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Do Peer Firms Affect Corporate Financial Policy?

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ABSTRACT

We show that peer firms play an important role in determining corporate capital structures and financial policies. In large part, firms' financing decisions are responses to the financing decisions and, to a lesser extent, the characteristics of peer firms. These peer effects are more important for capital structure determination than most previously identified determinants. Furthermore, smaller, less successful firms are highly sensitive to their larger, more successful peers, but not vice versa. We also quantify the externalities generated by peer effects, which can amplify the impact of changes in exogenous determinants on leverage by over 70%.

MOST RESEARCH ON CORPORATE financial policy assumes that capital structure choices are made independently of the actions or characteristics of their peers. In other words, a firm's capital structure is typically assumed to be determined as a function of its marginal tax rate, expected deadweight loss in default, information environment, and incentive structure. As such, the role for peer firm behavior in affecting capital structure is often ignored, or at most implicitly assumed to operate through its unmeasured impact on firm-specific determinants.

However, peer firms play a central role in shaping a number of corporate policies, and existing evidence suggests that the behavior of peer firms may matter for capital structure.[1] Survey evidence indicates that a significant

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

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number of CFOs cite the importance of peer firm financing decisions for their own financing decisions (Graham and Harvey (2001)). Furthermore, recent empirical work shows that industry average leverage ratios are an economically important determinant of firms' capital structures (Welch (2004), MacKay and Phillips (2005), and Frank and Goyal (2009)).

The goal of this paper is to identify whether, how, and why peer firm behavior matters for corporate capital structures. To ease the discussion and to provide some context for peer effects in corporate capital structure, consider peer effects arising from a learning motive. Managers are unsure of how to set optimal capital structure. The inputs are hard to measure and the true model is unknown. As such, managers consider the financing decisions and characteristics of peer firms as informative for their own financing decisions. For example, when a firm's peers increase their leverage ratios, that firm's leverage ratio is higher than it otherwise would have been had peer effects not been present. Likewise, firms may consider the growth opportunities or financial health of their peers in determining their own capital structure. Thus, peer effects in capital structure occur when the actions or characteristics of peer firms explicitly enter a firm's financing objective function.

While theoretically intuitive, identifying peer effects is empirically challenging because of the reflection problem (Manski (1993)). This problem refers to a specific form of endogeneity that arises when trying to infer whether the actions or characteristics of a group influence the actions of the individuals that comprise the group. In the current context, this problem is created by using measures of peer firm financial policy, such as industry average leverage, or peer firm capital structure determinants, such as industry average profitability, as explanatory variables for individual firms' financial policies. Any correlation between firms' financial policies and the actions or characteristics of their peers can be attributed to two broad explanations.

The first explanation is based on the endogenous selection of firms into peer groups or an omitted common factor. This selection results in firms from the same peer group facing similar institutional environments and having similar characteristics, such as production technologies and investment opportunities. The inability to accurately model the selection mechanism generates a role for peer firm measures in determining financial policy. This role arises because peer firm measures proxy for latent factors that are common to firms in a peer group and determine financial policy. In essence, the correlation between firms' financial policies and the policies or characteristics of their peers reflects an endogeneity bias.

The second explanation is that firms' financial policies are partly driven by a response to their peers. This response can operate through two channels: actions or characteristics. The first channel arises when firms respond to their peers' financial policies. The second channel arises when firms respond to changes in the characteristics of their peers—profitability, risk, etc. Thus, identifying peer effects poses two identification challenges. The first involves overcoming the endogenous selection. The second involves distinguishing between the two channels through which peer effects operate.

The first challenge can be overcome by showing that, controlling for characteristics of their own firm, firms' behaviors are significantly correlated with exogenous characteristics of their peers. We use peer firms' idiosyncratic equity returns (i.e., equity shocks) as a possible source of exogenous variation in peer firm attributes. Motivation for this approach comes from existing research. Substantial theoretical and empirical evidence links stock returns to financial policy (e.g., Myers (1977, 1984), Marsh (1982), Loughran and Ritter (1995)), suggesting that return shocks may be relevant for financing decisions. The firm-specific nature of idiosyncratic returns and the large asset pricing literature aimed at isolating this component suggest that return shocks offer a useful starting point for identifying exogenous variation.

Indeed, these shocks have a number of desirable properties. First, the shocks to different firms within a peer group are largely uncorrelated with one another. Second, the shocks are serially uncorrelated and serially cross-uncorrelated, implying that firms' shocks do not forecast future shocks for themselves or for other firms. Finally, the shocks are uncorrelated with firm characteristics typically used to explain variation in capital structure (e.g., profitability, tangibility, size, and market-to-book). While these features do not guarantee exogeneity, they are reassuring because they suggest that peer firm return shocks contain little common variation.

Our results show that firms' capital structures are significantly influenced by their peers. Leverage is strongly negatively related to peer firm equity shocks. Debt and equity issuance decisions are, respectively, negatively and positively related to peer firm equity shocks. Furthermore, these inferences are robust to a host of measurement and endogeneity concerns.

To ensure that latent common factors are not behind our results, we undertake a separate analysis in which we utilize equity return shocks to peer firms' *customers* that (1) are in an industry different from firm i, and (2) are not a customer of firm i. Cohen and Frazzini (2008) show that customer returns predict supplier returns, suggesting that there may be information in return shocks to peers' customers that is relevant for their behavior. This approach enables us to eliminate all within-industry variation for the purpose of identification because we can now control for firm i's industry average stock return. The identifying variation now comes from return shocks to firms in a different industry with no supply chain link to firm i. Furthermore, this variation is orthogonal to firm i's return, firm i's industry return, and all other included determinants. A placebo test using the return shocks of randomly selected firms in the customers' industries that are not customers of firm i or i's peers reveals insignificant peer effects. Thus, peer firms matter for financial policy.

To address the second identification challenge (i.e., the channel through which peer effects operate), we show that, conditional on peer firm financial policy, capital structure is largely insensitive to peer firms' idiosyncratic stock returns. In other words, firms' leverage ratios only respond to peer firms' equity shocks when those shocks are accompanied by changes to peer firms' leverage ratios. Furthermore, peer firm characteristics (other than their return shocks) are largely irrelevant for financial policy, both statistically and economically.

We also find that most other corporate policies—investment, dividends, research, and development—are insensitive to peer firm equity shocks. Taken together, this evidence suggests that the primary channel through which peer effects operate is via actions—firms respond to the financial policies of their peers.

To quantify the importance of peer effects in capital structure, we estimate the marginal effect of a change in peer firm leverage on firm i's own leverage, using peer firms' idiosyncratic equity return shocks as an instrument for their capital structures. We find that a one standard deviation increase in peer firms' leverage ratios is associated with a 10% increase in firm i's leverage ratio, an effect larger than any other determinant. Peer firms' decisions to issue equity, and their choice between equity and debt, have a similarly large effect on a firm's own issuance decisions.

With these estimates we are able to quantify the externalities generated by peer effects since a shock to one firm affects all of the other firms in the peer group. To illustrate, consider a shock to firm A's profitability. This shock affects not only firm A's financing choice, but also that of every other member of firm A's peer group. This impact on peer firms' financial policies feeds back onto firm A's financial policy, and so on. This link among peer firms implies that the marginal effect of any exogenous capital structure determinant can no longer be gleaned solely from that determinant's coefficient, even in linear models. Instead, the marginal effect is a function of an amplification term due to the action channel of peer effects, a spillover term due to the characteristics channel of peer effects, and the size of the peer group.

We find that the amplification term varies from a low of 8% in large peer groups to a high of over 70% in small peer groups. In other words, in industries with few firms, the impact of a change in profitability, for example, on leverage is 70% larger than that implied by models ignoring the presence of peer effects. We also show that the spillover effects from changing peer characteristics can either offset or further amplify the effect of changes in exogenous characteristics.

Finally, we examine heterogeneity in the peer effects to better understand why peer firms influence financial policy. Smaller, less successful (e.g., lower profitability), and more financially constrained firms are sensitive to the return shocks of industry leaders (i.e., larger, more profitable firms). However, the opposite is not true. Financial policies of industry leaders are insensitive to the return shocks of their less successful peers. These results are consistent with the implications of models based on learning (e.g., Conlisk (1980)) and reputational concerns (e.g., Scharfstein and Stein (1990) and Zwiebel (1995)), though they do not rule out alternatives based on feedback from the product markets (e.g., Brander and Lewis (1986) and Bolton and Scharfstein (1990)). While helping to shed light on the underlying mechanism behind peer effects, this analysis also reinforces our identification strategy as most alternative hypotheses leave little room for systematic heterogeneity in the peer effect.

Our study is most closely related to those documenting the importance of industry as a capital structure determinant.[2] However, past studies leave interpretation of these industry effects largely unresolved, a point explicitly noted by Frank and Goyal (2008, 2009). Ours is the first study to sift through these alternative meanings, identify policy interdependence as a substantial component of the industry leverage effect, and estimate the externalities induced by the presence of peer effects. Our study is also related to the work of MacKay and Phillips (2005) and Almazan and Molina (2005), who examine intraindustry variation in capital structures. Our study compliments their work by showing that this variation is accompanied by strong interdependencies in financial policy.[3]

An important by-product of our study is to highlight the salient empirical issues that appear in observational studies of peer effects, as opposed to randomized experiments (e.g., Duflo and Saez (2003), Lerner and Malmendier (2013)). Ordinary least squares regressions typically do not provide meaningful results because of the reflection problem, and thus a clear identification strategy is needed to rule out the null of omitted or mismeasured common characteristics. Furthermore, feedback and spillover effects arising from the presence of peer effects obscure the marginal effects of exogenous variables. Neither the direction nor the magnitude of the association between a covariate and the dependent variable can be inferred from that covariate's coefficient, even in linear specifications. We present closed-form expressions for the marginal effects of exogenous covariates in a general linear setting.

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

I. Data and Summary Statistics

Our primary data come from the merged Center for Research in Security Prices (CRSP)-Compustat database for the period 1965 to 2008. Because of its popularity, we relegate a complete discussion of the data, sample construction,

[2] Bradley, Jarrell, and Kim (1984) show that 54% of the cross-sectional variance in firm leverage ratios is explained by industrial classification. Graham and Harvey (2001) show that almost one-quarter of surveyed CFOs identify the behavior of competitors as an important input into their financial decision-making. Welch (2004) finds that deviations from industry leverage are among the most economically significant determinants of leverage changes.

[3] Other studies examining peer effects in corporate finance include: mutual fund voting (Matvos and Ostrovsky (2010)), governance (John and Kadyrzhanova (2008)), investment decisions (Duflo and Saez (2002)), entrepreneurship (Lerner and Malmendier (2013)), and compensation (Shue (2013)).

