Do Peer Firms Affect Corporate Financial Policy?*

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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 theoretical and empirical studies of corporate capital structure. Using instrumental variables, we show that firms' industry peers or competitors play an important role in shaping corporate financial policies. Both the characteristics and financial policies of competitors are important determinants of capital structure. On average, a one standard deviation change in peer firms' leverage ratios is associated with a 9% change in own firm leverage ratios — a marginal effect that is significantly larger than that of any other observable determinant. Driving this leverage effect is a linkage among firms' security (debt and equity) issuance decisions. We also show that these effects are driven largely by the efforts of younger, less successful firms that mimic industry leaders.

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

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

The first explanation is that firms in the same industry have similar firm characteristics or face similar institutional environments, such as production technologies and investment opportunities. The inability to perfectly measure or observe these determinants generates a role for peer firm financial policy in so far as it proxies for these omitted firm specific characteristics. The second explanation is that firms are responding to the characteristics of other firms in the industry, or the context in which they operate. For

[1]Theoretical examples include traditional tax-bankruptcy cost tradeoff theories, (Scott (1976)), agency-based theories (Jensen and Meckling (1976)), information asymmetry (Myers and Majluf (1984)), optimal contracting (DeMarzo and Fishman (2007)). Empirically, there are no studies of which we are aware that explicitly model the interplay between financing decisions of peer firms, though several studies have examined reduced form relations linking leverage to peer firm leverage (e.g., Frank and Goyal (2007) and Lemmon, Roberts, and Zender (2008)).

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

example, firms whose competitors are more financially sound may face lower liquidation costs, which lead to higher optimal debt ratios (Shleifer and Vishny (1992)). The last explanation is that firms' financial policies are responding directly to those of their peers.

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

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

To help ensure that this exclusion restriction is satisfied, we estimate firm-specific, rolling regressions of stock returns on the usual asset-pricing factors and an industry factor. This specification ensures that the estimated residual (i.e., instrument) is orthogonal to industry shocks, while enabling the sensitivity to these shocks to vary by firm and year. Indeed, the intra-industry correlations among idiosyncratic stock returns are virtually zero. Additionally, the correlations between firm i's leverage determinants (e.g., profitability, size, etc.) and other firms' idiosyncratic stock returns are all indistinguishable from zero. Thus, our instrument, *other* firms idiosyncratic stock returns, is serially uncorrelated, exhibits no cross-firm autocorrelation, and is completely uninformative about firm i's stock return and leverage determinants. While these features do not guarantee validity of our (or any) instrument, they are not only reassuring but also help guide our robustness tests aimed at addressing identification threats from alternative hypotheses.

Our first stage results show that idiosyncratic stock returns are strongly correlated with leverage, 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 contained in market equity prices when making financing decisions.

The second stage results show evidence that firms' capital structure choices are directly influenced by those of their industry peers, and to a lesser extent by the characteristics of their peers. Specifically, firms change their leverage ratios by nine percentage points, on average, in response to a one standard deviation change in leverage by peer firms. This marginal effect is the largest among observable determinants, including profitability, tangibility, firm size, and market-to-book, as well as a host of other explanatory variables. Importantly, this result is extremely robust, found in both book and market measures of leverage, and in both levels and changes in leverage. Further, the commonalities in leverage are driven by commonalities in financing decisions; firms are significantly more likely to issue a security (e.g., equity) when their peers issue that same security.

To better understand precisely why these commonalities exist, we examine heterogeneity in the peer effect. While shedding light on the underlying mechanism, this analysis also reinforces our identification strategy as most alternative hypotheses leave little room for systematic heterogeneity in the peer effect. We find that younger, less successful firms appear to mimic the capital structures of industry leaders — more mature, successful firms. More precisely, industry entrants and less profitable firms are very sensitive to the financial policies of industry incumbents and more profitable firms, respectively. However, the reverse is not true. 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 or learn from others.

We find less support for product market competition and signalling based explanations. For example, the impact of peer firms on financial policy shows virtually no variation across industries delineated by the degree of competition (i.e., Herfindahl-Hirschman Index (HHI)). Even the extreme comparison of industries defined by the justice department to be concentrated (HHI $>$ 1800) and unconcentrated (HHI $<$ 1000) reveals almost identical sensitivities of financial policy to peer firm behavior. Similarly, we find little consistent variation in the effect of peer firms across proxies for the cost of external financing. More financially constrained firms, as measured by the Whited and Wu or Kaplan and Zingales index, have capital structures that are more sensitive to the behavior of their peers. This result is puzzling if firms are using financial policy as a signal since more constrained firms, who face higher financing costs, should find it more difficult to mimic the behavior of their peers.

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

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

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

I. Data and Summary Statistics

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

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

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

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

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

As a first step, we re-examine the empirical link between industry leverage and corporate capital structures using the existing empirical literature as our guide. The goal is three-fold. First, we want to highlight the economic significance of this determinant. Second, we want to provide results against which we can benchmark subsequent findings. Finally, we want to ensure that this result is not spurious, or an artifact of statistics.

