Do Peer Firms Affect Corporate Financial Policy?*

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Abstract

We show that the most important observable capital structure determinant for many firms is the capital structure of their peers; firms make financing decisions in large part by responding to the financing decisions of peer firms, as opposed to changes in firm-specific characteristics. We also find that smaller and less successful firms are more likely to adjust their capital structures and financial policies in response to the actions of their larger, more successful peers. Finally, we quantify the externalities engendered 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 capital structure choices are made independent of the actions or characteristics of their peers. In other words, a firm's capital structure is typically assumed to be determined by a function of its marginal tax rate, expected deadweight loss in default, information environment, and incentive structure. As such, the role for peer firm behavior in affecting capital structure is often ignored, or at most an implicit one through its unmeasured impact on firm-specific determinants.

However, peer firms play a central role in shaping a number of corporate policies, and existing evidence suggests that the behavior of peer firms matters for capital structure.[1] Survey evidence indicates that a significant number of CFOs cite the importance of peer firm financing decisions for their own financing decisions (Graham and Harvey (2001)). Further, recent empirical work has shown that industry average leverage ratios are an economically important determinant of firms' capital structures (Welch (2004), Mackay and Phillips (2005), and Frank and Goyal (2007)).

The goal of this paper is to identify whether, how, and why peer firm behavior matters for corporate capital structures. 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 increases its leverage ratio, peer firms' leverage ratios are higher than they 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 financial 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 influences the actions of the individuals that comprise the group. In the current context, this problem is created by using measures of peer firm financial policy, such as industry average leverage, or peer firm capital structure determinants, such as industry average profitability, as explanatory variables for individual firms' financial policies. Any correlation between firms' financial policies and the actions or characteristics of their

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

peers can be attributed to two broad explanations.

The first explanation is based on the endogenous self-selection of firms into peer groups. 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 actions 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.

To address the first challenge, we use peer firms' idiosyncratic equity returns (i.e., return shocks) as an instrument for peer firms' financial policies. Motivation for this approach comes from the two conditions for instrument validity: relevance and exclusion. There is substantial theoretical and empirical evidence linking stock returns to financial policy (e.g. Myers (1977, 1984); Marsh (1980); 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 satisfying the exclusion restriction.

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, market-to-book). While these features do not guarantee validity of our instrument, they are reassuring because they suggest that our instrument contains little variation that is common among peer firms.

First stage estimates from the instrumental variables estimation show that idiosyncratic stock returns are strongly negatively correlated with leverage and debt issuance decisions, and positively correlated with equity issuance decisions. Statistically speaking, the first stage F-statistics are well above weak-instrument thresholds, ensuring that the instrument relevance condition is satisfied.

Second stage estimates show that firms' capital structure choices are strongly positively influenced by the financing choices of their peers. For example, firms change their market leverage ratios by ten percentage points, on average, in response to a one standard deviation change in leverage by peer firms. This marginal effect is the largest among the many observable leverage determinants that we examine. Closer inspection reveals that the commonality in leverage choices among peers is driven by a commonality in financing decisions: firms are significantly more likely to issue debt or equity when their peers issue that same security.

These inferences are robust. We find statistically and economically large peer effects in both book and market measures of leverage, and in both levels and changes in leverage. All of our results remain when we include own-firm stock returns — and a host of other variables — as an additional control variable. In other words, the identifying variation is orthogonal to firm i's own stock return, as well as all of the other included variables. Placebo tests reveal that our instrument has no explanatory power for corporate investment, allaying concerns that our instrument contains information about future investment opportunities.

To further ensure that latent common factors are not behind our results, we undertake a separate analysis in which we redefine our instrument for peer firm financial policies as the return shocks to peer firms' *customers* that are (1) in an industry different from firm i, and (2) not a customer of firm i. The relevance of the instrument is motivated by the insight of Cohen and Frazzini (2008), who show that customer return shocks predict supplier return shocks. To justify the exclusion restriction, we include firm i's own stock return and firm i's industry stock return as controls. The identifying variation now comes from return shocks to firms in a different industry with no supply chain link to firm i. Further, 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.