Table I
Summary Statistics

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

	Levels			First Differences		
	Mean	Median	*SD*	Mean	Median	*SD*
Peer Firm Averages						
Book Leverage (Total Debt/Book Assets)	0.238	0.229	0.094	0.004	0.003	0.031
Market Leverage	0.274	0.262	0.137	0.006	0.004	0.058
Log(Sales)	5.085	4.932	1.278	0.091	0.094	0.119
Market-to-Book	1.362	1.201	0.650	−0.032	−0.019	0.310
EBITDA/Assets	0.108	0.120	0.070	−0.002	−0.001	0.031
Net PPE/Assets	0.317	0.270	0.172	−0.002	−0.002	0.020
Firm-Specific Factors						
Book Leverage (Total Debt/Book Assets)	0.238	0.217	0.196	0.004	−0.000	0.098
Market Leverage (Total Debt/Market Assets)	0.274	0.216	0.246	0.006	0.000	0.123
Log(Sales)	5.085	5.018	2.172	0.091	0.089	0.357
Market-to-Book	1.362	0.966	1.244	−0.032	−0.006	0.829
EBITDA/Assets	0.108	0.129	0.155	−0.002	0.000	0.104
Net PPE/Assets	0.317	0.271	0.217	−0.002	−0.002	0.060
Industry Characteristics						
No. of Firms per Industry-Year	13.217	8.000	18.344			
Total No. of Industries	217					
Sample Characteristics						
Observations	80,279					
Firms	9,126					

and variable definitions to Appendix A. Table I presents summary statistics for our final sample of 80,279 firm-year observations corresponding to 9,126 unique firms. We define peer groups based on three-digit SIC industry groups.[4] There are 217 industries represented in our sample. The typical industry contains approximately 13 firms, though the distribution is right-skewed as indicated by the median number of firms, eight. We discuss potential measurement concerns regarding the definition of an industry (Hoberg and Phillips (2009)), as well as the documented intraindustry heterogeneity (MacKay and Phillips (2005)), below.

[4] Below we examine the robustness of our results to changes in the breadth of industry groups.

Summary statistics for a number of variables, in levels and first differences, used throughout this study are presented after Winsorizing all ratios at the 1^{st} and 99^{th} percentiles. We Winsorize to mitigate the influence of extreme observations and eliminate any data coding errors. Variables are grouped into two distinct categories: peer firm averages and firm-specific factors. The former category includes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. The latter group includes variables constructed as firm i's value in year t. At this point, we simply note the similarity of many statistics to those reported in previous empirical studies of capital structure, such as Frank and Goyal (2009).

II. The Empirical Model

Our empirical model of capital structure is a generalization of that used throughout the empirical capital structure literature (e.g., Rajan and Zingales (1995) and Frank and Goyal (2009)),

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

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

The outcome variable, y_{ijt}, is a measure of corporate financial policy, such as leverage. The covariate $\bar{y}_{-ijt}$ denotes peer firm average outcomes (excluding firm i). We use a contemporaneous measure because it limits the amount of time for firms to respond to one another. This choice makes it more difficult to identify mimicking behavior. It also mitigates the scope for confounding effects by reducing the likelihood of other capital structure relevant changes. The K-dimensional vectors $\bar{X}_{-ijt-1}$ and X_{ijt-1} contain peer firm average and firm-specific characteristics, respectively. Industry and year fixed effects are represented by the error components μ_j and ν_t, respectively. Finally, ε_{ijt} is the firm-year specific error term that is assumed to be correlated within firms and heteroskedastic. As such, all standard errors and test statistics are robust to these two departures from the classical regression model (Petersen (2009)).

The parameter vector is $(\alpha, \beta, \gamma', \lambda', \delta', \phi')$. We refer to these parameters as structural parameters only to distinguish them from the composite, or reduced form, parameters that appear in the context of instrumental variables. Like the vast majority of the empirical capital structure literature, we leave unspecified the precise optimization problem undertaken by the firm. The coefficients δ', along with λ' and ϕ', capture the first explanation for common industry behavior: shared characteristics or institutional environments. Peer effects are captured by β and γ', which measure the influence of peer firm actions and characteristics, respectively, on financial policy choices.

III. Identification

The empirical goal is to disentangle the various explanations for industry commonality in capital structure by statistically identifying the structural parameters. The primary difficulty arises from the presence of $\bar{y}_{-ijt}$ as a regressor in equation (1). Intuitively, if firms' financing decisions are influenced by one another, then firm *i*'s capital structure is a function of firm *j*'s and vice versa. This simultaneity implies that $\bar{y}_{-ijt}$ is an endogenous regressor and that the structural parameters are not identified. This section discusses the identification problem and our strategy for addressing it.

A. The Identification Problem

Ignoring the year fixed effects for notational convenience, consider the population version of equation (1)[5]

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

The corresponding mean regression of y on X and μ_j is

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

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

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

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

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

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

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

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

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

Immediately apparent is that the structural parameters cannot be recovered from the composite parameters since there are fewer equations than unknowns. However, as discussed by Manski (1993), estimation of the reduced-form model in equation (6) can solve the first identification challenge, that is, separating

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

some form of peer effect—via actions or characteristics—from an alternative explanation for common industry capital structures based on endogenous selection or an omitted common factor. If $\gamma^{*'}$ is not equal to zero, then either β or γ' is not equal to zero. Thus, a reduced-form test for the presence of peer effects is a test of the significance of $\gamma^{*'}$.[6]

B. The Identification Strategy

To identify $\gamma^{*'}$ in equation (6), we require an exogenous peer firm characteristic. Such a characteristic is not easy to find, even when controlling for firm i's own characteristics. Consider peer firms' average market-to-book ratio. Because the market-to-book ratio is a noisy measure of investment opportunities, the peer firm average may be a better measure of firm i's investment opportunities than is firm i's own market-to-book ratio. At a minimum, the peer firm average likely captures some variation in characteristics relevant for firm i's capital structure that is not captured by firm i's own market-to-book ratio. In other words, the peer firm average market-to-book ratio is not exogenous with respect to firm i's financial policy and $\gamma^{*'}$ is not identified.

To motivate our identification strategy, consider an event study approach to the problem. The challenge is to identify events that are relevant for peer firms but that are random—conditional on observables—with respect to firm i's capital structure. One might consider events such as losses due to natural disasters, accidental CEO deaths, accounting scandals, etc. However, there are two problems with this approach. First, events such as these are rare enough to raise concerns over statistical power and external validity. Second, and more importantly, it is unclear whether these, or any other, events are in fact exogenous because of spillover effects.

For example, an accidental CEO death at a peer firm may be relevant for firm i's financial behavior not only through the peer firms' financial response but also through the event's impact on the CEO labor market or anticipated shift in product market behavior. Likewise, an oil spill, such as the 2010 spill in the Gulf of Mexico attributed to British Petroleum, has broader implications for the industry via its impact on the product market, future regulatory environment, and expected liabilities. Thus, one may find events that are relevant for peer firms, but it is unlikely that these same events are also exogenous with respect to firm i's capital structure.

As such, we take an alternative approach that addresses these two concerns. We begin with a known capital structure determinant, stock returns (e.g., Marsh (1982)). We then extract the idiosyncratic variation in stock returns using a traditional asset pricing model that also incorporates an industry factor to purge common variation among peers. The residual from this model is

[6] Note that at least one covariate of the X vector must be correlated with y to ensure that λ is not a zero vector. Otherwise, $\gamma^{*'}$ could be zero even if β is nonzero. Furthermore, we require that $\beta \in (0, 1)$.

the return shock. We lag this shock 1 year and use it as a starting point for exogenous variation in peer firms' characteristics.

This approach has several positive aspects. First, the measure is available for a broad panel of firms and thus mitigates statistical power and external validity concerns. Second, stock returns are relatively free from manipulation when compared to other capital structure determinants such as earnings, sales, and other accounting measures. Third, stock returns impound many, if not all, value-relevant events. Fourth, a vast asset pricing literature focuses on estimating the expected and idiosyncratic components of returns. Finally, there is theoretical and empirical precedent for a relationship between stock returns and capital structure choices.[7]

Intuitively, our identification strategy builds on the event-study approach by addressing its shortcomings. Stock returns impound the effect of value-relevant events such as natural disasters, CEO deaths, accounting scandals, etc. The problem is that these events affect both the idiosyncratic and the common components that comprise stock returns. Our identification strategy is to purge this common variation so that the only variation remaining for identification of the peer effect is firm-specific. Thus, our identification strategy does not rely on particular firm-specific economic events, which, as discussed earlier, are not only rare but also virtually impossible to identify. Rather, our strategy relies on isolating the firm-specific variation in stock returns.

The weakness of this strategy is that the true data-generating process for equity returns is unknown. As such, any estimated equity return shock may contain traces of common variation that would fail to be exogenous. Addressing this weakness guides much of our analysis.

C. Construction of the Return Shock

We estimate return shocks with the following augmented market model for stock returns, r_{ijt}:

$$r_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(rm_t - rf_t) + \beta_{ijt}^{IND}(\bar{r}_{-ijt} - rf_t) + \eta_{ijt}, \tag{7}$$

where r_{ijt} refers to the total return for firm i in industry j over month t, $(rm_t - rf_t)$ is the excess market return, and $(\bar{r}_{-ijt} - rf_t)$ is the excess return on an equal-weighted industry portfolio excluding firm i's return. As with our peer groups, industries are defined by three-digit SIC code. While not a priced risk factor, this last factor is included to remove any variation in returns that is common across firms in the same peer group.

We estimate equation (7) for each firm on a rolling annual basis using historical monthly returns. We require at least 24 months of historical data and use

[7] For example, Myers and Majluf (1984) suggest that financial policy is linked to stock prices because of information asymmetry between managers and investors. Likewise, Myers (1977) suggests that financial policy is linked to stock prices because of debt overhang considerations. Empirically, Marsh (1982), Loughran and Ritter (1995), Baker and Wurgler (2002), and Welch (2004), among others, show a strong correlation between past returns and issuance choice or leverage ratios.

Table II

Stock Return Factor Regression Results

The sample consists of monthly returns for all nonfinancial, nonutility firms in the intersection of the annual Compustat and monthly CRSP databases between 1965 and 2008. The table presents mean factor loadings and adjusted R^2s from the regression

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

where R_{ijt} is the return to firm i in industry j during month t, $(RM_t - RF_t)$ is the excess return on the market, and $(\bar{R}_{-ijt} - RF_t)$ is the excess return on an equal-weighted industry portfolio excluding firm i's return, where industries are 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 1 year hence. Idiosyncratic returns are computed as the difference between realized and expected returns.

	Mean	Median	*SD*
α_{it}	0.008	0.007	0.017
β^{M}_{it}	0.399	0.422	0.803
β^{IND}_{it}	0.616	0.535	0.567
Obs. per Regression	59	60	5
Adjusted R^2	0.228	0.207	0.170
Avg. Monthly Return	0.013	0.000	0.182
Expected Monthly Return	0.015	0.014	0.090
Idiosyncratic Monthly Return	−0.002	−0.011	0.174

up to 60 months of data in the estimation. For example, to obtain expected and idiosyncratic returns for IBM between January 1990 and December 1990, we first estimate equation (7) using monthly returns from January 1985 through December 1989. Using the estimated coefficients and the factor returns from January 1990 through December 1990, we use equation (7) to compute the expected and idiosyncratic returns as follows:

$$\text{Expected Return}_{ijt} \equiv \hat{r}_{ijt} = \hat{\alpha}_{ijt} + \hat{\beta}^{M}_{ijt}(rm_t - rf_t) + \hat{\beta}^{IND}_{ijt}(\bar{r}_{-ijt} - rf_t),$$

$$\text{Idiosyncratic Return}_{ijt} \equiv \hat{\eta}_{ijt} = r_{ijt} - \hat{r}_{ijt}.$$

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 βs that are firm-specific and time-varying, hence the parameter subscripts in equation (7), but constant within a calendar year. Thus, our construction of idiosyncratic returns allows for heterogeneous sensitivities to aggregate shocks.