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

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

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

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

The first term, $\bar{y}_{-igt}$, denotes the average leverage for all firms in industry g, excluding firm i, during period t.[4] This variable corresponds to the peer effect, though the extent to which its coefficient (β) captures variation in leverage due to peer firm behavior is unclear at this stage. This identification issue is the focus of later sections. For consistency with the previous literature, we lag this variable one period in our regression analysis. Throughout the paper, we use the notation $\bar{x}$ to denote the sample mean of x, and the "$-i$" subscript to denote all observations other than the i^{th} observation.

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

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

In Panel A, specifications (1) through (3) show that in a pooled regression, average industry leverage is the most economically important determinant of capital structure. A one standard deviation change in average industry book leverage is associated with a 5.2% change in individual firms' book leverage ratios. This effect is almost 30% larger, in magnitude, than the next most important determinant, profitability. Additionally, a comparison of the adjusted R-squares for specifications (1) and (2) reveals that industry

[4]Using the median produces similar results.

average leverage, by itself, explains more variation in book leverage ratios than the other observable determinants combined.

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

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

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

Panel B examines whether this result is spurious by altering the definition of the peer group, industry. Specifically, we re-estimate the market leverage specification presented in column (8) of Panel A using four different definitions for industry. (We focus only on market leverage. Unreported book leverage results are similar.) The first definition randomly assigns firms to industries which are similar in size to industries defined by 3-digit SIC codes (approximately 19 firms per industry-year, on average).[5] The results reveal that there is no link between leverage and industry average leverage, whose coefficient and t-statistic are both zero.

[5]For the randomly assigned industries, we repeat the process of random assignment and model estimation 100 times to reduce the impact of simulation error. We then average the estimated coefficients and construct a corresponding standard error from the standard deviation of 100 estimated marginal effects. The R^2 is the average across the 100 estimations.

The second, third, and fourth definitions define industry using one-digit, two-digit, and three-digit SIC codes, respectively. The results show that the marginal effect of average industry leverage, as well as its precision, increases monotonically moving from the one-digit to the three-digit peer group definitions. In concert with the randomly assigned industries, the results of Panel B show that there is an economically meaningful relation between firms leverage ratios and average industry leverage. Further, the results in Panel A show that this relation is the most economically important one among observable capital structure determinants. We now turn to understanding why this relation exists.

III. Why Would Firms' Financial Policies Be Related?

There are a variety of reasons why firms' financial policies would affect one another. In this section, we outline three potential mechanisms suggested by existing theories: costly optimization, interactions between financial policy and product market strategy, and signalling with financial policy. While this list may not be exhaustive, it represents the more popular explanations and serves to motivate the empirical analysis below.

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

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

Anticipation of these product market effects can lead firms to make similar financing choices as their peers. For example, in the symmetric duopoly of Brander and Lewis (1986), both firms choose high debt levels in equilibrium to protect themselves from the aggressive commitment of the other. Similarly, if the potential cost of price predation

(Bolton and Scharfstein (1990)) or under-investment (Chevalier and Scharfstein (1996)) is severe enough, highly levered firms will mimic the capital structures of their less levered rivals.

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

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

IV. Empirical Model

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

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

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

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

The parameter vector is $(\alpha, \beta, \lambda', \gamma', \delta', \phi')$. We refer to these parameters as structural parameters only to distinguish them from the composite, or reduced form, parameters that appear in the context of instrumental variables. Like the vast majority of the empirical capital structure literature, we leave unspecified the precise optimization problem undertaken by the firm.[6]

The three explanations for industry commonality in financial structures are captured by the parameters β, γ, and δ. The peer effect coefficient, β, captures the direct effect of peer firms' financial policies, $\bar{y}_{-igt}$, on firm i's financial policy, y_{igt}. The contextual effects coefficients, γ, captures the effect of peer firms' *characteristics* on firm i's financial policy. Finally, the industry fixed effect coefficients, δ, captures the possibility that firms in the same industry have similar financial policies because they share common (possibly unobserved) characteristics or operate in the same institutional environment.[7]

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 below.

A. The Identification Problem

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

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

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

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

the endogeneity problem is unlikely to be useful exercise because of the persistence in leverage ratios.

More formally, Manski (1993) shows that without an instrument, one can not separately identify the structural parameters. Specifically, by invoking the equilibrium condition $E(y_i|\mu_g) = E(y_{-i}|\mu_g)$, we can derive the following reduced form model for the population version of equation (2) using the results in Manski (1993):[8]

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

Two features of the coefficients of equation (3) are noteworthy. First, we can only identify composite parameters, not the structural parameters themselves, since we are left with five unknowns and only four equations. Second, with $\lambda \neq 0$ the coefficient on the industry average characteristics (i.e., contextual effects) can only be zero if both β and γ are zero. In other words, non-zero coefficients on the contextual effects, as represented by $E(X|\mu_g)$, indicates that either a peer effect or a contextual effect is present. This finding is informative because it implies that interactions of some type — peer or contextual — are relevant for financial policy.

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

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

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

[8]See Appendix B for a formal derivation.

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

V. Disentangling Peer, Contextual, and Correlated Effects

A. The Instrument: Idiosyncratic Equity Shocks

A valid instrument satisfies both the 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 year is a plausible instrument. We first describe how we construct our instrument, followed by a discussion of its validity as an instrument.

