Follow the Leader: Strategic Interaction in Corporate Capital Structure*

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Abstract

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. Using an instrumental variables approach, we show that firms' industry peers play an important role in shaping corporate financial policies. A one standard deviation shift 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 learning from industry leaders.

Do firms' financing decisions affect one another? Most research on corporate capital structure focuses on traditional hypotheses, such as tradeoff and pecking order, which ignore interactions among firms' financial policies. However, there are a several reasons to believe that firms do not make financing decisions in isolation of one another. For example, 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, capital structure determinant. Further, survey evidence indicates that CFOs often consider the financing decisions of other firms in their industry when setting financial policy.[1]

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 median 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 is that firms in the same industry have similar firm characteristics or face similar institutional environments, such as production technologies and investment opportunities. The second explanation is that firms are responding to the characteristics of other firms in the industry, or the context in which they operate. This explanation is referred to as a contextual effect. For example, firms whose competitors are more financially sound may face lower liquidation costs (Shleifer and Vishny (1992)), leading to higher optimal debt ratios. The last explanation, and the focus of our study, is that a true peer effect exists, in which the decisions of firms' peers directly affect the decisions of each firm.

The goal of this paper is to disentangle these explanations to better understand

[1]See studies by Brander and Lewis (1986) and Maksimovic and Zechner (1989) (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.

the role played by firms' peers in determining financial policy. 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. While purging almost all of the correlation among firms' idiosyncratic returns, we also include as a control variable the own-firm idiosyncratic stock return. Doing so alleviates the concern that variation in the instrument which is correlated with the own-firm idiosyncratic return is being used for identification.

In other words, even if the shock to firm j's stock price is correlated with the shock to firm i's stock price, this correlation is absorbed by including firm i's idiosyncratic return as a regressor. Therefore, the threat to our identification strategy is isolated to an unobserved variable that is (1) correlated with firm i's financial policy, (2) correlated with *other* firms' idiosyncratic stock returns, and (3) *un*correlated with firm i's idiosyncratic stock return, as well as the systematic component and all other firm i-specific control variables. Ultimately, one must argue that the idiosyncratic component of other firms' stock returns is a better proxy for firm i's investment opportunities or risk, for example, than firm i's characteristics. While such a variable is not immediately apparent, we undertake several robustness tests to ensure proper identification of the peer effect.

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 that firms' capital structure choices are directly influenced by those of their industry peers. Moreover, this 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 by far the most important observable determinant of corporate capital structure.

While our primary contribution is to establish the existence and importance of peer effects in financial structure, we also examine the possible mechanisms behind these results. In particular, we show that younger, less successful firms mimic the capital structures of industry leaders — more mature, successful firms. However, the reverse is not true; industry leaders are not influenced by the policies of followers. 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. If peer effects are driven by the interaction between financing and product market strategies, we would expect peer effects to be strongest in less competitive industries and those producing more unique and specialized products. Neither of these predictions are supported by the data. On the other hand, if capital structure interdependence is driven by efforts to avoid separating equilibria, then peer effects should be strongest for those firms facing less severe financial constraints. This prediction receives some limited, if not robust, support in the data. Ultimately, the data are most suggestive of a learning mechanism.

Our study is most closely related to several studies that have documented 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.

In this sense, our study also helps shed light on the meaning of existing capital structure determinants. As Rajan and Zingales (1995) point out, there are a variety of factors that are correlated with corporate financial policy. Yet, the precise meaning of these correlations is not particularly well understood. Kurshev and Strebulaev (2006) undertake a similar exercise in understanding the relation between firm size and capital structure, albeit from a theoretical perspective.

Finally, our study is 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 (1989). 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 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.[2] Finally, we exclude observations in industries — defined by three-digit standard industrial classification (SIC) code — with fewer than 10 firms because we need a minimal number of firms to form peer groups.[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.

Table I presents summary statistics for our sample. The aforementioned screens produce 78,189 firm-year observations corresponding to 9,227 unique firms. There are 172 industries represented in our sample. The typical industry contains approximately 54 firms, though the distribution is highly right skewed as indicated by the median number of firms, 30. 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 five 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 3.4%, 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 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

[2]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.