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. Further, while peer firm characteristics are relevant for financial policy, their marginal effect is significantly smaller than that of peer firm actions and even firm-specific determinants. Thus, the primary channel through which peer effects operate appears to be financial policy, as opposed to changing characteristics.

An implication of peer effects in financial policy is the externalities that they engender. A shock to firm A's profitability not only affects firm A's financing choice, but also 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 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.

Our estimates reveal that the amplification term varies from a low of 7.5% in large peer groups to a high of 70.3% in small peer groups. In other words, in industries with few firms, the impact of a change in profitability, for example, on leverage is 70.3% larger than 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.

To understand why peer firms influence financial policy, we examine heterogeneity in the estimated effect by examining which firms mimic their peers and which firms are being mimicked. Consistent with models of reputational concerns and learning, we find that smaller, less successful (i.e., lower profitability and stock returns), and more financially constrained firms mimic the financial policies of industry leaders (i.e., larger, more profitable firms with higher stock returns). By contrast, the financial policies of industry leaders are not influenced by those of non-leaders. 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 have left the interpretation of these

[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.

industry effects largely unresolved, a point explicitly noted by Frank and Goyal (2007, 2008). Ours is the first study to sift through these alternative meanings, identify policy interdependence as a substantial element of the industry leverage effect, and estimate the externalities induced by the presence of peer effects. Our study is also related to the work of Mackay and Phillips (2005) and Almazan and Molina (2005), both of whom examine intra-industry variation in capital structures. Our study compliments theirs by showing that this variation is accompanied by strong interdependencies in financial policy.[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 (2012)). Ordinary least squares regressions will typically not provide meaningful results because of the reflection problem, and, as such, a clear identification strategy is needed to rule out the null of omitted or mismeasured common characteristics. Further, feedback and spillover effects arising from the presence of peer effects obscure the marginal effects of exogenous variables. Neither the direction nor magnitude of association between a covariate and the dependent variable can be inferred from that covariate's coefficient, even in linear specifications. We present closed form expressions for the marginal effects of exogenous covariates in a general linear setting.

The paper proceeds as follows. Section I introduces the data and presents summary statistics. Section II develops the empirical model and highlights the identification challenge. Section III discusses our identification strategy, focusing on the construction of our instrument, its economic and statistical properties, and potential identification threats. Section IV presents our 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 comes from the merged CRSP-Compustat database during the period 1965 to 2008. Because of its popularity, we relegate a complete discussion of the data, sample construction, and variable definitions to Appendix A. Table I presents summary statistics for our final sample of 80,279 firm-year observations corresponding to 9,126 unique firms. There are 217 industries, defined by three-digit SIC code, represented in

[3]Other studies examining peer effects in corporate finance including: mutual fund voting (Matvos and Ostrovsky (2009)), governance (John and Kadyrzhanova (2008)), investment decisions (Duflo and Saez (2002)), entrepreneurship (Lerner and Malmendier (2012)), and compensation (Shue (2011)).

our sample. The typical industry contains approximately 13 firms, though the distribution is right skewed as indicated by the median number of firms, 8. To address potential measurement concerns regarding the definition of an industry (Hoberg and Phillips (2009)), as well as the documented intra-industry heterogeneity (Mackay and Phillips (2005)), we investigate alternative peer group definitions in our empirical analysis below.

Summary statistics for a number of variables, in levels and first differences, used throughout this study are presented after Winsorizing all ratios at the upper and lower one percentiles. We Winsorize to mitigate the influence of extreme observations and eliminate any data coding errors. 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 found in previous empirical studies of capital structure, such as Frank and Goyal (2007).

II. The Empirical Model

Our empirical model of capital structure is a generalization of that used throughout the empirical capital structure literature (e.g., Rajan and Zingales (1995) and Frank and Goyal (2007)),

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

where the indices i, j, and t correspond to firm, industry, and year, respectively. We focus on a linear specification to emphasize the intuition and highlight the salient econometric issues. Extensions are 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. 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 confounding 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 heteroscedastic. As such, all standard errors and test-statistics are robust to these two departures from the classical regression model (Petersen (2009)).