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

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

The indices are unchanged from above. The first four factors are those typically found in empirical asset pricing studies: the excess market return $(rm_t - rf_t)$, the small minus big portfolio return (SMB_t), the high minus low portfolio return (HML_t), and the momentum portfolio return (MOM_t).[9] 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 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

[9] 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.

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

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

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.[10] 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 qualitatively similar using the second.

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

B. Instrument Validity

Relevance of the instrument is motivated by economic theory suggesting a linkage between stock returns and financial policy. For example, Myers and Majluf (1984) suggest

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

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.[11] What is unknown is whether or not the idiosyncratic component of stock returns contains information relevant for financial policy. Fortunately, this condition is empirically testable.

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

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

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

Statistically, the concern is that ε_{igt} from equation (2) is correlated with $\bar{\hat{\eta}}_{-igt-1}$. But recall that any element of ε_{igt} must be both relevant for firm i's financial policy *and* not captured by any of the included capital structure determinants. Likewise, $\bar{\hat{\eta}}_{-igt-1}$ by definition includes only that portion of other firms returns that is uncorrelated with any of the systematic return factors, including the industry return. Economically, then, any identification threat must come from an omitted variable satisfying the following conditions: (1) it is correlated with the *non-systematic* portion of *other* firms' stock returns, and (2) it is correlated with firm i's financial policy, even after partialing out firm i's idiosyncratic stock return and all other variables included in the model.

Broadly speaking, variables relevant to financial policy could be of three types: characteristics of firm i, broader macroeconomic or industry conditions, and characteristics of peer firms — assuming that such contextual effects are relevant. Therefore, the relevant issue is whether there exists an omitted or mismeasured variable from one of these categories that satisfies the two conditions from the previous paragraph.

[11]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)).

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

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

It is also unlikely that any omitted market conditions or macroeconomic variables could threaten identification. First, these are likely captured by the year fixed effects in equation (2) or by the systematic return components. Second, any identification threat would have to be reflected in firm j's idiosyncratic return, but not firm i's. This would rule out even sector-specific macro shocks that might not be fully captured by the year fixed effects. Further, heterogeneous sensitivities to sector shocks are unlikely to contaminate our results since the return regression (equation (4)) allows the factor loadings to vary by firm and year.

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

While possible, we note that for this to be a concern, several tenuous conditions must hold. First the omitted variable must be specific to a firm's competitors but not shared by the firm itself. Any industry shocks, for example, would be captured by the industry return in equation (4) or by firm i's characteristics and returns. Second, the omitted factor would have to be important enough to affect the competitor's characteristics and the financing choices of both the competitor and firm i, but at the same time not be reflected in firm i's return, which we include as a control variable in the regression model. For example, suppose a competitor receives a firm-specific shock to investment opportunities that is expected to reduce future profitability. This may increase expected liquidation costs and thereby affect firm i's financing choice. However, it also affects the competitive landscape facing firm i and is therefore likely to be reflected in firm i's stock price and return, control variables in our regression.[12]

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

In unreported analysis, we find that there are no statistically significant correlations between our instrument, the industry average equity shock ($\bar{\hat{\eta}}_{-igt}$), and any of the firm-specific characteristics (X_{igt}). In fact, the R-square from a regression of the industry average equity shock on the firm-specific characteristics is less than 0.001. In addition, the correlation between the instrument ($\bar{\hat{\eta}}_{-igt}$) and firm i's idiosyncratic equity shock ($\hat{\eta}_{igt}$) is economically tiny (less than 0.05). Ultimately, the average equity shock of other firms in an industry bears little relation to the characteristics or stock returns 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. Additionally, our instrument is serially uncorrelated and exhibits no cross-autocorrelation.

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

Nonetheless, we investigate potential identification threats in our empirical analysis.

C. Leverage

Panel A of Table V presents the estimated marginal effects, t-statistics (in parentheses) and model statistics from two-stage least squares (2SLS) regressions of equation (2). We present results for book and market leverage in both levels and first differences. More precisely, the level specifications uses the levels for all of the variables on both left and right hand side of the equation. The fist difference specifications uses first differences for all of the variables on both left and right hand side of the equation. The only exception is the instrument, which is the same across the functional form specifications. Namely, we instrument the endogenous peer effect the average idiosyncratic stock returns of the peer firms.

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

The second stage results reveal that — with the exception of changes in book leverage — *both* peer effects and contextual effects play a role in leverage policy. We first note that the estimated firm-specific effects are similar to those found in Table II, and similar to that found in the existing literature. For example, comparing column (9) from Table II with column (2) in Table IV, we note that the coefficients on each firm specific characteristic are all within one percentage point of one another. Similarly, column (4) from Table II reveals marginal effects that are quantitatively close to those in column (1) of Table IV. These similarities are not surprising in light of the earlier discussion noting the orthogonality between our instrument and firm-specific characteristics.

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

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

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

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

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

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

C.1. Robustness Tests

In Panel B of Table V we present a number of robustness checks to mitigate concerns about the potential identification threats. Recall that the general concern is that there is an omitted, or mismeasured, variable relevant to firm i's capital structure that is correlated with our instrument, the lagged equity shock to other firms. While the specification in Panel A of Table V includes the most robust empirical capital structure determinants, we explore a number of relevant alternative hypotheses in this subsection by expanding the basic leverage specification along a number of dimensions. In light of the similarity in results across market and book leverage measures, we focus our attention here on market leverage for brevity and use the same two stage least squares approach for dealing with the endogenous industry average leverage.