[3]Changing this requirement to five or 15 makes no substantive difference for our results or inferences.

statistics for several variations of the following model of leverage,

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

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, $\bar{y}_{-igt-1}$, is the peer effect, equal to the average leverage for firm i in industry g during period $t-1$, excluding firm i's outcome.[4] 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 firm (ω_i), industry (μ_g), and year (ν_t) fixed effects to capture common components of leverage ratios. For identification, in each specification we restrict either the firm or the 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 leverage is associated with a 5.3% change in individual firms' leverage ratios. This effect is almost 30% larger, in magnitude, then 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 all of the other observable determinants combined.

Specifications (4) and (5) incorporate industry and firm fixed effects to address unobserved heterogeneity concerns (Lemmon, Roberts, and Zender (2009)). While no longer

[4] Using the median produces similar results.

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, though its meaning is unclear, 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 (2009), 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.

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. It also shows that industry average leverage is the most economically significant determinant, after the lagged dependent variable. This ranking is unaffected by the inclusion of alternative 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 decision making is costly. Conlisk (1980) shows that 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 (1989) 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 and Identification Strategy

A. 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,

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

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

The parameter vector is $(\alpha, \beta, \lambda', \gamma', \psi', \delta', \phi')$. 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 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.

B. 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 firm and 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).

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

We defer a formal derivation of the identification problem to Appendix C. Instead, we discuss here the intuition behind the problem, which 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 peer effect $\bar{y}_{-igt}$ is an endogenous regressor because all of its components are simultaneously determined with the dependent variable, y_{igt}.

Due to this simultaneity, we need an instrument to identify the coefficient vector, and by extension, the effect of peer behavior on financing behavior. Specifically, we require a variable that enters into the equation for firm j's leverage, but does not belong in the equation for firm i's leverage. In the next subsection we propose an instrument that meets these criteria.

C. 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.

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.[6] 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

[6]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)).

instruments for their financing decisions,

$$y_{igt} = \alpha^* + \beta^* \bar{\eta}_{-igt-1} + \lambda^{*'} X_{igt-1} + \gamma^{*'} \bar{X}_{-igt-1} + \psi^{*'} \eta_{igt-1} + \delta^{*'} \mu_g + \phi^{*'} \nu_t + \varepsilon_{igt}. \quad (3)$$

Idiosyncratic stock returns are denoted by η, and we identify the reduced form parameters with " * " to distinguish them from the structural parameters in equation (2). There are two changes to note in equation (3). 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.

Before discussing the threat to our identification strategy, 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 close to zero. These facts will become clearer when we discuss the estimation of idiosyncratic returns below.

Returning to the identification problem, Equation (3) shows that any identification threat must come from an omitted variable satisfying the following conditions: (1) it is correlated with our instrument, *other* firms' idiosyncratic stock returns, (2) it is correlated with firm i's financial policy, and (3) it is *un*correlated with firm i's idiosyncratic stock return, as well as the systematic component of returns and all other variables included in the model. Consider an obvious threat, investment opportunities, which are poorly measured and likely correlated with 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 the investment opportunities affecting firm i then firm i's idiosyncratic stock 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 variable relevant to both firm i's financial policy and other firms' idiosyncratic stock return should be better captured by firm i's characteristics than the idiosyncratic component of firm j's stock return. However, this argument highlights the importance of isolating the idiosyncratic component of stock returns. We are assuming that the average idiosyncratic returns of other firms is not a better measure of investment opportunities, for example, than the firm's own measures (e.g., idiosyncratic return, market-to-book, size, etc.). It also highlights why we do not use total stock 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.

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 our robustness tests found in Appendix B.

D. Estimation of Idiosyncratic Equity Shocks

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

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

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).[7] 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

[7] 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.

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.[8] Thus, our instrument explicitly allows for heterogeneous sensitivities to aggregate shocks.

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 unchanged using the second.

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.

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

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.

V. Disentangling Peer, Contextual, and Firm-Specific Effects

A. 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). Specifically, we instrument for the endogenous peer effect with the average idiosyncratic stock returns of the peer firms. For completeness, we examine both book and market leverage. However, we focus on linear specifications here, leaving an investigation of more flexible functional forms to the robustness tests found in Appendix B.