The parameter vector is $(\alpha, \beta, \gamma', \lambda', \delta', \phi')$. We refer to these parameters as structural parameters only to distinguish them from the composite, or reduced form, parameters that appear in the context of instrumental variables. Like the vast majority of the empirical capital structure literature, we leave unspecified the precise optimization problem undertaken by the firm.[4] 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.

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]

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

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

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

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

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

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

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

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

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

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

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

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.

B. The Identification Strategy

Our identification strategy is to find an instrument for peer firm financial policy. A valid instrument satisfies both the relevance and exclusion conditions. In our setting, these conditions translate into a variable that affects the peer groups' financing decisions (relevance), and affects the firm's financing decision *only* through the peer groups' financing decisions (exclusion). In other words, a valid instrument is a determinant of capital structure that is unique to a given firm — one not shared by firm i and its peers.

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' capital structures 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 satisfy the exclusion restriction 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 regulations, and expected liabilities. Thus, one may find events that are relevant for peer firms' capital structures 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 (1980)). 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 the return shock. We lag this shock one year and use it as an instrument for a firm's financing decision one year hence. That is, our instrument for a peer firm's financing decision this year is its equity return shock from the previous year.

Motivation for this choice of instrument comes from several sources. First, this instrument is available for a broad panel of firms and, consequently, 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, there is a vast asset pricing literature focused on estimating the expected and idiosyncratic components of returns. Finally, there is theoretical and empirical precedent for a relationship between stock returns and capital structure choices.[6]

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 common components that comprise stock returns, thereby invalidating the exclusion restriction. Our identification strategy is to purge this common variation so that the only variation remaining for identification of the peer effect is that which is firm-specific. Thus, our identification strategy does not rely on particular firm-specific economic events, which as discussed above are not only rare but virtually impossible to identify. Rather, our strategy relies on isolating the firm-specific variation in stock returns induced by capital structure-relevant events.

The weakness of this strategy is that the true data generating process for equity returns is unknown. As such, any estimated equity return shock will contain traces of

[6]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 (1980), Loughran and Ritter (1995), Baker and Wurgler (2002), and Welch (2004) among others have shown a strong correlation between past returns and issuance choice or leverage ratios.

common variation that would fail to satisfy the exclusion restriction. Addressing this potential contamination guides our analysis.

C. Construction of The Instrument

We estimate idiosyncratic component of stock returns with the following augmented market model for stock returns, r_{ijt}:

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

where r_{ijt} refers to the total return for firm i in industry j over month t, $(rm_t - rf_t)$ is the excess market return, and $(\bar{r}_{-ijt} - rf_t)$ is the excess return on an equal weighted industry portfolio excluding firm i's return. As with our peer groups, industry is defined by three-digit SIC code. While not a priced risk factor, this last factor is included to remove any variation in returns that is common across firms in the same peer group.[7]

We estimate equation (7) for each firm on a rolling annual basis using historical monthly returns. We require at least 24 months of historical data and use up to 60 months of data in the estimation. For example, to obtain expected and idiosyncratic returns for IBM between January 1990 and December 1990, we first estimate equation (7) using monthly returns from January 1985 through December 1989. Using the estimated coefficients and the factor returns from January 1990 through December 1990, we use equation (7) to compute the expected and idiosyncratic returns as follows:

$$\begin{aligned} \text{Expected Return}_{ijt} \equiv \hat{r}_{ijt} &= \hat{\alpha}_{ijt} + \hat{\beta}^{M}_{ijt}(rm_t - rf_t) + \hat{\beta}^{IND}_{ijt}(\bar{r}_{-ijt} - rf_t) \\ \text{Idiosyncratic Return}_{ijt} \equiv \hat{\eta}_{ijt} &= r_{ijt} - \hat{r}_{ijt} \end{aligned}$$

To obtain expected and idiosyncratic returns for 1991, we repeat the process by updating the estimation sample from 1986 through 1990 and using factor returns during 1991. This process generates betas that are firm-specific and time-varying, 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 five-year window. Additionally, we see that the average adjusted R-square is

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

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).