Column (1) begins by including a firm specific (i.e., lagged firm i values) and a contextual (i.e., lagged industry averages excluding firm i's value) effect for a host of additional control variables. For example, one concern is that the shock to other firms' stock prices may reflect changes in their investment strategy — be it capital expenditures, research and development, or marketing — that are also correlated with their financial policy. Therefore, what we are identifying is not firm i's response to its competitors' financial policy, but firm i's response to its competitors new investment strategy. That is, we are identifying a contextual effect, not a peer effect.

To address this concern, we incorporate capital expenditures normalized by the previous period's capital stock, research and development (R&D) expenses normalized by total sales, and selling, general and administrative (SG&A) expenses normalized by total sales. Because we include both firm-specific and contextual effects, any correlation between competitors equity shock and their new investment strategy should be subsumed by the contextual effects.

We also include a number of additional capital structure determinants that have been shown to be empirically relevant by previous studies, if not particularly robust (Frank and Goyal (2007)). These determinants include cash flow volatility, an indicator variable equal to one if the firm paid a dividend (Titman and Wessels (1988)), Altman's Z-Score

(Graham (1996)), intra-industry standard deviation of leverage (Mackay and Phillips (2005)), and Graham's marginal tax rate (Graham (2000)). Finally, we incorporate the systematic component of stock returns. While this variable is, by construction, largely orthogonal to the instrument, it may be relevant for firm i's capital structure and correlated with other variables that are correlated with the instrument. Ultimately, as revealed by the results in column (1), this kitchen sink model has little impact on either the first or second stage results.

Column (2) addresses the concern that commonality among firms' capital structures is simply due to the use of common banks (commercial or investment) within the industry. In other words, firms within an industry may be behaving similarly with respect to their financial policies because they are using the same banker, who is giving similar advice. We use Thompson's SDC and Reuters Loan Pricing Corporation's Dealscan database to identify lead underwriters and banks for public and private, debt and equity issuances.[13] We then create bank fixed effects for each firm in the overlap of our sample and these two databases by forward imputation. That is, we assume that the firm uses the same bank each year until either the end of the sample or until we find a different bank being used, regardless of the security being issued. For example, if IBM floated equity with Goldman Sachs as the lead underwriter in 1991, we assume that IBM used Goldman Sachs for each year including and after 1991, until the end of our sample or until they used another bank for a future equity *or* debt issuance. (Results obtained by backward imputation — assuming that the firm used the same bank in all years prior to the issuance until either the beginning of our sample or a new bank was found — generate similar results.)

There are two points to make concerning column (2). First, incorporating bank fixed effects has little impact on our results. Second, bank effects explain a significant amount of variation in leverage ratios. In unreported analysis, the difference in *adjusted* R-squares due to the bank effects is nine percentage points. So, while banks seem to have significant influence on corporate capital structures, they are not responsible for the commonality in financial policies that we are identifying.

Column (3) incorporates firm i's lagged leverage ratio to capture and any dynamic feedback from the explanatory variables onto leverage ratios. Column (4) includes quadratic and cubic polynomials of each firm-specific and contextual effect in our primary

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

specification (i.e., firm size, profitability, tangibility, market-to-book). Both specification changes have little effect on our results.

Column (5) incorporates contemporaneous contextual effects to address concerns over a latent shock to competitors. Using the earlier example, assume that firm i's competitors alter their investment strategy (or pricing strategy, etc.) in a way that impacts the idiosyncratic portion of their stock price and ultimately affects their financial policy. If, in addition, the change in competitors' investment strategies is not captured by observable measures (e.g., capital expenditures, R&D, SG&A), then our peer effect may still be capturing a contextual effect if firm i is responding to the latent shock to its competitors, as opposed to their leverage policy. By inserting contemporaneous contextual effects, and in particular competitors' contemporaneous market-to-book ratio, we hope to mitigate this problem since the latent shock to competitors that impacts their stock return is, by assumption, impounded in their contemporaneous stock price. We see a slight attenuation in both the first and second stage results when we incorporate contemporaneous contextual effects. However, economically and statistically speaking, there is little difference.

Finally, column (6) examines peer groups defined by size groups within each three-digit SIC code (e.g., Bizjak, Lemmon, and Naveen (2008) and Byrd, Johnson, and Porter (1998)). We sort firms within each industry-year by sales, though using total assets or market capitalization produces similar results. We then define three intra-industry groups based on the lower, middle, and upper third of the size distribution. The results show a somewhat weaker first stage estimate, though still far from a statistically weak instrument. The second stage estimate shows an even larger peer effect, consistent with the results from Panel B of Table II.

While no instrument is "perfect," we believe that these results leave little room for alternative explanations based on either omitted firm specific characteristics or contextual effects. Corporate leverage ratios appear to be closely related to competitors' leverage ratios. The next subsection takes a first step at understanding why?