Table II presents summary statistics for the estimated factor regressions. On average, each of the rolling regressions has 59 monthly observations, though the majority rely on a full 5-year window. The average adjusted R^2 is approximately 23%. The regressions load positively on both market and industry factors, whose factor loadings sum to approximately one. The average idiosyncratic return is less than 20 basis points in magnitude—an artifact of rounding and sample selection on nonmissing data for the accounting variables (see Appendix A).

To maintain consistency with the periodicity of the accounting data, we compound the monthly returns to obtain an annual measure. We then average this measure over peer firms within each year and lag it 1 year with respect to the outcome variables. Thus, our source of exogenous variation for peer firms' characteristics is the lagged average peer firm equity return shock, $\bar{\hat{\eta}}_{-ijt}$.

Intuitively, our strategy can be viewed as matching each firm to every other firm in its industry. Consider an industry with just two firms, A and B. Our identification strategy uses firm B's return shock to capture the effect of its behavior—financing decisions and characteristics—on firm A's financing decision, and vice versa. Now consider an industry with three firms, A, B, and C. Our identification strategy uses the return shocks to firms B and C to capture the effect of their behavior on firm A's financing decisions. Averaging provides a convenient tool to reduce the dimensionality of the problem and summarize the salient information. Averaging also ensures that nonlinearities are not responsible for our identification. However, averaging does reduce the noise in individual return shocks, which can threaten identification when individual returns are noisy. We discuss this concern below.

Note that, conditional on a properly specified asset pricing model (equation (7)), the average peer firm return shock need not be zero. This measure is a conditional average, conditional on industry and year. In addition, the measure is not exactly the industry average since it excludes the i^{th} observation. Panel A of Figure 1 illustrates the variation in peer firm average return shocks with a histogram. The unconditional mean is zero, as suggested by the approximately zero average idiosyncratic return shown at the bottom of Table II and the zero balance point in the figure. Panels B and C show what happens to our measure as the industry definition becomes coarser and the size of the peer group increases. We see that the distribution collapses around zero, and more so for the one-digit (Panel C) than the two-digit (Panel B) industry definition. Thus, consistent with the economic notion of a peer group, we rely on a restriction on the size of the group to ensure sufficient variation in our measure.

D. Identification Threats

Identification threats come from correlation between our measure of peer firm idiosyncratic return shocks and omitted or mismeasured firm i capital structure determinants. We refer collectively to these determinants as common factors. This subsection takes a first step toward addressing this concern by examining the statistical properties of peer firm equity shocks and their economic implications.

Before doing so, we emphasize that the scope for potential identification threats is limited to the fraction of variation remaining after conditioning on the observable control variables. A useful taxonomy of the variation in our measure is between industries, within industries, and over time. The inclusion of control variables in equation (1) eliminates much of this variation. Industry

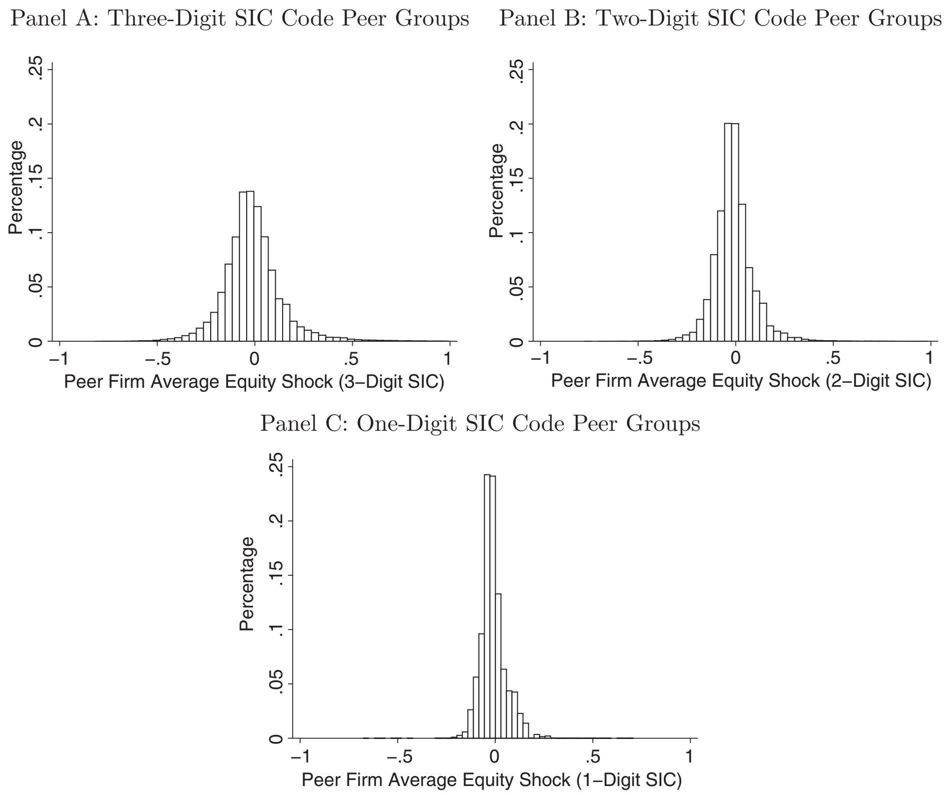

Figure 1. Industry average idiosyncratic stock returns distribution. The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The figure presents the empirical distribution of our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

fixed effects remove all between-industry variation. Inclusion of firm i's shock as a control variable eliminates all within-industry-year variation.[8] This implies that the identifying variation is within-industry time-series variation in the component of peer firm return shocks that is orthogonal to all of the included control variables, X_{ijt-1} and $\bar{X}_{-ijt-1}$. Though correlation with unobservables is always a concern, we show that the remaining identifying variation reduces the scope for alternative hypotheses.

Previous empirical work shows that observable leverage determinants do a relatively poor job of controlling for systematic variation in capital structures

[8] Intuitively, the difference between the industry average shock and the peer firm average shock is the exclusion of firm i's shock. Since the industry average shock does not vary within an industry-year, the variation in the peer firm average shock within an industry-year is perfectly negatively correlated with firm i's shock.

(e.g., Welch (2004), Lemmon, Roberts, and Zender (2008), and Strebulaev and Yang (2012)). The relevant issue in the current context is whether the remaining omitted variables or measurement errors are correlated with peer firm average equity shocks conditional on other observable characteristics. Thus, we focus on ensuring, as much as possible, that the average idiosyncratic equity shock to peer firms (1) is not a better measure of firm *i*'s capital structure determinants than are the other included firm characteristics (including firm *i*'s own return shock), and (2) is not capturing a common factor shared among firms within the peer group.

The first consideration highlights the importance of isolating the idiosyncratic component of stock returns rather than using total returns. Table II shows that the idiosyncratic component accounts for a significant portion of the variation in stock prices—the average R^2 is equal to 23%. This result suggests that the average total return of other firms in an industry may provide a less noisy measure of the investment opportunities, for example, facing each individual firm than their own individual stock return or market-to-book ratios. Intuitively, the averaging of returns smooths out any noise in individual stock returns.

Table III examines the partial correlations between peer firm average equity shocks and firm *i* characteristics. We examine the correlations with both contemporaneous and one-period lead effects, to determine whether our measure contains information about current or future firm *i* characteristics. Note that correlation with the characteristics is not problematic because the characteristics are all included in the regression as control variables. However, economically large associations between our measure and observable firm characteristics would raise concerns about the extent to which our measure may be correlated with unobservable factors, and the extent to which we have removed common variation among firms' returns via the asset pricing model.

The results reveal one statistically significant coefficient among the firm *i* characteristics in the contemporaneous specification, and none in the one-period-lead specification. The economic magnitudes of the coefficient estimates are all tiny as well. For the only statistically significant coefficient, *EBITDA/Assets*, a one standard deviation increase in this covariate is associated with a 10 basis point decline in contemporaneous peer firm equity shocks. This change in equity shocks is less than 0.01 standard deviations. Thus, the peer firm equity shocks contain no significant information related to firm *i*'s current or near-future observable capital structure determinants.

Regarding an omitted common factor, consideration (2), we note the following findings from untabulated results. The correlation between firm *i*'s total return and the average industry total return excluding firm *i*'s total return is 0.37. The correlation between firm *i*'s idiosyncratic return shock and the average peer firm shock is 0.02. This decline suggests that the asset pricing model purges most, though not all, of the intraindustry correlation in returns. We include firm *i*'s shock in equation (1) to help absorb this remaining correlation. The peer firm return shocks are also serially uncorrelated and serially

Table III

Peer Firm Return Shock Properties

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients and t-statistics robust to heteroskedasticity and within-firm dependence in parentheses. The dependent variable is the average peer firm equity return shock. All independent variables are in levels and are either contemporaneous with or a one-period-lead relative to the dependent variable, as indicated at the top of the columns. Firm-Specific Factors denotes variables corresponding to firm i's value in year t. Peer Firm Average Characteristics are peer firm averages of the same variables listed under firm-specific factors in the table: log of sales, the market-to-book ratio, the ratio of EBITDA to assets, and the ratio of net PPE to assets. Peer firm averages are constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industries are defined by three-digit SIC code. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

	Peer Firm Average Equity Shock	
	Contemporaneous Independent Vars.	1-Period-Lead Independent Vars.
Firm-Specific Factors		
Log(Sales)	−0.000	−0.000
	(−0.565)	(−0.334)
Market-to-Book	−0.001	0.000
	(−1.444)	(0.104)
EBITDA/Assets	−0.009*	−0.000
	(−2.336)	(−0.048)
Net PPE/Assets	0.008	0.004
	(1.934)	(0.994)
Peer Firm Average Characteristics	Yes	Yes
Firm i Equity Return Shock	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Obs.	80,279	80,119
Adj. R^2	0.128	0.127

cross-uncorrelated, implying that firms' shocks do not forecast future shocks for themselves or for other firms.