We construct our instrument by first compounding the monthly returns to obtain an annual measure consistent with the periodicity of the accounting data. We then average over peer firms within each year to maintain consistency with the peer effect measures. Finally, we lag the instrument one year to remove any mechanical relationship between peer firm returns and market leverage ratios. Thus, our instrument for the average peer firm financing decision, $\bar{y}_{-ijt}$ in equation (1), 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 idiosyncratic stock return as an instrument for the effect of its financing decision 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 as instruments for the effect of their financing decisions 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 variation or noise in the individual return shocks, which has implications for identification. We address this issue below.

Note that, conditional on a properly specified asset pricing model (equation (7)), the instrument need not be zero. Our instrument is a conditional average, conditional on industry and year. Additionally, the instrument is not exactly the industry average since it excludes the i^{th} observation. Panel A of Figure 1 illustrates the variation in our instrument with a histogram. The average of our instrument (i.e., 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 instrument as the industry definitions become coarser and the size of the peer group increases. We see that the distribution collapses around zero, and more so for the one-digit (Panel C) industry definition than the two-digit industry definition (Panel B). Thus, 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 instrument.

D. Identification Threats

Identification threats come from correlation between our instrument and omitted or mismeasured capital structure determinants that are correlated with our instrument. We refer collectively to these determinants as common factors because, by definition, they affect both firm i's capital structure and firm j's capital structure via correlation with firm j's return shock. This subsection takes a first step towards addressing this concern by examining the statistical properties of our instrument and their economic implications.

Before doing so, we begin by noting that the scope for potential identification threats is limited to the component of leverage variation that is used to identify the peer effect. Our, and every other, instrumental variables approach uses only a fraction of the variation in peer firm leverage to identify the peer firm coefficient, β, in equation (1). Specifically, we use the fraction that is correlated with our instrument, peer firm return shocks, and orthogonal to all other included control variables. A useful taxonomy of the variation in our instrument is between industries, within industries, and over time. However, the inclusion of control variables in equation (1) eliminates much of this variation.

Industry fixed effects remove all between-industry variation. Inclusion of firm i's shock as a control variable eliminates all within industry-year variation. [8] These results imply 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 will show that the remaining identifying variation dramatically reduces the scope for alternative hypotheses.

D.1. Distinguishing Peer Effects from Omitted or Mismeasured Common Factors

Previous empirical work shows that observable leverage determinants do a relatively poor job of controlling for systematic variation in capital structures (e.g., Welch (2004), Lemmon, Roberts and Zender (2008), and Strebulaev and Yang (2009)). The relevant issue in the current context is whether the remaining omitted variables or measurement errors are correlated with our instrument conditional on other observable characteristics. Thus, we focus on ensuring, as much as possible, that the average idiosyncratic equity shock to peer firms is (1) not a better measure of firm i's capital structure determinants

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

than are the other included firm characteristics, and (2) not capturing a common factor shared among firms within the peer group.

The first consideration highlights the importance of isolating the idiosyncratic component of stock returns rather than using total returns as an instrument. Table II shows that the idiosyncratic component accounts for a significant portion of the variation in stock prices — average R-square 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 extent to which our instrument correlates with firm i characteristics. We examine the correlations with both contemporaneous and one-period lead effects, to determine whether the instrument contains information about current or future firm i characteristics. Note that correlation with the characteristics is not problematic because the characteristics are all included in the regression as control variables. However, economically large associations between the instrument and firm characteristics would raise potential concerns about the extent to which our instrument may be correlated with unobservable factors, and the extent to which we have removed common variation among firms' returns via the asset pricing model.