D. Financial Policy

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

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

The first stage results reveal that the idiosyncratic component of stock returns is strongly correlated with equity issuance decisions. This effect is both economically and statistically significant, again highlighting that the idiosyncratic component of stock returns is as important for financial policy if not more so than the systematic component. The second stage results show that the peer effect is also significant. A one standard deviation increase in the probability of issuing equity by peer firms leads to 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.[14] 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 debt is met with a 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. Closer inspection reveals that it fails to pass the weak instrument test of Stock and Yogo (2005), suggesting that the second stage estimate may be severely biased. Column (4) reveals analogous results for the relative amount of debt issued - an insignificant peer effect and relatively weak first-stage estimate.

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

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, conditional on an issuance. The results show that firms exhibit a strong preference for equity *and* debt when their peers exhibit a similar preference. A one standard deviation increase in 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 their role in shaping individual financing decisions.

VI. What is the Mechanism Behind the Peer Effect?

Given the importance of peer firm behavior for firms' capital structures, the question that remains is: Why is it so important? In other words, which of the mechanisms discussed earlier in Section III are responsible for the interactions between firms' corporate financial policies? Unfortunately, answering this question is complicated by the fact that the theories motivating our analysis are not mutually exclusive and, in some cases, do not provide unique hypotheses. However, as we discuss below, they do offer some guidance with respect to the firms and industries in which peer effects should be most prevalent.

A. Learning

Following our discussion in section III, the first mechanism we examine is whether firms learn from one another when optimal capital structure is difficult to discern. In particular, if this mechanism is what generates peer effects in the data, one would expect to see differences in behavior between industry leaders and followers: followers' capital structure decisions should be influenced by those of the leaders, but not vice versa.

Because there is no formal criteria with which to define an industry leader, we examine several definitions to determine whether some firms within an industry mimic the behavior of other firms within the same industry. Specifically, we hypothesize that industry leaders in market share, experience, and performance will also be viewed as leaders in financial policy. Formally, we define leaders in market share, experience, and performance as those firms with sales, within industry tenure, and profitability falling in the top third of the within industry-year distributions, respectively. 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 VII presents the estimation results. Under each industry leader definition, we see that the first stage results are highly statistically significant, mitigating any weak instrument concerns. We also note that the peer effects are all positive (though not significant in the case of market share), implying that industry leaders do affect follower firm financial policy. The effects are largest when leaders are defined in terms of industry experience and success, as opposed to market share. A one standard deviation change in incumbent firms' or the most profitable firms' leverage ratios are associated with a 7.6% and 10.4% change in follower firm leverage ratios, respectively. These effects are of similar magnitude to those found in Table V, and suggest that industry newcomers and poor performers leverage ratios are strongly influenced by those of incumbents and good performers.

For robustness and additional insight, we again examine the change in leverage in which *all* variables other than the instrument are first differences. We see that smaller and less profitable firms' leverage changes are more sensitive to those of larger and more profitable firms. The large, but insignificant, peer effect coefficient on incumbent firm average leverage should be discounted if not completely disregarded. The first stage estimate is statistically insignificant at all conventional levels suggesting significant biases in the second stage estimate.

The differential effects in the size grouping suggest that while small firms tend to increase (or decrease) their leverage ratios in tandem with large firms, the level to which they change is quite different. Likewise, new firms to an industry (i.e., recent IPOs, primary industry switchers, diversifying firms) and less profitable firms tend to mimic the level of leverage of incumbent firms and more profitable firms, as well as the changes in the latter case. Ultimately, the broad consistency of results is reassuring in that the leverage of follower firms appears to be strongly influenced by that of leader firms.

Panel B of Table VII presents a series of falsification tests examining whether we find symmetric results when we reverse the leaders and followers. Specifically, 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. Reassuring, we find that not only are all of the estimated peer effects statistically insignificant, but they are all significantly smaller in magnitude. In other words, while followers appear to mimic industry leaders' leverage policies, the reverse is not true.

One acute issue with identification in this analysis concerns mean reversion (Flannery and Rangan (2006) and Kayhan and Titman (2006)) or leverage rebalancing (Leary and Roberts (2005)). While the Column (3) of Panel B in Table V showed that our primary results is robust to incorporating the lagged dependent variable, 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. In other words, the similarity between follower and leader capital structures is an artifact of leverage rebalancing, as opposed to a true peer effect. However, inclusion of firm i's lagged leverage ratio has little impact on the results, suggesting that this targeting behavior is not behind this finding.

Further, a useful by-product of this evidence is further support for our identification strategy. Consider the most likely threat to our identification - a latent contextual effect such as competitor investment opportunities or risk. It is not clear why such an omitted factor would have an asymmetric effect across leaders and followers. Arguably, leaders should be sensitive to changes in their competitors strategies, particularly new entrants if not less profitable firms. This point is reemphasized in the analysis below, which shows additional dimensions on which the peer effect exhibits significant heterogeneity.

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 Tables V and VI, we would expect variation in the strength of this effect across industries distinguished by their concentration and product uniqueness. More precisely, recall that 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.

Additionally, 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.[15]

Based on these predictions, we evaluate the potential role of product market competition by studying how peer effects vary with proxies for industry competitiveness and product uniqueness. We use the Herfindahl-Hirschman Index (HHI) to measure industry competitiveness, and the level of R&D spending, and SG&A expenses to proxy for product uniqueness. We use the justice departments classification of industry competition to identify concentrated (HHI $\geq$ 1800), moderately concentrated (1000 $\geq$ HHI $<$ 1800), and unconcentrated (HHI $<$ 1000) industries. For R&D and SG&A, 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 industries with the highest levels of R&D or SG&A spending and with the highest average leverage fall in group 3; the least R&D or SG&A intensive industries fall in group 1.