The first stage results reveal that the average equity shock is strongly negatively associated with average industry leverage. 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 indicate that even after instrumenting and controlling for own firm characteristics, contextual effects, and industry fixed effects, peer effects are statistically and economically significant. In fact, the economic magnitude of the peer effect is dramatically larger in the 2SLS estimation relative to the OLS estimation. For example, specification (2) of Table VI 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 2.0%, almost identical to that found in specification (9) of Table II.

While our primary interest is in the interaction among financing choices, the contextual effects reveal some additional insight into the importance of industry in explaining leverage. Keeping in mind that all variation is within industry because of the fixed effects, we note the following. Firms in industries undergoing increases in demand, as indicated by log(sales), tend to reduce their leverage. Firms in industries with greater growth in profits and improving investment opportunities tend to increase their leverage. 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.

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.

Also of interest is the relation between the contextual effects and their corresponding firm characteristics, the signs of which are generally opposite of one another. Consider firm profitability (EBITDA / Assets). The contextual effect has a positive sign, while the firm-specific effect has a negative sign. Thus, while firms in industries whose profitability is increasing tend to increase leverage, more profitable firms within an industry tend to reduce their leverage, perhaps via passive accumulation of profits (e.g., Strebulaev (2007)) or to mitigate adverse selection costs (Myers and Majluf (1984)). Firm size displays a similar dichotomy. Firms in growing industries tend to reduce their leverage, though larger firms within an industry tend to be more levered. These results suggest that, consistent with the findings of MacKay and Phillips (2005), it is not only a firm's absolute characteristics that affect its capital structure choice, but its relative position within its industry.

We also note that many of the industry fixed effects are highly statistically significant. Thus, all three of the potential explanations for industry commonality – peer effects, contextual effects and correlated unobserved characteristics – are empirically relevant. The peer effects, however, are especially important. In fact, the direct affect of firms' peers is significantly more important than any other observable determinant of corporate capital structure. Looking at market leverage, we see that the second most economically important determinant behind industry leverage is a firm's market-to-book ratio, whose marginal effect is less than 70% that of the peer effect.

B. Financial Policy

In Panel B of Table IV, 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 presented in Appendix B.

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.[9] 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.

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

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

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.

C. 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 V presents estimated marginal effects, t-statistics (in parentheses), and model statistics from 2SLS regressions of equation (2). The model specifications are identical to those found in Panels A and B 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 IV. 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. Likewise, the propensity to issue equity, relative to any other action or relative to issuing debt, is strongly positively related to peer firm decisions. One noticeable change 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 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 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 in order to avoid the costs of optimization. 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 define industry leaders using three different criteria based on market share, industry experience, and performance.

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 VI 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, 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 6.5% and 9.6% change in follower firm leverage ratios, respectively. These effects are of similar magnitude to those found in the industry as a whole (Table IV).

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 followers mimic leaders' financial policies (panel A), leaders do not appear to consider follower decisions when setting financial policy (panel B).

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:

$$\begin{aligned} y_{igt} &= \alpha + \beta \bar{y}_{-igt} I_{igt-1}(Group1) + \beta \bar{y}_{-igt} I_{igt-1}(Group2) + \beta \bar{y}_{-igt} I_{igt-1}(Group3) \\ &+ \lambda' X_{igt-1} + \delta' \mu_g + \phi' \nu_t + \varepsilon_{igt}, \end{aligned} \quad (5)$$

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 VII. 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 VIII. 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 5 with the financial constraint based group indicators are shown in table VIII. 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 (statistically insignificant)

3.1% increase in leverage, compared to a highly significant 9.5% increase in leverage for big firms. The results from columns 2 and 3 of Table VII 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 VII.

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: Robustness

Table IX displays the estimated marginal effects and t-statistics in parentheses from several robustness tests. 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 firm i's expected return as an additional explanatory variable to control for any mechanical effect of returns on market leverage. The estimated peer effect is virtually unchanged from that reported in column (2) of Table IV. The specification in Column (2) is also the same as in equation (2) but for the inclusion of three additional firm-specific effects and contextual effects based on Altman's Z-Score, Graham's marginal tax rate, and earnings volatility. The results are again nearly identical to those found in Table IV, suggesting that peer effects are not proxying for any of these factors.