IV. The Role and Implications of Peer Effects

A. Reduced-Form Results

Panel A of Table IV presents the results of estimating equation (6). The dependent variable is indicated at the top of the columns. The body presents coefficient estimates and t-statistics in parentheses. We present results for market and book leverage in levels (columns (1) and (2)) and first differences (columns (3) and (4)). The latter specifications help to address concerns over omitted firm i characteristics, since they are similar to levels specifications that include firm fixed effects. The level specifications use the levels for all

Table IV

Peer Effects in Financial Policy: Reduced-Form Estimates

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). Both panels present OLS estimated coefficients and *t*-statistics robust to heteroskedasticity and within-firm dependence in parentheses. The dependent variable is indicated at the top of columns. All independent variables are lagged 1 year and are in levels or first differences (Δ) for consistency with the dependent variable indicated at the top of the columns. The exception is stock returns, which are in level form across all specifications. Equity (Debt) Issuance is equal to one if Net Stock (Debt) Issuances normalized by lagged book assets is greater than 1%. The last column of Panel A isolates the subsample of observations in which either an equity or debt issuance, but not both, occurred. In Panel B, the change in market leverage is the dependent variable in all specifications, which include all firm-specific and peer firm averages used in Panel A as control variables. Stock Return Controls includes firm *i*'s lagged and contemporaneous total stock return. Additional Control Variables includes lagged firm-specific and peer firm averages for changes in cash flow volatility, a dividend payer indicator, Altman's (1968) Z-score, Graham's (2000) marginal tax rate, capital investment, R&D expenditures, and SG&A expenditures as well as the intraindustry standard deviation of leverage. See Appendix A for complete variable definitions. Polynomials of Controls includes quadratic and cubic terms of all independent variables other than industry average leverage. Contemporaneous Controls replaces the lagged firm-specific and peer firm averages control variables with contemporaneous values. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

	Market Leverage (1)	Book Leverage (2)	Δ Market Leverage (3)	Δ Book Leverage (4)	Equity Issuance (5)	Debt Issuance (6)	(Issuers) Debt Issuance (7)
Panel A: Financial Policy							
Peer Firm Averages							
Equity Shock	−0.024**	−0.016**	−0.020**	−0.008**	0.021*	−0.029*	−0.034*
	(−4.965)	(−3.997)	(−6.312)	(−3.109)	(2.440)	(−2.469)	(−2.313)
Log(Sales)	−0.002	−0.002	0.030**	0.009*	−0.008*	0.008	0.014**
	(−0.869)	(−0.994)	(5.941)	(2.398)	(−2.295)	(1.790)	(2.810)
Market-to-Book	0.001	0.001	−0.001	−0.001	0.024**	0.030**	−0.011
	(0.314)	(0.426)	(−0.431)	(−0.343)	(4.817)	(5.079)	(−1.505)
EBITDA/Assets	0.045	0.118**	−0.026	−0.021	0.038	0.357**	0.306**
	(1.574)	(4.666)	(−1.475)	(−1.377)	(0.909)	(7.130)	(4.840)
Net PPE/Assets	0.078**	0.025	0.057*	0.050*	0.066	−0.008	−0.006
	(2.700)	(1.005)	(1.972)	(2.392)	(1.836)	(−0.192)	(−0.131)
Firm-Specific Factors							
Equity Shock	−0.008**	−0.002	0.001	−0.002	0.062**	0.020**	−0.052**
	(−5.812)	(−1.624)	(1.317)	(−1.844)	(21.199)	(6.282)	(−12.219)
Log(Sales)	0.010**	0.010**	0.016**	0.006**	−0.012**	0.014**	0.024**
	(9.260)	(10.812)	(8.071)	(3.274)	(−9.353)	(11.251)	(13.173)
Market-to-Book	−0.053**	−0.014**	−0.002**	−0.002**	0.077**	0.005*	−0.071**
	(−43.272)	(−11.384)	(−3.500)	(−3.057)	(35.226)	(2.421)	(−28.260)
EBITDA/Assets	−0.308**	−0.231**	−0.033**	−0.024**	−0.258**	−0.041**	0.161**
	(−28.937)	(−20.865)	(−5.400)	(−3.511)	(−17.546)	(−2.689)	(7.991)
Net PPE/Assets	0.161**	0.195**	0.068**	0.053**	0.042**	0.185**	0.086**
	(12.007)	(16.169)	(6.851)	(5.685)	(3.094)	(12.220)	(4.422)
Industry Fixed Effects	Yes	Yes	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	80,279	80,279	80,279	80,279	80,279	80,279	35,363
Adj. R^2	0.31	0.20	0.10	0.01	0.16	0.05	0.27

(Continued)

Table IV—*Continued*

	Δ Market Leverage					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Change in Leverage Robustness Tests						
Peer Firm Averages						
Equity Shock	−0.014**	−0.019**	−0.014**	−0.019**	−0.015**	−0.021**
	(−4.866)	(−5.522)	(−3.102)	(−6.131)	(−5.318)	(−6.487)
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Return Controls	Yes	No	No	No	No	No
Additional Control Variables	No	Yes	No	No	No	No
Bank × Market Return Effects	No	No	Yes	No	No	No
Lagged Dependent Variable	No	No	No	Yes	No	No
Contemporaneous Controls	No	No	No	No	Yes	No
Polynomials of Controls	No	No	No	No	No	Yes
Obs.	80,279	69,578	33,674	80,230	80,119	80,279
Adj. R^2	0.26	0.10	0.11	0.10	0.18	0.10

of the variables on both the left- and right-hand sides of the equation.[9] The first difference specifications uses first differences for all of the variables on both the left- and right-hand sides of the equation. The only exception are the equity shocks, both for firm i and peer firms, which are the same across all specifications.

The results in columns (1) and (2) reveal that the average peer firm equity shock is strongly negatively associated with both market and book leverage. The negative sign suggests that equity shocks to peers affect firm i in a similar manner as firm i's equity shocks. However, we emphasize that a precise interpretation of the sign or magnitude of this coefficient is difficult because it represents a composite of the underlying structural parameters (see Section III). Columns (3) and (4) reinforce these findings by showing similar results for changes in leverage ratios. This finding is reassuring because it shows that the unobserved firm-specific heterogeneity is not responsible for our findings (Lemmon, Roberts, and Zender (2008)).

The effects of other peer firm characteristics (besides the equity shock) on capital structure are not robust and economically small. Peer firm asset tangibility is the most robust relation, though it is statistically insignificant in the second specification. This finding is suggestive evidence that the primary channel through which peer firms may influence financial policy is via actions

[9] All control variables are lagged 1 year relative to the dependent variable.

(i.e., peer firms' policy choices), as opposed to characteristics. We examine this issue in more detail below in Section IV.D.

In columns (5) through (7) of Table IV, Panel A, we examine net equity- and net debt-issuing activity to understand whether peers are influencing specific financing decisions. While a logit or probit model may be more appropriate from a forecasting perspective, we present results using a linear probability model (equation (1)) to ease interpretation and comparison with other findings. Unreported results using a probit model reveal qualitatively similar findings.

Column (5) presents results where the dependent variable is an indicator equal to one if the firm issues equity net of repurchases in excess of 1% of total assets, and zero otherwise. This regression models the probability that firms issue equity relative to not issuing equity, which includes debt issuances, debt retirements, stock repurchases, and no financing activity. Column (6) presents analogous results for the probability of issuing debt. In both models, the peer firm return shocks are statistically significantly associated with issuance decisions. Column (7) conditions on an issuance decision (debt or equity), thereby eliminating a number of inactive periods. The results reinforce those in the first two columns. Firms alter their financing behavior in response to their peers.

In sum, the results in Table IV, Panel A, suggest that peer effects play a significant role in determining variation in corporate leverage ratios and security issuance decisions. When making these choices, firms respond to their competitors.

B. Robustness Tests: Peer Effects versus Omitted and Mismeasured Common Factors

In this section, we further reduce the identifying variation by conditioning on additional control variables motivated by alternative hypotheses. Panel B of Table IV presents the results. For brevity, we only report results using the change in market leverage as the dependent variable. In unreported results, we repeat the analysis for the level of market leverage, as well as the level and change in book leverage. The results are qualitatively similar to those presented here.

All specifications include firm-specific factors and peer firm averages for log(sales), the market-to-book ratio, *EBITDA/Assets*, and *Net PPE/Assets*. The presence of fixed effects and all control variables are indicated in the bottom part of the panel. We restrict attention to the key variable of interest, namely, peer firm equity shocks.

In column (1), we replace the lagged firm-specific equity shock with lagged and contemporaneous firm-specific total stock returns, r_{ijt}. We see a slight attenuation in the estimated effect compared to the baseline estimate of −0.020 in Panel A, though the coefficient is still highly significant, both statistically and economically. This specification change ensures that the identifying variation from peer firms' idiosyncratic returns is orthogonal to firm *i*'s stock returns (lagged and contemporaneous). In other words, alternative hypotheses must now rely on lagged idiosyncratic stock returns of peer firms containing information about firm *i*'s capital structure determination that is not contained in firm *i*'s stock returns, as well as any of the other control variables. This fact allays a number of identification concerns related to correlated returns.

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

Another concern is that firms receive industry-wide shocks to their equity valuations and that these shocks are asynchronous, so that the year fixed effects are inadequate controls. For example, industries may experience "hot" and "cold" equity markets due to shifting investor demands, which cause equity valuations for all firms in an industry to move in the same direction (e.g., the tech sector in the late 1990s). Because these shifts in investor demand are reflected in prices, this concern is largely eliminated by including firm *i*'s stock returns in the specification. Furthermore, by including both the contemporaneous and lagged stock return, we eliminate concerns regarding the timing of equity price shocks whereby some firms in an industry get shocked earlier than their peers.[10]

Column (2) of Table IV, Panel B, examines a "kitchen sink" model of capital structure including additional explanatory variables previously identified as relevant for capital structure. Specifically, we include lagged firm-specific and peer firm averages for an indicator identifying whether a dividend was paid, Altman's *Z*-score, Graham's (2000) marginal tax rate, capital investment, R&D expenditures, SG&A expenditures, and intraindustry leverage dispersion. The results are unaffected by their inclusion.

Column (3) incorporates bank fixed effects, and bank fixed effects interacted with the CRSP value-weighted market return.[11] This specification addresses the concern that commonality among firms' capital structures is due to the use of common banks (commercial or investment) within the industry and that financial advice from these banks varies over the business cycle. This change

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

[11] See Appendix A for a description of the construction of bank fixed effects. In unreported results, we interact the bank effects with the yield spread on Baa over Aaa corporate bonds as an alternate measure of market conditions. The results are qualitatively similar.

has little effect on our results, despite the sharp decline in observations due to the additional data requirements.[12]

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

Column (5) of Table IV, Panel B replaces the lagged control variables with contemporaneous controls to address the concern that capital structure-relevant shocks affect our firm-specific and peer firm characteristics with a lag. Finally, column (6) includes quadratic and cubic polynomials of each firm-specific factor and peer firm average characteristic in our primary specification (i.e., firm size, profitability, tangibility, market-to-book). Again, we see little change in the results, suggesting that functional form misspecification in the control variables is unlikely to be behind our results.

C. Customer–Supplier Links

In Table V, we take a different approach to defining peer groups and our measure of peer firm behavior to address remaining identification concerns. In particular, the noise in individual stock returns may leave room for our measure of peer firm equity shocks to provide additional information about firm i's capital structure through the smoothing effect of averaging, or through traces of correlation between our measure and an industry factor that is relevant for all firms' leverage but for which independent variables do not adequately control.