We then estimate the following model of market leverage:

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

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, 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.

[15] 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 — consistent with the more general prediction that financial structure interdependence is more likely to result from models of imperfect competition.

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,

$$\begin{aligned}
\left[\bar{\hat{\eta}}_{-igt-1} \times I_{igt-1}(Group1)\right] &\text{ instruments for } \left[\bar{y}_{-igt} \times I_{igt-1}(Group1)\right] \\
\left[\bar{\hat{\eta}}_{-igt-1} \times I_{igt-1}(Group2)\right] &\text{ instruments for } \left[\bar{y}_{-igt} \times I_{igt-1}(Group2)\right] \\
\left[\bar{\hat{\eta}}_{-igt-1} \times I_{igt-1}(Group3)\right] &\text{ instruments for } \left[\bar{y}_{-igt} \times I_{igt-1}(Group3)\right]
\end{aligned}$$

The results are presented in Table VIII. The first stage F-statistics all reveal highly statistically significant instruments across each of the three specifications. The second stage results in the first column show almost no variation in peer effects across industries defined by their concentration, though individually each effect is economically large and statistically significant. The second and third columns show greater variation in the peer effect across industries classified by R&D (SG&A) intensity, though the pairwise differences in the peer effects are almost all statistically insignificant at the 5% level. The one exception is the difference between the medium (group 2) and high (group 3) R&D intensity peer effects, as indicated by the superscript "B".

In general, the evidence does not support a role for product market interactions in generating peer effects in capital structure. However, these findings do *not* imply that product market interactions are unimportant for capital structure decisions. Rather, our results here suggest that product market interactions do not manifest themselves in capital structure via 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. 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 external 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, i.e., it's cost of mimicking peers.

Results from estimating equation (6) with the financial constraint based group indicators are shown in table IX. The superscript letters "A", "B", and "C" denote statistically significant pairwise differences in the peer effects of groups 1 and 2, 2 and 3, and 3 and 1, respectively.

The first stage F-statistics again reveal highly statistically significant instruments. The second stage results reveal mixed evidence. If firms follow their peers' financing choices in an effort to prevent signaling, we would expect to see the strongest evidence of peer effects among the least constrained firms. In support of this prediction, we find that peer effects are larger for firms with a credit rating than for those without. We also see that the sensitivity to peer effects increases monotonically as we move from small (Group 1) to large (Group 3) firms. For small firms, a one standard deviation increase in peer firm leverage is associated with a 5.5% increase in leverage, compared to a highly significant 13.3% increase in leverage for big firms. The results from columns 2 and 3 of Table VIII 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 VIII.

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. Finally, 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 most traditional capital structure determinants.

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

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

Appendix A: Variable Definitions

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

Book Leverage = (data9 + data34) / data6.

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

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

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

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

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

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

Tangibility = Net PPE / Assets = data8 / data6.

Profitability = EBITDA / Assets = data13 / data6.

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

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

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

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

Appendix B: The Identification Problem

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

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

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

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

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

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

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

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

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

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

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

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

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

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Table I
Summary Statistics

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

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

Table II

Industry Leverage and Capital Structure: OLS Regressions

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2006 with nonmissing data for all of the variables used in the regressions. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses from various leverage regressions. All models are estimated by OLS. All variables are in levels and all right hand side variables are lagged one year relative to the dependent variable, either book or market leverage as indicated above the columns. Panel B presents results for four different definitions of industry: randomly assigned, 1-digit SIC, 2-digit SIC, and 3-digit SIC. All t-statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

Panel A: Different Leverage Specifications

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

Panel B: Different Industry Definitions

	Market Leverage			
	Random Industry	1-Digit SIC Industry	2-Digit SIC Industry	3-Digit SIC Industry
Ind. Avg. Leverage	-0.000	0.024**	0.057**	0.071**
	(-0.007)	(9.545)	(23.380)	(29.177)
Log(Sales)	0.033**	0.030**	0.022**	0.022**
	(14.650)	(13.350)	(10.151)	(9.891)
Market-to-Book	-0.079**	-0.078**	-0.070**	-0.066**
	(-46.483)	(-46.136)	(-43.137)	(-41.474)
EBITDA / Assets	-0.048**	-0.047**	-0.045**	-0.046**
	(-28.859)	(-28.455)	(-27.982)	(-28.466)
Net PPE / Assets	0.047**	0.040**	0.031**	0.030**
	(21.362)	(17.241)	(14.165)	(13.727)
Fixed Effects				
Firm	No	No	No	No
Industry	No	No	No	No
Year	Yes	Yes	Yes	Yes
Obs	77,010	76,930	76,930	77,098
Adj. R^2	0.245	0.252	0.287	0.295