Columns (3) and (4) also present linear models of market leverage estimated using 2SLS. In the former, the same model as in equation (2) is used but for the inclusion of lagged market leverage as an additional explanatory variable. The results are virtually identical to those found in column (2) of Table VI. This similarity suggests that mean reversion in leverage is not responsible for our findings. In the latter, 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.

Columns (5) and (6) reexamine the equity issuance decision using maximum likelihood (ML) estimation of a probit model, while simultaneously accounting for the endogeneity of the peer effect. The only distinction between the two specifications is the exclusion (column (5)) or inclusion (column (6)) of second and third order polynomial terms for all of the exogenous variables. The results are strikingly similar to those found in column (1) of Panel B, Table IV, after making the appropriate adjustments to compute marginal effects.[10]

[10] The marginal effects of the probit model are computed as the difference between two predicted probabilities. The first probability is evaluated at the mean value for all explanatory variables but for the peer effect, which is set to one half standard deviation below the sample mean. The second probability is also evaluated at the mean value for all explanatory variables but for the peer effect, which is set to one half standard deviation above the sample mean. Subtracting the former from the latter produces the estimated marginal effect of a one standard deviation change in the peer effect on the estimated probability of issuing equity.

Appendix C: 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),

$$y = \alpha + \beta E(y|\mu_g) + \lambda' X + \gamma' E(X|\mu_g) + \delta' \mu_g + \varepsilon. \tag{6}$$

The two conditional expectations on the right hand side of equation (6) 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

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

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

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

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

$$E(y|\mu_g) = \frac{\alpha}{1-\beta} + \left(\frac{\gamma+\lambda}{1-\beta}\right)' E(X|\mu_g) + \left(\frac{\delta}{1-\beta}\right)' \mu_g. \tag{9}$$

Equation (9) 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 (9) into equation (7).

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

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 (10) 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 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	0.034	0.000	0.216
$I(NetDebtIssuance/BookAssets > 0.1)$	0.396	0.000	0.489
Net Debt Issuance / Book Assets	0.029	0.000	0.160
Firm Characteristics			
Log(Sales)	4.925	4.865	2.146
Market-to-Book	1.394	0.967	1.369
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	53.645	30.000	90.935
Total # of Industries	172		
Sample Characteristics			
Observations	78,189		
Firms	9,227		

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 variations of the following model of leverage

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

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt-1}$ is the lagged average industry leverage excluding firm i's outcome. The term X_{igt-1} is a vector of lagged firm specific characteristics. Firm, industry, and year fixed effects are denoted by ω_i, μ_g, and ν_t, respectively. All models are estimated by OLS. 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 defined in Appendix A.

	Book Leverage					Market Leverage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Industry Avg. Leverage	0.067**		0.053**	0.018**	0.021**	0.102**		0.071**	0.020**	0.040**
	(35.179)		(25.531)	(7.111)	(8.924)	(42.713)		(29.342)	(6.597)	(14.583)
Log(Sales)		0.022**	0.017**	0.018**	0.040**		0.033**	0.021**	0.020**	0.082**
		(11.861)	(8.996)	(9.036)	(7.734)		(14.664)	(9.817)	(9.037)	(14.973)
Market-to-Book		-0.024**	-0.017**	-0.018**	-0.004**		-0.079**	-0.066**	-0.066**	-0.029**
		(-17.156)	(-12.175)	(-12.479)	(-2.647)		(-47.021)	(-41.668)	(-41.212)	(-22.862)
EBITDA / Assets		-0.035**	-0.035**	-0.036**	-0.033**		-0.048**	-0.046**	-0.046**	-0.043**
		(-20.664)	(-20.672)	(-20.955)	(-18.832)		(-29.130)	(-28.554)	(-28.321)	(-24.578)
Net PPE / Assets		0.049**	0.031**	0.045**	0.032**		0.047**	0.029**	0.041**	0.039**
		(24.729)	(15.607)	(16.484)	(10.510)		(21.522)	(13.597)	(13.922)	(11.864)
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	77,328	78,189	77,328	77,328	77,328	77,327	78,189	77,327	77,327	77,327
Adj. R^2	0.118	0.113	0.166	0.187	0.059	0.201	0.245	0.296	0.315	0.142