As such, we define the peer group for firm i as the subset of firms in the same industry as firm i with at least one customer firm that satisfies the following three criteria: (1) the customer is in an industry different from firm i, (2) the customer is not a customer of firm i, and (3) the customer accounts for at least 10% of the peer firm's sales. The motivation for this peer group definition comes from Cohen and Frazzini (2008), who show that shocks to customers predict equity returns and real outcomes for supplier firms, but not for firms in the same supplier industry without an active customer–supplier link. Using this insight, we use the average equity return shock to the *customers* of peer firms that are not also customers of firm i as a measure of peer firm behavior.[13]

[12] We also believe that common institutional ownership is not likely to be responsible for our findings. The large majority of institutional investors are passive and unlikely to be dictating financial policy. Brav et al. (2008) estimate that the activist share of total institutional equity ownership ranges from 0.7% to 2.3% from 2000 to 2007.

[13] We thank Lauren Cohen for kindly sharing his updated data on linking customers and suppliers in the CRSP database. See Cohen and Frazzini (2008) for details on these data.

Table V

Customer–Supplier Tests

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). Panel A presents OLS estimates using peer groups defined as the subset of firms in the same industry as firm i that satisfy the following two criteria: (1) they have customers in an industry different from firm i, and (2) their customers are not customers of firm i. Panel B presents OLS estimates in which we replace each customer from the analysis in Panel A with a randomly selected noncustomer in the same industry as the customer. The average shock to the randomly selected noncustomers is then used in place of the shock to the customer. We perform the random selection and OLS estimation 100 times to obtain a distribution of estimated coefficients and t-statistics on the noncustomer equity return shocks. All specifications include firm-specific and peer firm averages for firm size, profitability, tangibility, and the market-to-book ratio. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

	Market Leverage (1)	Δ Market Leverage (2)	Issue Debt (3)
Panel A: Customer Return Shocks			
Avg. Peer Customer Equity Shock	−0.012*	−0.011**	−0.036*
	(−2.398)	(−3.535)	(−2.027)
Industry Avg. Equity Return	−0.044**	0.009**	−0.042**
	(−10.898)	(3.553)	(−3.211)
Peer Firm Averages			
Log(Sales)	0.004*	0.018**	0.002
	(2.339)	(4.978)	(0.589)
EBITDA/Assets	0.062**	0.002	0.130**
	(5.031)	(0.278)	(3.431)
Market-to-Book	0.001	−0.002*	−0.001
	(0.759)	(−2.294)	(−0.216)
Net PPE/Assets	−0.013	0.055**	−0.049
	(−0.842)	(2.942)	(−1.256)
Firm-Specific Factors			
Log(Sales)	0.009**	0.024**	0.027**
	(8.271)	(12.219)	(11.015)
EBITDA/Assets	−0.176**	−0.035**	0.134**
	(−20.583)	(−6.440)	(6.143)
Market-to-Book	−0.039**	−0.003**	−0.062**
	(−39.523)	(−5.795)	(−24.398)
Net PPE/Assets	0.199**	0.063**	0.148**
	(13.153)	(5.366)	(5.701)
Equity Shock	−0.009**	0.004**	−0.044**
	(−6.719)	(3.878)	(−9.187)
Industry Fixed Effects	Yes	No	Yes
Year Fixed Effects	Yes	No	Yes
Obs.	54,599	52,222	21,410
Adj. R^2	0.28	0.08	0.26

(Continued)

Table V—*Continued*

	Percentiles					
	Mean	5	25	50	75	95
Panel B: Placebo Tests						
Coefficient Estimates						
Market Leverage	0.004	−0.002	0.001	0.004	0.006	0.010
Δ Market Leverage	0.001	−0.004	−0.001	0.000	0.003	0.006
Issue Debt	0.001	−0.019	−0.006	0.001	0.007	0.021
Peer Effect t-stats						
Market Leverage	1.496	−0.831	0.283	1.537	2.499	4.033
Δ Market Leverage	0.414	−2.738	−0.887	0.274	1.704	3.475
Issue Debt	0.080	−2.016	−0.638	0.111	0.763	2.398

The benefit of this approach is a more compelling identification strategy. Because the customers are in a different industry and do not share a supply chain link with firm i, there is less concern over latent common factors driving the results. Furthermore, because the measure is now based on shocks from a different industry, we can include firm i's industry return, in addition to firm i's own stock return, as a control variable. Thus, the identifying variation now comes from return shocks to firms in another industry that are orthogonal to firm i's stock return and firm i's industry return, as well as all of the other included control variables.

The drawback of this approach is a noisy definition of firms' peer groups. In fact, the second criterion above ensures that the most similar firms from a demand perspective are not included in the peer group. The consequences of this noise are a reduction in statistical power and a possible attenuation of the estimated peer effect.

The results in Panel A of Table V show a slight attenuation in the coefficient relative to the estimates of Table IV. However, peer firm customer equity shocks are still significantly negatively correlated with both leverage and net issuance decisions, the latter of which conditions the sample on either net equity issuance or net debt issuance. Unreported results examining book leverage are similar. We also find a significant relation between firm i's industry stock return and financial policy, though the coefficients on peer firm customer equity shocks remain significant.

To ensure that the customer–supplier link is unique, Panel B presents the results from a placebo test. We replace each customer of firm i's peers with a randomly selected firm from the same industry as the customer but with no economic ties to firm i's industry. We call these firms "noncustomers." We then construct the exogenous peer firm measure using the return shocks to the noncustomers and rerun our analysis from Panel A. We repeat this process of replacing each customer with a randomly selected noncustomer, constructing the return shock measure, and estimating the regressions 100 times. The distribution of the coefficient estimates on the return shock and the corresponding t-statistics are presented in Panel B of Table V. To address outlier estimates, we Winsorize the results at the 5^{th} and 95^{th} percentiles.

The results in the top half of the panel show that the average and median peer effect estimates are all significantly smaller in magnitude than those in Panel A. Focusing on the median, we see that the placebo estimate for the level of leverage is 0.004, compared with −0.012. The placebo estimate for the first difference in leverage is 0.000 versus −0.011. Finally, the placebo estimate for debt issuances is 0.001 versus −0.036 The differences in Winsorized means are similar. Panel B shows that most of the placebo estimates are statistically insignificant as well. For the level and first difference in leverage, there appears to be a power distortion because more than 5% of the estimates are statistically significant. Nonetheless, the evidence is supportive of the previous findings, further suggesting identification of a peer effect.

D. Peer Effects Channels: Actions versus Characteristics

While our reduced-form results establish the presence of significant peer effects, they are subject to two limitations. First, as discussed in Section III they do little to distinguish between the two channels through which peer effects operate. In this section, we provide additional analyses to aid with this distinction. Second, since we estimate composite parameters, it is difficult to assess the economic magnitude of the peer effects. We turn to this issue in the next subsection.

To illustrate the challenge of distinguishing between the two peer effect channels, consider the following hypothetical example. Firm A introduces a new product, which positively impacts the idiosyncratic component of its stock return. In the following period, firm A issues equity to finance an increase in production and reduce its leverage ratio. In response, peer firm B issues equity and reduces its leverage too. The question is: is firm B responding to the change in financial policy, or to the introduction of the new product (i.e., the information about their competitor embedded in the stock return)?

To help distinguish between these alternatives, we exploit heterogeneity in firms' capital structure responses to their peers' equity shocks. We do so by performing a double sort of the data based on quintiles of our peer firm average equity shocks and peer firm leverage changes. Within each quintile combination, we compute the average change in leverage for firm i and a t-statistic of whether this change is significantly different from zero. We perform this analysis on both book and market measures of leverage, but present only the market leverage results for brevity.

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

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents average market leverage changes for 25 groups of observations. The groups are formed by the intersection of quintiles based on: (1) peer firm average equity return shocks lagged 1 year and (2) peer firm average change in market leverage. The column labeled "5 − 1" presents the difference in means between columns 5 and 1. The row labeled "5 − 1" presents the difference in means between rows 5 and 1. t-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. Statistical significance at the 1% level is denoted by **.

Lagged Peer Firm	Peer Firm Avg Leverage Change Quantiles					
Avg Equity Shock	1 (Low)	2	3	4	5 (High)	5 − 1
1 (Low)	−0.033**	−0.008**	0.007**	0.021**	0.062**	0.095**
	(−14.176)	(−4.026)	(3.158)	(9.857)	(29.059)	
2	−0.044**	−0.014**	0.007**	0.020**	0.062**	0.106**
	(−18.302)	(−6.574)	(4.348)	(9.665)	(26.558)	
3	−0.042**	−0.014**	−0.000	0.023**	0.066**	0.108**
	(−18.608)	(−7.284)	(−0.253)	(13.002)	(25.001)	
4	−0.047**	−0.013**	0.003	0.017**	0.066**	0.114**
	(−22.532)	(−7.628)	(1.566)	(8.202)	(28.275)	
5 (High)	−0.046**	−0.024**	0.006**	0.016**	0.062**	0.108**
	(−27.376)	(−11.640)	(2.644)	(7.327)	(24.489)	
5 − 1	−0.014**	−0.016**	−0.000	−0.005	−0.000	

The results are presented in Table VI, where quintile "1" represents the lowest 20% of the distribution and quintile "5" the highest. For example, the average change in leverage among firms in the lowest peer firm equity shock quintile and the highest peer firm leverage change quintile is 6.2% with a t-statistic of 29.06. We note a monotonic increase in the average leverage change across each row. In other words, holding fixed the peer firm equity shock, leverage changes are strongly positively correlated with changes in peer firm leverage. The converse is not true. Average leverage changes are largely uncorrelated with the peer firm equity shock, holding fixed peer firms' average leverage change. In fact, in column (3), where the average peer firm leverage change is indistinguishable from zero, the cell averages are all economically small and two are statistically insignificant. Thus, firms only change their leverage in response to a peer firm equity shock if it is accompanied by a change in peer firm leverage.

These findings reinforce the implication of the regression results and suggest that peer firm average equity shocks are more likely capturing a response to peer firm financial policies, as opposed to characteristics. However, they come with a caveat. It may be the case that peer firm characteristics only matter for firm i's financial policy when they are accompanied by a change in peer firm financial policy as well. Thus, the results in Table VI diminish the scope for our measure to capture a peer effect operating through characteristics, but they cannot completely rule it out.

In unreported analysis, we examine whether other corporate policies are affected by peer firms' return shocks. We find no relation between peer firms return shocks and the investment, research and development, or dividend policies of firm i. This finding reinforces our identification because, if latent investment opportunities are behind our earlier findings, then this should show up in the investment regression. This finding also further supports the view that the primary channel through which peer effects in financial policy operate is via actions, that is, peers' capital structure decisions. The next subsection investigates this inference more formally.

E. The Economic Importance of Peer Effects

To estimate the magnitude of peer effects in financing policy, we need to estimate the structural parameters in equation (1). This requires an instrument for the endogenous peer firm outcome variable, $\bar{y}_{-ijt}$. In this section, we estimate equation (1) via two-stage least squares, using our measure of peer firm equity shocks to instrument for peer firm financial policies.[14]

In employing this strategy, we acknowledge that the identification assumptions are now more stringent than when estimating the reduced-form model. The relevance condition requires that peer firm equity shocks be significantly correlated with peer firm capital structure choices. This assumption is testable. More important, our estimates may be biased if the average peer firm return shocks are correlated with either (i) an omitted firm i capital structure determinant or (ii) an omitted peer firm characteristic that is relevant for firm i's capital structure. While the former concern is mitigated by our previous analyses, we cannot completely rule out the latter. However, the results discussed in Section IV.D suggest a limited role for peer firm characteristics in capital structure choices, implying that any remaining bias is likely to be small.