Table III

Reduced Form OLS Leverage Regressions

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

	Book Leverage						Market Leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Contextual Effects (Industry Avg.)										
Log(Sales)	0.007**		-0.002	-0.015**	-0.013**	0.026**		0.015**	-0.009	-0.014**
	(2.576)		(-0.640)	(-3.325)	(-3.123)	(7.386)		(4.460)	(-1.780)	(-2.819)
Market-to-Book	-0.020**		-0.013**	0.001	-0.004*	-0.056**		-0.031**	0.001	-0.010**
	(-9.017)		(-6.021)	(0.354)	(-2.535)	(-20.666)		(-12.354)	(0.604)	(-5.233)
EBITDA / Assets	-0.002		0.010**	0.018**	0.006**	-0.015**		-0.002	0.009**	0.001
	(-0.833)		(4.178)	(7.326)	(2.791)	(-5.584)		(-0.914)	(3.231)	(0.497)
Net PPE / Assets	0.034**		0.001	0.006	0.012*	0.031**		0.002	0.019**	0.023**
	(15.208)		(0.375)	(1.056)	(2.238)	(11.854)		(0.503)	(3.024)	(3.714)
Firm Specific Factors										
Log(Sales)		0.022**	0.020**	0.018**	0.041**		0.033**	0.023**	0.021**	0.083**
		(11.915)	(10.083)	(9.087)	(8.061)		(14.745)	(9.905)	(9.163)	(15.246)
Market-to-Book		-0.024**	-0.019**	-0.018**	-0.004*		-0.079**	-0.069**	-0.067**	-0.029**
		(-17.000)	(-12.725)	(-12.595)	(-2.416)		(-46.827)	(-41.780)	(-41.281)	(-22.788)
EBITDA / Assets		-0.035**	-0.037**	-0.037**	-0.033**		-0.048**	-0.048**	-0.047**	-0.044**
		(-20.586)	(-21.459)	(-21.204)	(-18.903)		(-29.112)	(-28.907)	(-28.559)	(-24.845)
Net PPE / Assets		0.049**	0.045**	0.045**	0.032**		0.047**	0.041**	0.041**	0.039**
		(24.682)	(16.299)	(16.538)	(10.543)		(21.502)	(13.365)	(13.844)	(11.940)
Firm Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes
Industry Fixed Effects	No	No	No	Yes	No	No	No	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	146.388**		23.453**	14.151**	5.593**	351.506**		91.117**	5.105**	14.863**
Obs	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023	78,023
Adj. R^2	0.064	0.112	0.118	0.186	0.056	0.160	0.245	0.261	0.314	0.135

Table IV
Stock Return Factor Regression Results

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

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

where r_{igt} is the return to firm i in industry g during period t, $(rm_t - rf_t)$ is the excess return on the market, SMB_t is the small minus big portfolio return, and HML_t is the high minus low portfolio return, MOM_t is the momentum 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. Expected returns are computed using the estimated factor loadings and realized factor returns. Idiosyncratic returns are computed as the difference between realized and expected returns.

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

Table V
2SLS Leverage Regressions

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

Panel A: Leverage Regressions

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

Panel B: Robustness Tests

	Market Leverage					
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effect						
Industry Avg.	0.094**	0.098**	0.093**	0.095**	0.090**	0.130**
	(6.206)	(3.342)	(6.394)	(4.769)	(2.718)	(3.162)
First Stage Instrument						
Avg. Equity Shock	-0.041**	-0.027**	-0.026**	-0.028**	-0.018**	-0.010**
	(-26.592)	(-13.398)	(-19.887)	(-21.472)	(-14.100)	(-7.815)
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
Additional Control Variables	Yes	No	No	No	No	No
Investment Bank Indicators	No	Yes	No	No	No	No
Lagged Dependent Variable	No	No	Yes	No	No	No
Polynomials of Control Vars	No	No	No	Yes	No	No
Contemporaneous C.E.s	No	No	No	No	Yes	No
Industry-Size Peer Groups	No	No	No	No	No	Yes
Obs	73,533	33,516	78,015	78,016	77,805	77,399
Adj. R^2	0.354	0.404	0.771	0.377	0.311	0.276

Table VI
2SLS Financing Decision Regressions

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

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

Table VII
2SLS Regressions: 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. Panels A and B present results from six market leverage regressions - three in levels and three in first differences. All models are estimated by linear 2SLS where the endogenous peer effect is the industry average leverage ratio, Industry Avg., and the instrument is the one period lagged industry average idiosyncratic component of stock returns, Avg. Equity Shock. Contextual Effects refer to industry averages excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. All specifications include firm-specific and contextual effects for firm size, profitability, tangibility, and the market-to-book ratio. Firms are classified as either "Leaders" or "Followers" based on three different measures: firm size, industry age, and profitability., Leaders are defined as those firms falling in the upper third of the distribution, while Followers are defined as those firms falling in the lower and middle thirds. Panel A restricts attention to the sample of Followers (i.e., small firms, industry entrants, and unprofitable firms) and regresses their leverage ratio on the average leverage ratio of Leaders (i.e., big firms, industry incumbents, and profitable firms), as well as the control variables indicated towards the bottom of the table. Panel B restricts attention to the sample of Leaders and regresses their leverage ratio on the average leverage ratio of Followers, as well as the control variables indicated towards the bottom of the table. First stage marginal effects and t-statistics for the instrument are also presented. 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 Follower Firms, Peer Effect = Industry Leader Average Leverage

