged firm specific characteristics. The term $\bar{X}_{-igt-1}$ is a vector of contextual effects computed as the lagged average industry-size category firm characteristics excluding firm i's outcome. the lagged average industry-size category firm characteristics excluding firm i's outcome. Industry and year fixed effects are denoted by μ_g, and ν_t, respectively. The table also presents the estimated marginal effect and t-statistic for the instrument from the first stage regression. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Panel A: Sample of Non-Leader Firms - Industry Leader Peer Effects

	Industry Leaders		
	Big Firms	Incumbent Firms	Profitable Firms
Peer Effect			
Leader Firm Avg.	0.025	0.076*	0.104**
	(1.127)	(2.217)	(2.850)
First Stage Instrument			
Leader Firm Avg. Equity Shock	-0.030**	-0.021**	-0.012**
	(-16.346)	(-9.309)	(-8.523)
Contextual Effects	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	45,434	39,555	49,267
Adj. R^2	0.319	0.315	0.305

Panel B: Sample of Leader Firms - Industry Non-Leader Peer Effects

	Industry Non-Leaders		
	Small Firms	Entrant Firms	Unprofitable Firms
Peer Effect			
Non-Leader Firm Avg.	0.025	0.056	0.064
	(1.473)	(1.374)	(1.723)
First Stage Instrument			
Non-Leader Firm Avg. Equity Shock	-0.019**	-0.007**	-0.013**
	(-16.953)	(-7.425)	(-9.245)
Contextual Effects	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	56,781	55,236	54,968
Adj. R^2	0.346	0.325	0.324

Table IX
The Role of Product Market Competition and Predation

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from variations of the following model of market leverage

$$y_{igt} = \alpha + \beta' \bar{y}_{-igt-1} \times I_{igt-1} + \gamma \bar{X}_{-igt-1} + \lambda' X_{igt-1} + \psi' \omega_i + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt},$$

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt-1}$ is the lagged average industry market leverage excluding firm i's outcome and is the endogenous regressor. The term I_{igt-1} is a group indicator variable corresponding to the upper, middle, or lower third of the distribution for an interaction variable. The interaction varibles are the herfindahl index of the industry, the market leverage of the industry, the average ratio of R&D expenditures to sales for the industry, and the average ratio of SG&A expenditures to sales for the industry. The term X_{igt-1} is a vector of lagged firm specific characteristics. The term $\bar{X}_{-igt-1}$ is a vector of contextual effects computed as the lagged average industry-size category firm characteristics excluding firm i's outcome. Industry and year fixed effects are denoted by μ_g and ν_t, respectively. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments. All models are estimated using two stage least squares. All test statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Superscript "A", "B", and "C" correspond to statistically significant (5% level) differences in the peer effects coefficients between groups 1 and 2, 2 and 3, and 1 and 3, respectively. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Herfindahl Index (3=Concentrated)	R&D Exp. (3=Large)	SG&A Exp. (3=Large)	Market Leverage (3=High)
Peer Effects				
Industry Avg. × Group 1	0.108**	0.079**	0.127**	0.047*
	(4.173)	(4.533)	(4.224)	(2.164)
Industry Avg. × Group 2	0.107**	0.068**	0.102**	0.082**
	(4.149)	(4.520)^{B}	(4.281)^{B}	(2.650)
Industry Avg. × Group 3	0.104**	0.057**	0.082**	0.138**
	(4.528)	(5.090)^{C}	(5.237)^{C}	(3.870)
First Stage Multivariate F-stat	133.534**	176.473**	129.373**	94.961**
Contextual Effects	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Obs	78,016	78,016	78,016	78,016
Adj. R^2	0.312	0.311	0.310	0.314

Table X
The Role of Financial Constraints

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from variations of the following model of market leverage

$$y_{igt} = \alpha + \beta' \bar{y}_{-igt-1} \times I_{igt-1} + \gamma \bar{X}_{-igt-1} + \lambda' X_{igt-1} + \psi' \omega_i + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt},$$

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt-1}$ is the lagged average industry market leverage excluding firm i's outcome and is the endogenous regressor. The term y_{igt-1} is the lagged dependent variable. The term I_{igt-1} is a group indicator variable corresponding to the upper, middle, or lower third of the distribution for an interaction variable. The interaction varibles are whether or not the firm has a credit rating, whether or not the firm pays a dividend, the size of the firm, the Whited & Wu index of financial constraints, the Kaplan & Zingales index of financial constraints. The term X_{igt-1} is a vector of lagged firm specific characteristics. The term $\bar{X}_{-igt-1}$ is a vector of contextual effects computed as the lagged average industry-size category firm characteristics excluding firm i's outcome. Industry and year fixed effects are denoted by μ_g and ν_t, respectively. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments. All models are estimated using two stage least squares. All test statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Superscript "A", "B", and "C" correspond to statistically significant (5% level) differences in the peer effects coefficients between groups 1 and 2, 2 and 3, and 1 and 3, respectively. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Credit Rating (2=Yes)	Dividend Payer (2=Yes)	Firm Size (3=Big)	WW Index (3=Constrained)	KZ Index (3=Constrained)
Peer Effects					
Industry Avg. × Group 1	0.110**	0.146**	0.055*	0.082**	0.024
	(4.214)^{A}	(5.648)^{A}	(2.068)^{A}	(3.749)^{A}	(1.060)^{A}
Industry Avg. × Group 2	0.130**	0.098**	0.098**	0.098**	0.097**
	(6.782)	(3.503)	(3.784)^{B}	(4.668)	(4.421)^{B}
Industry Avg. × Group 3			0.133**	0.095**	0.190**
			(5.103)^{C}	(4.449)^{C}	(8.395)^{C}
First Stage Multivariate F-stat	198.676**	196.543**	126.674**	163.484**	139.333**
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	78,016	78,016	78,016	78,016	78,016
Adj. R^2	0.308	0.351	0.287	0.322	0.477