E.1. Instrumental Variables Results

Table VII displays the results of two-stage least squares estimation of equation (1). The first four columns show results with leverage as the outcome variable, both market and book in levels and changes. The coefficients on the instrument from the first-stage regressions are shown at the bottom of the table. The first-stage results reveal that the average equity shock is strongly negatively correlated with both the level and first difference in average industry leverage ratios. The sign of the estimate is consistent with previous findings relating total returns to leverage and with theoretical arguments relating investment opportunities and risk to optimal leverage and financing choices (e.g.,

[14] This strategy follows Duflo and Saez (2002) and Case and Katz (1991), who similarly use average exogenous characteristics of the peer group as an instrument for peers' behavior in the context of retirement savings plan participation and neighborhood effects on socioeconomic outcomes, respectively.

Table VII

Peer Effects in Financial Policy: Structural Estimates

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents two-stage least squares (2SLS) estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within-firm dependence in parentheses. The dependent variable is indicated at the top of each column. The endogenous variable is the peer firm average of the dependent variable. The instrument is the one-period-lagged peer firm average equity return shock. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industries are defined by three-digit SIC code. Firm-Specific Factors denotes variables corresponding to firm i's value in year t. All variables are in levels or first differences as indicated at the top of the columns. All independent variables, including the instrument but excluding the endogenous variable, are lagged 1 year relative to the dependent variable unless otherwise specified. Equity (Debt) Issuance are indicator variables equal to one if Net Stock (Debt) Issuances normalized by lagged book assets is greater than 1%. The last column of Panel A isolates the subsample of observations in which either an equity or debt issuance, but not both, occurred. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

	Market Leverage (1)	Book Leverage (2)	Δ Market Leverage (3)	Δ Book Leverage (4)	Equity Issuance (5)	Debt Issuance (6)	(Issuers) Debt Issuance (7)
Peer Firm Averages							
Dependent Variable	0.100**	0.100**	0.077**	0.045*	0.046*	−0.631	0.105*
	(4.803)	(3.573)	(5.431)	(2.566)	(2.423)	(−1.249)	(2.230)
Log(Sales)	−0.011**	−0.015**	−0.004*	−0.001	−0.003	0.095	0.001
	(−2.719)	(−3.111)	(−2.440)	(−0.777)	(−0.599)	(1.387)	(0.120)
Market-to-Book	0.032**	0.011**	0.001	0.002	−0.002	0.092	0.017
	(4.403)	(2.791)	(1.463)	(1.602)	(−0.278)	(1.555)	(1.410)
EBITDA/Assets	0.021**	0.020**	0.002*	0.001	0.008*	0.102	0.006
	(4.618)	(4.949)	(2.416)	(1.151)	(2.244)	(1.632)	(0.744)
Net PPE/Assets	−0.013	−0.033**	−0.001	−0.001	0.007	0.083	−0.001
	(−1.659)	(−2.858)	(−1.788)	(−1.251)	(1.095)	(1.200)	(−0.144)
Firm-Specific Factors							
Log(Sales)	0.021**	0.021**	0.005**	0.002**	−0.026**	0.035**	0.051**
	(9.113)	(10.435)	(6.541)	(2.640)	(−9.161)	(7.432)	(12.410)
Market-to-Book	−0.067**	−0.018**	−0.002**	−0.002**	0.095**	0.015	−0.097**
	(−42.570)	(−11.257)	(−3.661)	(−3.081)	(34.880)	(1.871)	(−27.751)
EBITDA/Assets	−0.048**	−0.037**	−0.003**	−0.002**	−0.040**	0.005	0.026**
	(−28.700)	(−20.769)	(−5.128)	(−3.280)	(−17.645)	(0.514)	(7.661)
Net PPE/Assets	0.034**	0.042**	0.004**	0.003**	0.009**	0.040**	0.018**
	(11.281)	(15.105)	(5.955)	(4.680)	(2.940)	(8.654)	(4.137)
Equity Shock	−0.003**	−0.000	0.002**	−0.000	0.032**	0.007	−0.028**
	(−4.468)	(−0.484)	(3.030)	(−0.713)	(21.071)	(1.535)	(−12.039)
First-Stage Instrument							
Peer Firm Avg Equity Shock	−0.033**	−0.015**	−0.015**	−0.005**	0.074**	0.009	−0.091**
	(−13.126)	(−7.350)	(−8.713)	(−4.383)	(19.430)	(1.530)	(−8.146)
Industry Fixed Effects	Yes	Yes	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	80,279	80,279	80,279	80,279	80,279	80,279	34,578

Scott (1976) and Myers (1977)). Statistically speaking, the instrument easily passes weak instrument tests (e.g., Stock and Yogo (2005)).

The row labeled "Dependent variable" at the top of the table reports $\hat{\beta}$, the estimated coefficient on the instrumented peer firm average outcome variable. For each specification, the results indicate that firms' leverage choices are significantly positively influenced by the leverage choices of their peers. To ease interpretation of magnitudes, all coefficients are scaled by the corresponding variable's standard deviation. Thus, from columns (1) and (2), a one standard deviation increase in peer firm average leverage leads to a 10 percentage point increase in firm i's leverage. Compared to traditional firm-specific determinants, peer firm financial policies have a significantly larger effect. For example, in the market leverage regression (column (1)), the next-most impactful determinant is the market-to-book ratio, whose scaled coefficient is -6.7%—almost 40% smaller. For book leverage, the effect of asset tangibility is less than half that of peer firm average leverage.

The results in column (5) reinforce these findings by showing that firms' equity issuance decisions are significantly influenced by their peers' issuance decisions. The first stage indicates a strong positive association between peer firms' return shocks and their equity issuance decisions. Second-stage results show that a one standard deviation increase in the probability of issuing equity by peer firms leads to a 4.6% increase in the probability of firm i issuing equity. The peer effect is one of the most economically important determinants, second only to firm i's own market-to-book ratio. Column (6) presents analogous results for the decision to issue debt. Nether first- nor second-stage estimates are statistically significant. Column (7) shows that this result is due largely to the comparison set. When we restrict attention to the subsample of active financing decisions (net debt issuance or net equity issuance), we find an economically large peer effect. Specifically, the first-stage estimate is statistically significantly negative because we are modeling the debt, as opposed to equity, decision. The second-stage estimate reveals a statistically and economically large positive peer effect. Thus, conditional on financing activity, peer firms play an important role in the likelihood of net issuing activity.

In sum, the peer effects play an economically significant role in determining variation in corporate leverage ratios. This variation in leverage is driven by peer effects in financing choices. These effects are economically large, significantly larger than almost any other estimated effect.

E.2. Amplification, Spillover, and Marginal Effects

An important implication of the empirical model in equation (1) is the presence of externalities whereby changes to one firm affect the outcomes at another firm. These externalities imply that the total derivative is no longer equal to the partial derivative, even in a linear model, because of the presence of the peer firm outcome variable on the right-hand side of the equation. Since the total derivative is the economic quantity of interest, the effect of a change in any exogenous capital structure determinant cannot be inferred solely from its coefficient. Rather, the derivatives of interest are

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

where i and l denote firm-year observations and m denotes the regressor. Thus, dy_i/dx_{lm} measures the change in y for firm i given a one unit change in x_m for firm l. The number of firms in the peer group is denoted by N. (See Appendix B for a derivation.)

In the typical linear model without peer effects, both β and γ are equal to zero and the derivative reduces to $\partial y_i/\partial x_{lm} = \lambda_m$ for all i and l. With peer effects, there are several distinctions. When $i = l$, the peer firm average leverage coefficient, β, amplifies the effect of a change in an exogenous variable on y. This amplification mechanism is represented by the parenthetical expression multiplying λ_m. For β in the open unit interval and $N > 1$, this expression is strictly greater than one. Because of the presence of peer firm characteristics, this amplification may be either further amplified or offset depending on the correlation between the outcome variable and the peer firm characteristics, γ_m. (The second term in the case $i = l$.) When $i \neq l$, the derivative is no longer zero. Instead, cross-observation effects are determined by the relative importance of peer firm actions (β) and characteristics (γ).

The estimation of the structural parameters in Table VII allows us to estimate these effects. The results are presented in Table VIII. The first two columns repeat the scaled coefficients on the firm-specific and peer firm average characteristics from column (2) of Table VII (market leverage specification). The exception is the estimate of β, which is presented unscaled to verify that it is between zero and one.

In the remaining columns, the bottom panel presents estimates of the amplification term (the first parenthetical expression in the case $i = l$), spillover term 1 (the second parenthetical expression in the case $i = l$), spillover term 2 (the second parenthetical expression in the case $i \neq l$), and their corresponding χ^2 test statistics in parentheses. The upper panel reports the marginal effect of a one standard deviation change in own firm and peer firm characteristics.[15] Because the size of the industry, N, plays a central role in the derivative expressions, we present estimates for three different size industries based on the 10^{th} (three firms), 50^{th} (eight firms), and 90^{th} (26 firms) percentiles of the industry size distribution.

We note several findings. First, the amplification term, though noisily estimated, varies dramatically across industry size categories and is economically large. Changes in capital structure determinants are magnified by 71% in small industries and 8% in large industries. Intuitively, each firm has a smaller effect on its peers the larger is the peer group.