The results reveal one statistically significant coefficient in the contemporaneous specification and none in the one-period lead specification. The economic magnitudes of the coefficient estimates are all tiny. For the only statistically significant coefficient, a one standard deviation increase in EBITDA / Assets is associated with a 10 basis point decline in contemporaneous leverage. A 10 basis point change in market leverage is approximately 0.007 standard deviations (see Table I). In unreported results, we also find that our instrument is unrelated to contemporaneous and future capital expenditures, suggesting that investment opportunities for firm i are not captured by our instrument. Thus, the instrument contains 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 the average industry total return excluding firm i's total return and firm i's total return is 0.37. The correlation between our instrument and firm i's shock is 0.02. This decline suggests that the asset pricing model purges much, though not all, of the intra-industry correlation in returns. We include firm i's shock in equation (1) in order to help absorb this remaining correlation.

D.2. *Distinguishing Between Channels: Actions and Characteristics*

In addition to identifying a peer effect, we would like to distinguish between the two channels through which peer effects work, actions and characteristics. The fixed effects and observable characteristics of peer firms in equation (1) aid with this distinction. However, by themselves, these controls are insufficient to disentangle the two channels since the true model for leverage is unknown. Further, our instrumental variables approach cannot distinguish between these two channels because it does not identify to what firms are responding.

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, to what is firm B responding: the change in financial policy or 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 the capital structure response by peer firms to their equity shocks. We do so by performing a double sort of the data based on quintiles of our instrument and the endogenous variable. Within each quintile combination, we compute the average change in leverage and a t-stat of whether this change is significantly different from zero. We perform this analysis on both book and market measures of leverage, but present only the market leverage results for brevity.

The results are presented in Table IV, 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 the peer firms' average leverage change. In fact, in column (3), where the average peer firm leverage change is indistinguishable from zero, the cell averages are all economically small 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 suggest that our instrument is more likely capturing a response to peer firm financial policies, as opposed to characteristics.[9] They also speak to the validity of the instrument more generally. We want an instrument that is uncorrelated with firm i's leverage, but through its correlation with peer firms' capital structures. The results in Table IV show that conditional on peer firms' capital structures, there is no correlation between the instrument and firm i's leverage change.

IV. The Role and Implications of Peer Effects

A. Main Results

Panel A of Table V presents the leverage results. The estimation method and dependent variable are indicated at the top of the columns. The body presents coefficient estimates scaled by the corresponding variables' standard deviations, and t-statistics in parentheses.[10] Columns (1) and (2) present ordinary least squares (OLS) estimates of existing models for book and market leverage levels. These results provide a means of comparison with previous studies that have identified industry leverage as an important determinant of capital structure.

Columns (3) through (6) present 2SLS estimates for equation (1). We present results for book and market leverage in both levels (columns (3) and (4)) and first differences (columns (5) and (6)). The latter specifications help address concerns over omitted firm i characteristics, since they are similar to levels specifications that include firm fixed effects. The level specifications uses the levels for all of the variables on both left and right hand sides of the equation.[11] The first difference specifications uses first differences for all of the variables on both left and right hand sides of the equation. The only exception is the instrument, peer firm average idiosyncratic equity returns, which is the same across all specifications.

The first stage results reveal that the average peer firm equity shock is strongly negatively associated with both the level and first difference in the average peer firm

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

[10]Standard errors in the two stage least squares estimates may be biased downward because of estimation error in our instrument. Our attempt to address this issue via the bootstrap ran into computational hurdles. For each bootstrap sample of monthly stock returns, we need to re-estimate the rolling asset pricing regressions. One iteration of this process currently takes approximately two hours on a 3.5 GHz, dual processor workstation with 48 Gb of RAM.

[11]All control variables are lagged one year relative to the dependent variable.

leverage ratio. The negative sign of the estimate is consistent with previous findings relating total returns to leverage and with theoretical arguments relating investment opportunities and risk to optimal leverage and financing choices (e.g., Myers (1977) and Scott (1976)). The magnitude of the effects are economically significant as well, stronger than many of the included determinants (not reported). Statistically speaking, the instrument easily passes weak instrument tests (e.g., Stock and Yogo (2005)).

The second stage results reveal that peer firm financial policies are strongly positively related to leverage. A one standard deviation increase in peer firm leverage, book or market, leads to a 10% increase in own firm leverage. Compared to traditional firm-specific determinants, peer firm financial policies have a significantly larger effect. In the market leverage regression, 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.