	Market Leverage					
	Levels			1^{st} Differences		
	Size	Age	Profitability	Size	Age	Profitability
Peer Effect						
Leader Firm Avg. Leverage	0.025	0.076*	0.104**	0.044**	0.313	0.122**
	(1.127)	(2.217)	(2.850)	(4.722)	(1.569)	(3.852)
First Stage Instrument						
Leader Firm Avg. Equity Shock	-0.030**	-0.021**	-0.012**	-0.017**	-0.002	-0.004**
	(-16.346)	(-9.309)	(-8.523)	(-14.421)	(-1.613)	(-5.236)
Contextual Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	45,434	39,555	49,267	44,812	38,933	48,659
Adj. R^2	0.319	0.315	0.305	0.051		

Panel B: Sample of Leader Firms, Peer Effect = Industry Follower Average Leverage

	Market Leverage					
	Levels			1^{st} Differences		
	Size	Age	Profitability	Size	Age	Profitability
Peer Effect						
Follower Firm Avg.	0.025	0.056	0.064	0.029	0.075	-0.064
	(1.473)	(1.374)	(1.723)	(0.532)	(1.587)	(-1.887)
First Stage Instrument						
Follower Firm Avg. Equity Shock	-0.019**	-0.007**	-0.013**	-0.001*	-0.002**	0.004**
	(-16.953)	(-7.425)	(-9.245)	(-2.078)	(-2.938)	(4.113)
Contextual Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	56,781	55,236	54,968	56,428	54,904	54,569
Adj. R^2	0.346	0.325	0.324	0.079		

Table VIII
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. We rank industry-year observations into three groups based on the lower, middle, and upper third of the distribution of the Herfindahl index, average industry R&D Expenditures and average industry SG&A Expenditures, each lagged one year. We then interact the peer effect (average industry leverage) with indicator variables for these three groups. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses for the peer effects from a regression of market leverage on the interacted peer effects and control variables as indicated toward the bottom of the table. All models are estimated by linear 2SLS where the endogenous peer effect is the industry average leverage ratio, Industry Avg., and the instrument is the one period lagged industry average idiosyncratic component of stock returns, Avg. Equity Shock. Contextual Effects refer to industry averages excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. All specifications include firm-specific and contextual effects for firm size, profitability, tangibility, and the market-to-book ratio. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments (First Stage Multivariate F-stat). All test statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Superscript "A", "B", and "C" correspond to statistically significant (5% level) differences in the peer effects coefficients between groups 1 and 2, 2 and 3, and 1 and 3, respectively. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Herfindahl Index (3=Concentrated)	R&D Exp. (3=Large)	SG&A Exp. (3=Large)
Peer Effects			
Industry Avg. × Group 1	0.108**	0.131**	0.131**
	(4.173)	(4.367)	(4.367)
Industry Avg. × Group 2	0.107**	0.106**	0.099**
	(4.149)	(4.424)^{B}	(4.190)
Industry Avg. × Group 3	0.104**	0.079**	0.080**
	(4.528)	(5.093)	(4.696)
First Stage Multivariate F-stat	133.534**	136.018**	127.930**
Contextual Effects	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	78,016	78,016	78,016
Adj. R^2	0.312	0.311	0.311

Table IX

The Role of Financial Constraints and Signalling

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. We rank industry-firm-year observations into three groups based on the lower, middle, and upper third of the distribution of lagged values for firm size, the Whited-Wu index and the Kaplan-Zingales index. We also classify firms according to the presence of a credit rating and whether or not they paid a dividend the previous year. We then interact the peer effect (average industry leverage) with indicator variables for these groups. The table presents estimated marginal effects, computed as the product of the estimated coefficient and corresponding variable standard deviation, and t-statistics in parentheses for the peer effects from a regression of market leverage on the interacted peer effects and control variables as indicated toward the bottom of the table. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments (First Stage Multivariate F-stat). Contextual Effects refer to industry averages excluding the i^{th} observation. Firm Specific Factors refer to the i^{th} observation's characteristic. All test statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Superscript "A", "B", and "C" correspond to statistically significant (5% level) differences in the peer effects coefficients between groups 1 and 2, 2 and 3, and 1 and 3, respectively. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. All variables are formally defined in Appendix A.

	Credit Rating (2=Yes)	Dividend Payer (2=Yes)	Firm Size (3=Big)	WW Index (3=Constrained)	KZ Index (3=Constrained)	Market Leverage (3=High)
Peer Effects						
Industry Avg. × Group 1	0.110**	0.146**	0.055*	0.082**	0.024	0.023
	(4.214)^{A}	(5.648)^{A}	(2.068)^{A}	(3.749)^{A}	(1.060)^{A}	(1.142)^{A}
Industry Avg. × Group 2	0.130**	0.098**	0.098**	0.098**	0.097**	0.096**
	(6.782)	(3.503)	(3.784)^{B}	(4.668)	(4.421)^{B}	(4.629)^{B}
Industry Avg. × Group 3			0.133**	0.095**	0.190**	0.237**
			(5.103)^{C}	(4.449)^{C}	(8.395)^{C}	(10.731)^{C}
First Stage Multivariate F-stat	198.676**	196.543**	126.674**	163.484**	139.333**	133.212**
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	78,016	78,016	78,016	78,016	78,016	78,016
Adj. R^2	0.308	0.351	0.287	0.322	0.477	0.602