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

Table VIII

Exogenous Variable Derivatives, Marginal Effects, and Leverage Multipliers

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents 2SLS estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within-firm dependence in parentheses from a regression of market leverage on peer firm leverage, peer firm characteristics, and firm-specific factors. All variables are in levels. Peer Firm Averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industries are defined by three-digit SIC code. Firm-Specific Factors denotes variables corresponding to firm i's value in year t. Derivatives are computed for three peer groups differing in their size: small (10^{th} percentile = three firms), medium (50^{th} percentile = eight firms), and large (90^{th} percentile = 26 firms). The derivative $\partial y_i/\partial x_{im}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation i (x_{im}). The derivative $\partial y_i/\partial x_{km}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation k (x_{km}). Both derivatives are scaled by the standard deviation of the corresponding x variable, (σ_x). Amplification Term is the multiplicative factor due to the peer effect action variable and is equal to $(1+\frac{\beta^2}{(N-1+\beta)(1-\beta)})$. The terms Spillover 1 and Spillover 2 are the additive factors due to the peer firm actions and characteristics, and are equal to $(\frac{\beta}{(N-1+\beta)(1-\beta)})$ and $(\frac{1}{(N-1+\beta)(1-\beta)})$, respectively. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

	Firm-Specific Factor	Peer Firm Average	Peer Group Size: Small		Peer Group Size: Medium		Peer Group Size: Large	
Variable	Scaled Coefs ($\lambda \times \sigma_x$)	Scaled Coefs ($\gamma \times \sigma_x$)	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	$\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$
Log(Sales)	0.021**	−0.011**	0.018*	−0.004	0.020**	−0.002	0.021**	−0.000
	(9.113)	(−2.719)	(2.564)	(−0.502)	(5.803)	(−0.500)	(8.252)	(−0.499)
Market-to-Book	−0.067**	0.032**	−0.055**	0.016	−0.063**	0.006	−0.065**	0.002
	(−42.570)	(4.403)	(−4.597)	(1.225)	(−13.751)	(1.178)	(−32.156)	(1.161)
EBITDA/Assets	−0.048**	0.021**	−0.038**	0.015	−0.045**	0.005	−0.047**	0.002
	(−28.700)	(4.618)	(−3.678)	(1.337)	(−11.231)	(1.285)	(−23.794)	(1.266)
Net PPE/Assets	0.034**	−0.013	0.042**	0.011	0.036**	0.004	0.035**	0.001
	(11.281)	(−1.659)	(5.298)	(1.257)	(8.988)	(1.241)	(10.984)	(1.235)
Peer Firm Avg. Leverage (β)	0.727**							
	(4.803)							
Amplification Term			1.710		1.251		1.078	
			(1.092)		(1.051)		(1.037)	
Spillover 1			0.977		0.345		0.108	
			(1.414)		(1.346)		(1.322)	
Spillover 2			1.343*		0.474		0.148	
			(2.004)		(1.870)		(1.824)	

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

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

V. Why Do Firms Mimic One Another?

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

A. Theoretical Motivation

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

Additional motivation for mimicking behavior in capital structure comes from rational herding models (Devenow and Welch (1996)).[17] Zeckhauser, Patel,

[16] Another related model is the duopoly market model of Brander and Lewis (1986), in which feedback between product markets and financial policy leads to capital structure mimicking among competitors. Maksimovic and Zechner (1991) also examine the interaction between product markets and financial policy. However, the implications of this study are geared more toward differential positioning within the industry, as opposed to mimicking behavior. See Phillips (1995) and MacKay and Phillips (2005) for empirical examinations.

[17] As Devenow and Welch (1996) discuss, there also exist models of irrational herding in which agents blindly follow one another and forgo rational analysis. We believe that such theories are less

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

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

Managers may also mimic other firms' policies to influence their perceived relative quality in the labor market. In the model of Scharfstein and Stein (1990), higher quality investment managers receive correlated signals about investment opportunities, while lower quality managers receive independent signals. Managers therefore mimic the investment choice of others in order to increase their perceived type. In this environment, herding is more important than making efficient investment choices because blame is shared in the event of a bad outcome. Zwiebel (1995) shows that corporate managers' types are inferred from their relative performance. Because managers perceived to be below a cutoff type are fired, they prefer to mimic the investment choices of others to minimize the volatility of their relative performance.

B. Empirical Results

To shed light on the potential mechanisms behind peer effects in financial policy, we examine heterogeneity in the coefficient on peer firm leverage, β, from equation (1). To avoid redundancy, we focus our attention on the change in market leverage as the outcome variable of interest. Specifically, we interact peer firm return shocks with indicator variables identifying the lower and

relevant in the current setting. Rather, the underlying mechanism behind any herd-like behavior among corporate managers is more likely due to information or incentive distortions, or limited cognitive abilities of managers.

[18] Because our source of identifying variation is firm-specific, one must acknowledge an additional assumption for a learning mechanism to be behind our results. Specifically, one must assume that managers cannot disentangle the variation in peer firms' actions that come from common and idiosyncratic variation in peer firms' stock returns. If they could, then they would rationally respond only to the variation that contains information about their own firm. We believe that it is unlikely that nonfinancial corporate managers are performing such a decomposition.

upper thirds of each interaction variable's distribution. For binary variables, the interaction is directly with the binary variable. Our inferences come from any differences in the estimated scaled (by standard deviation) coefficients across these areas of the distribution.

In Table IX, we examine whether some firms within the industry are more or less sensitive to their peers' financial policies. For each industry-year combination, we rank firms into three groups based on firm-specific characteristics and focus on the low and high thirds of the distribution of continuous interaction variables. The results show that smaller (market share), nondividend paying, unrated firms are more sensitive to their peers than are their counterparts. Similarly, firms defined as more financially constrained according to the Whited–Wu (2006) index are more sensitive to peer firms. These results suggest that mimicking behavior is strongest among those firms with the greatest learning motive and perhaps the greatest need to build reputation.

In Table X, we examine more directly whether peer firm relevance is driven by a leader–follower model in which less successful firms are sensitive to more successful firms but not vice versa. To do so, we categorize firms within each industry-year into two groups that we call leaders and followers. We define these two groups by sorting firms within each industry-year into three groups based on various measures of success—profitability, market share, and earnings growth. Followers are those firms in the bottom two-thirds and leaders are those firms in the top third of the distribution.

In Panel A of Table X, we exclude the top third of the distribution (i.e., the leaders) from the sample. We then estimate via two-stage least squares equation (1) on this subsample using the peer firm leverage of the leader firms in place of the follower firms. In essence, we are estimating the extent to which follower firms are sensitive to the financial policies of leader firms. The dependent variable is the change in market leverage, though results are qualitatively similar if we use levels.

The results show that the financial policies of smaller (market share), less profitable firms with low earnings growth are sensitive to the leverage changes of their more successful counterparts. The results provide a useful interpretation of the findings in Table IX, which suggest that financially constrained firms are more sensitive to peers than unconstrained firms. This finding may be odd since one would expect mimicking to be more costly for financially constrained firms, given their higher cost of external financing. However, the results here suggest that this cost may be swamped by the perceived benefit associated with mimicking the behavior of leader firms.

As a robustness check on these findings, we perform a falsification test by rerunning the analysis using the sample of leaders and the peer firm leverage change of the followers. This analysis asks whether leaders are sensitive to follower return shocks. The results are reported in Table X, Panel B and show no significant results, statistically or economically. In other words, leader firms' financial policies appear insensitive to the return shocks of follower firms.

While insightful, we note that these results do not reject a particular theory per se. The evidence is consistent with the broad implications of

Table IX

Which Firms Mimic?

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents 2SLS estimated coefficients for the peer firm average market leverage change interacted with indicator variables identifying the lower and upper third of the within-industry-year distribution of lagged values for firm-specific measures of whether the firm has a credit rating, whether the firm paid a dividend in year $t-1$, market share, profitability, market-to-book ratio, and the Whited–Wu (2006) Index of financial constraints. We exclude the middle third of the distribution for each of these regressions. The coefficient estimates are scaled by the corresponding variable standard deviation. The dependent variable is the change in market leverage ratio. All models are estimated by linear 2SLS where the endogenous variables are the peer firm average leverage ratio changes interacted with indicator variables, and the instruments are the one-period-lagged peer firm average idiosyncratic component of stock returns interacted with the same indicator variables. The table also presents the heteroskedasticity-corrected Cragg–Donald (1993) statistic testing for weak instruments (First-Stage Multivariate F-stat). Industries are defined by three-digit SIC code. All variables are in first differences except the instrument. All independent variables, including the instrument but excluding the endogenous variable, are lagged 1 year relative to the dependent variable unless otherwise specified. All test statistics are computed using standard errors that are robust to within-firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively. F-stat statistical significance implying less than 15% or 10% size distortion is denoted by * and **, respectively.

	Credit Rating (2=Yes)	Dividend Payer (2=Yes)	Market Share (2=Large)	Profitability (2=High)	Market-to-Book (2=High)	Whited–Wu Index (2=Cnstrd)
Peer Firm Avg Leverage Change × Group 1	0.073**	0.061**	0.050**	0.056**	0.054**	0.031*
	(5.332)	(5.312)	(3.811)	(4.808)	(4.056)	(2.391)
Peer Firm Avg Leverage Change × Group 2	0.027**	0.046**	0.041**	0.055**	0.056**	0.053**
	(3.387)	(4.933)	(2.861)	(4.047)	(4.513)	(3.639)
First-Stage Multivariate F-stat	37.987**	38.149**	19.528**	23.618**	28.189**	21.081**
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Specific Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	80,279	80,279	47,338	55,416	55,418	40,655

Table X
Which Firms Are Mimicked?

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

	Change in Market Leverage		
	Profitability	Market Share	Stock Return
Panel A: Do Follower Firms Respond to Leaders?			
Leader Firm Avg Leverage Change	0.076**	0.084**	0.087**
	(5.055)	(6.045)	(3.830)
First-Stage Univariate F-stat	62.913**	92.725**	34.530**
Peer Firm Average Characteristics	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes
Industry Effects	No	No	No
Year Fixed Effects	Yes	Yes	Yes
Obs.	51,588	43,677	51,590
Panel B: Do Leader Firms Respond to Followers?			
Follower Firm Avg Leverage Change	−0.019	−0.002	−0.088
	(−0.890)	(−0.042)	(−1.711)
First-Stage Univariate F-stat	17.688**	5.235*	6.021*
Peer Firm Average Characteristics	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes
Industry Effects	No	No	No
Year Fixed Effects	Yes	Yes	Yes
Obs.	53,554	45,529	53,552

reputational and learning models. It is also consistent with finance textbooks suggesting that "[F]irms in a business tend to follow the leader... When this firm chooses a financing mix, presumably based upon its fundamentals, other firms in that sector then imitate the leader, hoping to imitate its success" (Damodaran (2010, p. 443)). Likewise, Ross, Westerfield, and Jaffe (2010,

p. 549) note that “After all, the existing firms in any industry are the survivors. Therefore we should pay at least some attention to their decisions.” We hope future research will provide additional, and more powerful, evidence on the precise mechanism behind the peer effects. Alternatively, sharper predictions from theory may lead to more powerful tests.

VI. Conclusions

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

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

Our hope is that this study inspires future work on better understanding the mechanisms driving the strong interdependencies among financial policies. Furthermore, an open empirical question is whether this mimicking behavior is optimal in a value-enhancing sense. Finally, we hope that the findings of this study shift the direction of capital structure research towards models, both theoretical and empirical, that explicitly recognize the interactions among firms.

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Appendix A: Variable Definitions

Corporate accounting data come from the merged Center for Research in Security Prices (CRSP)-Compustat database available on the Wharton Research Data Services server. We draw a sample of firm-year observations for the period 1965 to 2008. We choose 1965 as the start year to mitigate the selection bias toward large, successful firms that exists in the early part of the Compustat sample. To maintain consistency with previous empirical studies and to avoid capital structures dictated by regulatory considerations, we exclude financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999), as well as government entities (SIC codes greater than or equal to

9000).[19] Stock return data for our sample of firms come from the CRSP monthly stock price database.

To ensure consistency throughout our primary analysis, we require each firm-year observation to have nonmissing data for the levels and first differences of the following variables: net equity issuances, net debt issuances, book leverage, market leverage, sales, market-to-book ratio, profitability, tangibility, stock returns, and the idiosyncratic component of stock returns.