Columns (5) and (6) reinforce these findings by showing similar results for changes in leverage ratios. A comparison of the determinants' effects on leverage reveals that peer firm average leverage changes have a larger impact on leverage ratio changes than any other included determinant. This finding is reassuring because it shows that the unobserved firm specific heterogeneity found by Lemmon, Roberts, and Zender (2008) is not responsible for our findings. Also reassuring is that the estimated firm-specific effects in columns (3) and (4) are similar to those found in the OLS results of columns (1) and (2). These similarities reinforce our previous finding that our instrument is largely uncorrelated with firm-specific characteristics (Table III).

The significant coefficients on peer firm average characteristics suggest that capital structure decisions are affected not only directly by the leverage choices of a firm's competitors, but also indirectly by their competitors' characteristics. That is, controlling for firm i's characteristics and peer firms' financing decisions, the results in column (3) imply that firms whose competitors are smaller, more profitable or have higher market-to-book ratios tend to have higher leverage ratios. These latter two results are consistent with the industry equilibrium argument of Shleifer and Vishny (1992). As a firm's competitors become more financially healthy, liquidation values increase. As such, debt becomes less costly allowing firms to increase leverage.

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

Comparing coefficient magnitudes suggests that peer effects work primarily through financial policy, as opposed to characteristics. The effect of average peer firm capital structure on firm i's leverage ratio is significantly larger than that of a change in any average peer firm characteristic. These findings reinforce those of Table IV. While both actions and characteristics of peers are relevant for financial policy, the former appear to be the more economically important channel.

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

Column (1) presents results where the dependent variable is an indicator equal to one if the firm issues equity net of repurchases in excess of 1% of total assets, and zero otherwise. This regression models the probability that firms will issue equity relative to not issuing equity, which includes debt issuances, debt retirements, stock repurchases, and no financing activity. The first stage results reveal that the idiosyncratic component of stock returns is strongly positively correlated with equity issuance decisions. This effect is both economically and statistically significant, again highlighting that the idiosyncratic component of stock returns is important for financial policy. The second stage results show that the peer effect is also significant. A one standard deviation increase in the probability of issuing equity by peer firms leads to a 4.6% increase in the probability of firm i issuing equity. In fact, other than firm i's own market-to-book ratio, the peer effect is the most economically important determinant. The other firm-specific factors show similar relations to equity issuance decisions as found in previous studies (e.g., Hovakimian, Opler, and Titman (2001) and Leary and Roberts (2005)).

Column (2) presents analogous results for the decision to issue debt. Nether first nor second stage estimates are statistically significant. Column (3) 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. In this specification, the dependent variable takes the value of one for debt issuances and zero for equity issues. The first stage estimate is statistically significantly negative because we are modeling the debt, as opposed to equity, decision. The second stage reveals a statistically and economically large positive peer effect. Thus, conditional on financing activity, peer firms play an important role in the choice of security issued.

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.

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

B.1. Specification Changes

In this section we further reduce the identifying variation by conditioning on additional control variables motivated by alternative hypotheses. Table VI 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 and reinforce the inferences discussed 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 variables of interest: the first stage estimate of the instrument parameter, and the second stage estimate of the peer firm leverage parameter.

In column (1), we replace the lagged firm-specific equity shock with the lagged and contemporaneous firm-specific total stock returns. The first stage instrument estimate is unaffected and we note an attenuation in second stage peer effect estimate; however, the coefficient is still economically larger than any other observable determinant (not reported) and highly statistically significant. This specification change ensures that the identifying variation from peer firm's idiosyncratic returns is orthogonal to firm i's stock returns - lagged and contemporaneous. In other words, alternative hypotheses must now rely on lagged idiosyncratic stock returns of peer firms containing information about firm i's capital structure 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. Further, by including both the contemporaneous and lagged stock return, we eliminate concerns regarding the timing of equity price shocks whereby some firms in an industry get shocked earlier than their peers.[12]