Table III
Stock Return Factor Regression Results

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

$$r_{igt} = \alpha + \beta^m_{it}(rm_t - rf_t) + \beta^{SMB}_{it} SMB_t + \beta^{HML}_{it} HML_t + \beta^{MOM}_{it} MOM_t + \beta^g_{it}(rg_t - rf_t) + \eta_{igt},$$

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	1.565
β^M_{it}	0.208	0.281	0.818
β^{SMB}_{it}	0.123	0.112	0.940
β^{HML}_{it}	0.000	0.020	0.845
β^{IND}_{it}	0.810	0.709	0.684
β^{MOM}_{it}	-0.013	-0.013	0.574
Obs Per Regression	58	60	5
Adjusted R^2	0.299	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 IV

2SLS Regressions: Leverage and Financing Decisions

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

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

where i, g, and t correspond to firm, industry, and time period, respectively. The term $\bar{y}_{-igt-1}$ is the lagged average industry leverage excluding firm i's outcome and is the endogenous regressor. 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 term X_{igt-1} is a vector of lagged firm specific characteristics. 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. In Panel A, all models are estimated using two stage least squares — (2) and (4) employ a within firm version. In Panel B, all models are estimated using two stage least squares. 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 defined in Appendix A.

Panel A: Leverage Regressions

	Book Leverage	Market Leverage
	(1)	(2)
Peer Effect		
Industry Avg.	0.057**	0.096**
	(2.685)	(4.349)
Contextual Effects (Industry Avg.)		
Log(Sales)	-0.013**	-0.014**
	(-2.814)	(-2.640)
Market-to-Book	0.009*	0.030**
	(2.366)	(4.171)
EBITDA / Assets	0.017**	0.021**
	(7.045)	(5.251)
Net PPE / Assets	-0.019	-0.013
	(-1.689)	(-1.262)
Firm Specific Factors		
Log(Sales)	0.017**	0.021**
	(8.773)	(8.995)
Market-to-Book	-0.018**	-0.066**
	(-12.230)	(-40.716)
EBITDA / Assets	-0.037**	-0.047**
	(-21.202)	(-28.201)
Net PPE / Assets	0.044**	0.040**
	(16.312)	(13.441)
Equity Shock	-0.002*	-0.003**
	(-2.349)	(-4.364)
First Stage Instrument		
Avg. Equity Shock	-0.016**	-0.026**
	(-15.977)	(-19.878)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Obs	78,016	78,016
Adj. R^2	0.182	0.312

Panel B: Security Issuance Regressions

	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 V

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 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 VI

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 VII

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 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 VIII
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 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

Table IX
Robustness Tests

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 peer effects and first stage instrument coefficients from several models of financial policy. The dependent variable is denoted at the top of the columns: market leverage and an indicator variable equal to one if the firm issues stock in excess of 1% of book assets (Issue Stock). Included independent variables and estimation methods are denoted below the parameter estimates. Exogenous variables refers to all contextual effects and firm-specific factors. Additional control variables refers to Altman's Z-score, Graham's marginal tax rate, and earnings volatility. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are defined in Appendix A.

	Market Leverage				Issue Stock	
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effect						
Industry Avg.	0.090**	0.093**	0.093**	0.095**	0.067**	0.043**
	(4.041)	(4.148)	(6.394)	(4.769)	(2.888)	(2.853)
First Stage Instrument						
Avg. Equity Shock	-0.026**	-0.026**	-0.026**	-0.028**		
	(-19.754)	(-18.870)	(-19.887)	(-21.472)		
Contextual Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Functional Form	Linear	Linear	Linear	Linear	Probit	Probit
Estimation Method	2SLS	2SLS	2SLS	2SLS	MLE	MLE
Expected Return Control Variable	Yes	No	No	No	No	No
Additional Control Variables	No	Yes	No	No	No	No
Lagged Dependent Variable	No	No	Yes	No	No	No
Polynomials of Exogenous Variables	No	No	No	Yes	No	Yes
Obs	78,016	74,371	78,015	78,016	77,963	77,963
Adj. R^2	0.315	0.324	0.771	0.377		