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

Total Book Assets = **at**.
Total Debt = Short-Term Debt + Long-Term Debt = **dltt** + **dlc**.
Book Leverage = Total Debt/Total Book Assets.
Market Value of Assets (MVA) = **prcc_f** * **cshpri** + **dlc** + **dltt** + **pstkl** − **txditc**.
Market Leverage = Total Debt/MVA.
Net Debt Issuances = [(**dltt**(t) + **dlc**(t)) − (**dltt**($t - 1$) + **dlc**($t - 1$))]/**at**($t - 1$).
Debt Issuance Indicator = 1 if Net Debt Issuances > 1%; 0 otherwise.
Net Equity Issuances = (**sstk**(t) − **prstkc**(t))/**at**($t - 1$).
Equity Issuance Indicator = 1 if Net Equity Issuances > 1%; 0 otherwise.
Firm Size = Log(Sales) = Log(**sale**).
Tangibility = Net PPE/Assets = **ppent/at**.
Profitability = EBITDA/Assets = **oibdp/at**.
Market-to-Book Ratio = MVA/Total Book Assets.
Common Dividends = **dvc**.
Common Dividend Indicator = 1 if **dvc** > 0; 0 otherwise.
Sales, General, and Administrative Expenses = **xsga**/Firm Size.
Research and Development Expenses = **xrd**/Firm Size.
Capital Expenditures = **capx**.
Capital Investment = Capital Expenditures(t)/Net PPE($t - 1$).
Altman's (1968) Z-Score = (3.3 * **pi** + **sale** + 1.4 * **re** + 1.2 * (**act** − **lct**))/**at**.

Earnings Volatility is computed each year as the historical standard deviation of $EBITDA/Assets$. We require at least 3 years of nonmissing data.

Marginal Tax Rates are obtained from John Graham's website.

We construct bank fixed effects for each firm with available issuance data by assuming that the firm uses the same bank each year until either the end of the sample or we find a different bank being used, regardless of the security being issued. Results obtained assuming that the firm used the same bank in all years prior to the issuance until either the beginning of our sample or a new bank was found are similar.

[19] We include firms that undertook a significant acquisition during the sample period as indicated by Compustat variable **aftnt1** equal to "AB." However, all of our results are insensitive to their exclusion, which affects less than 3% of the sample observations.

We use Thompson's SDC and Reuters Loan Pricing Corporation's Dealscan database to identify lead underwriters and arrangers or agents for (public and private) debt and equity issuances. Specifically, SDC provides underwriter information for public debt and equity offerings, as well as Rule 144a offerings. We rely on Dealscan to identify the lead bank (or arranger) on sole-lender and syndicated loans. We match SDC to Compustat by matching cusips and dates of issuance in SDC to cusips and dates in the Compustat historical company information file. We match Dealscan to Compustat using the link file from Chava and Roberts (2008).

Appendix B: Exogenous Variable Derivatives

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

$$y = \frac{\beta}{N-1} Qy + X\lambda + \frac{1}{N-1} QX\gamma + Z\delta + \varepsilon, \tag{B1}$$

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

Solving equation (B1) for y yields

$$y = \left(I - \frac{\beta}{N-1} Q\right)^{-1} \left(X\lambda + \frac{1}{N-1} QX\gamma + Z\delta + \varepsilon\right). \tag{B2}$$

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

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

Induction and matrix algebra shows that the first matrix is symmetric and has two distinct elements. The diagonal elements equal $\frac{N-1-\beta(N-2)}{(N-1+\beta)(1-\beta)}$, and the off-diagonal elements equal $\frac{\beta}{(N-1+\beta)(1-\beta)}$. The second matrix is also symmetric with two distinct elements. The diagonal elements equal $\frac{\beta}{(N-1+\beta)(1-\beta)}$, and the off-diagonal elements equal $\frac{1}{(N-1+\beta)(1-\beta)}$. Therefore, the derivative of an arbitrary element y_i in the vector y with respect to an arbitrary element x_{lm} in the matrix

X is equal to

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

where we use the equality

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

REFERENCES

Almazan, Andres, and Carlos A. Molina, 2005, Intra-industry capital structure dispersion, *Journal of Economics and Management Strategy* 14, 263–297.

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589–609.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–30.

Banerjee, Abhijit V., 1992, A simple model of herd behavior, *Quarterly Journal of Economics* 107, 797–817.

Bertrand, Joseph, 1883, Theorie Mathematique de la Richesse Sociale, *Journal des Savants* 67, 499–508.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1998, Learning from the behavior of others: Conformity, fads and informational cascades, *Journal of Economic Perspectives* 12, 151–170.

Bizjak, John M., Michael L. Lemmon, and Lalitha Naveen, 2008, Has the use of peer groups contributed to higher levels of executive compensation? *Journal of Financial Economics* 90, 152–168.

Bolton, Patrick, and David Scharfstein, 1990, A theory of predation based on agency problems in financial contracting, *American Economic Review* 80, 93–106.

Bradley, Michael, Gregg A. Jarrell, and E. Han Kim, 1984, On the existence of an optimal capital structure: Theory and evidence, *The Journal of Finance* 39, 857–878.

Brander, James A., and Tracy R. Lewis, 1986, Oligopoly and financial structure: The limited liability effect, *American Economic Review* 76, 956–970.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas, 2008, Hedge fund activism, corporate governance, and firm performance, *Journal of Finance* 63, 1729–1775.

Case, Anne C., and Lawrence F. Katz, 1991, The company you keep: The effects of family and neighborhood on disadvantaged youths, NBER Working Paper 3705.

Chava, Sudheer, and Michael R. Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085–2121.

Chevalier, Judith A., and David S. Scharfstein, 1996, Capital-market imperfections and countercyclical markups: Theory and evidence, *American Economic Review* 85, 703–725.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.

Conlisk, John, 1980, Costly optimization versus cheap imitators, *Journal of Economic Behavior and Organization* 1, 275–293.

Cournot, Augustin, 1838, *Recherches sur les Principes Mathematiques de la Theorie des Richesses* (Hachette, Paris).

Cragg, John G., and Stephen G. Donald, 1993, Testing identifiability and specification in instrumental variable models, *Econometric Theory* 9, 222–240.

Damodaran, Aswath, 2010, *Applied Corporate Finance*, 3rd edn. (John Wiley & Sons, Hoboken, NJ).

Devenow, Andrea, and Ivo Welch, 1996, Rational herding in financial economics, *European Economic Review* 40, 603–615.

Duflo, Esther, and Emmanuel Saez, 2002, Participation and investment decisions in a retirement plan: The influence of colleagues' choices, *Journal of Public Economics* 85, 121–148.

Duflo, Esther, and Emmanuel Saez, 2003, The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment, *Quarterly Journal of Economics* 118, 815–842.

Flannery, Mark, and Kasturi Rangan, 2006, Partial adjustment toward target capital structures. *Journal of Financial Economics* 79, 469–506.

Frank, Murray Z., and Vidhan K. Goyal, 2008, Tradeoff and pecking order theories of debt, in Espen Eckbo, ed.: *The Handbook of Empirical Corporate Finance* (Elsevier, Amsterdam).

Frank, Murray Z., and Vidhan K. Goyal, 2009, Capital structure decisions: Which factors are reliably important? *Financial Management* 38, 1–37.

Graham, John R., 2000, How big are the tax benefits of debt? *Journal of Finance* 55, 1901–1941.

Graham, John R., and Campbell Harvey, 2001, The practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 186–243.

Hoberg, Gerald, and Gordon Phillips, 2009, Dynamic product-based industry classifications and endogenous product differentiation, Working paper, University of Maryland.

John, Kose, and Dalida Kadyrzhanova, 2008, Relative governance, Working paper, University of Maryland.

Kayhana, Ayla, and Sheridan Titman, 2007, Firms' histories and their capital structures, *Journal of Financial Economics* 83, 1–32.

Lemmon, Michael, Michael R. Roberts, and Jaime Zender, 2008, Back to the beginning: Persistence and the cross-section of corporate capital structures, *Journal of Finance* 63, 1575–1608.

Lerner, Josh, and Ulrike Malmendier, 2013, With a little help from my (random) friends: Success and failure in post-business school entrepreneurship, *Review of Financial Studies* 26, 2411–2457.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

MacKay, Peter, and Gordon M. Phillips, 2005, How does industry affect firm financial structure? *Review of Financial Studies* 18, 1433–1466.

Maksimovic, Vojislav, and Josef Zechner, 1991, Debt, agency costs, and industry equilibrium, *Journal of Finance* 46, 1619–1643.

Manning, Alan, 2005, *Monopsony in Motion: Imperfect Competition in Labour Markets* (Princeton University Press, Princeton, NJ).

Manski, Charles, 1993, Identification of endogenous social effects: The reflection problem, *Review of Economic Studies* 60: 531–542.

Marsh, Paul, 1982, The choice between equity and debt: An empirical study, *Journal of Finance* 37, 121–144.

Matvos, Gregor, and Michael Ostrovsky, 2010, Heterogeneity and peer effects in mutual fund proxy voting, *Journal of Financial Economics* 98, 90–112.

Myers, Stewart C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics* 5, 147–175.

Myers, Stewart C., 1984, The capital structure puzzle, *Journal of Finance* 39, 575–592.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.

Petersen, Mitchell, 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435–480.

Phillips, Gordon, 1995, Increased debt and industry product markets: An empirical analysis, *Journal of Financial Economics* 37, 189–238.

Rajan, Raghuram G., and Luigi Zingales, 1995, What do we know about capital structure: Some evidence from international data, *Journal of Finance* 50, 1421–1460.

Romer, David, 1993, Rational asset-price movements without news, *American Economic Review* 83, 1112–1130.

Ross, Stephen A., Randolph W. Westerfield, and Jeffrey Jaffe, 2010, *Corporate Finance*, 9th edn. (McGraw-Hill Irwin, New York, NY).

Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, *The American Economic Review*, 80, 465–479.

Scott, James H., 1976, A theory of optimal capital structure, *Bell Journal of Economics* 7, 33–54.

Shue, Kelly, 2013, Executive networks, and firm policies: Evidence from random assignment of MBA peers, *Review of Financial Studies* 26, 1401–1442.

Stigler, George, 1968, Price and non-price competition, *Journal of Political Economy* 76, 149–154.

Stock, James, and Motohiro Yogo, 2005, Asymptotic distributions of instrumental variables statistics with many weak instruments, in D.W.K. Andrews and J.H. Stock, eds.: *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Cambridge University Press, Cambridge).

Strebulaev, Ilya, and Baozhong Yang, 2012, The mystery of zero-leveraged firms, Working paper, Stanford University.

Trueman, Brett, 1994, Analyst forecasts and herding behavior, *Review of Financial Studies* 7, 97–124.

Welch, Ivo, 2004, Capital structure and stock returns, *Journal of Political Economy* 112, 106–131.

Whited, Toni M., and Guojun Wu, 2006, Financial constraint risk, *Review of Financial Studies* 19, 531–559.

Zeckhauser, Richard, Jayendu Patel, and Darryll Hendricks, 1991, Nonrational actors and financial market behavior, *Theory and Decisions* 31, 257–287.

Zwiebel, Jeffrey, 1995, Corporate conservatism and relative compensation, *Journal of Political Economy* 103, 1–25.