Column (2) examines a "kitchen sink" model of capital structure including additional explanatory variables previously identified as relevant for capital structure. Specifically, we include lagged firm-specific and peer firm averages for: an indicator identifying whether a dividend was paid, Altman's Z-score, Graham's marginal tax rate, capital investment, R&D expenditures, SG&A expenditures, and intra-industry leverage dispersion. 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.[13] This specification addresses the concern that commonality among firms' capital structures is due to the use of common banks, commercial or investment, within the industry, and that the financial advice from these banks varies over the business cycle. This change has little effect on our results, despite the sharp decline in observations due to the additional data requirements. However, the adjusted R-square — not reported — is 9% higher relative to that from a comparable model without the bank effects estimated on the same sample. So, while banks seem to have significant influence over corporate capital structures, they are not responsible for

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

[13]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.

the commonality in financial policies that we are identifying.[14]

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

Column (5) replaces the lagged control variables with contemporaneous controls to address the concern that capital structure relevant shocks affect our firm-specific and peer firm characteristics with a lag. 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 behind our results.

C. Customer-Supplier Links

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

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 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 firms' 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

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

are not also customers of firm i as an instrument for peer firm financial policy.[15]

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. Further, because the instrument 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 orthongonal 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 criteria 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. In addition, the first stage estimate is likely to be weaker with this approach, since we are relying on a relationship between a peer firm's leverage or issuance decisions and their customer's return shock, rather than the return shock of the peer firm itself.

The results in Panel A of Table VII reveal only the former drawback. We find statistically significantly negative first stage estimates, consistent with our earlier findings. We find statistically significant peer effects in the two leverage specifications. The security issuance specification is significant only at the 10% level. However, the economic magnitudes of all three estimates are large.

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 "non-customers." We then construct the instrument using the return shocks to the non-customers and re-run our analysis from Panel A. We repeat this process of replacing each customer with a randomly selected non-customer, constructing the instrument, and estimating the regressions via 2SLS 100 times. The distribution of the second stage peer effect estimates, β from equation (1), and the corresponding t-statistics are presented in Panel B of Table VII. To address outlier estimates, we Winsorize the results at the upper and lower five percentiles.

The results in the top half of the panel show that the average and median peer effect estimates are all economically smaller in magnitude than those in Panel A. Focusing on

[15]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 this data.

the median, we see that the placebo estimate for the level of leverage is 0.03, compared with 0.06. The placebo estimate for the first difference in leverage is 0.02 versus 0.03. Finally, the placebo estimate for debt issuances is 0.01 versus 0.14. The differences in Winsorized means are even larger. 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. Amplification, Spillover, and Marginal Effects

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

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

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

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

In the typical linear model without peer effects, both β and γ are equal to zero and the derivative reduces to $\partial y_i/\partial x_{lm} = \lambda_m$ for all i and l. With peer effects, there are several distinctions. When $i = l$, the peer firm average leverage coefficient, β, amplifies the effect of a change in an exogenous variable on y. This amplification mechanism is represented by the parenthetical expression multiplying λ_m. For β in the open unit interval and $N > 1$, this expression is strictly greater than 1.[16] Because of the presence of peer firm characteristics, this amplification may either be further amplified or offset depending on the correlation between the outcome variable and the peer firm characteristics, γ_m. (The second term in the case $i = l$.) When $i \neq l$, the derivative is no longer zero. Instead, cross-observations effects are determined by the relative importance of peer firm actions (β) and characteristics (γ).

Using the estimated market leverage model in column (3) of Panel A in Table VI, we estimate the derivatives in equation (8). Table VIII presents these estimates, scaled by their corresponding variable standard deviation, and the corresponding chi-square test statistics in brackets. We also present estimates of the amplification term (the first parenthetical expression in the case $i = l$), spillover term 1 (the second parenthetical expression in the case $i = l$), spillover term 2 (the second parenthetical expression in the case $i \neq l$), and their corresponding chi-square test statistics in brackets.[17] Because the size of the industry, N, plays a central role in the derivative expressions, we present estimates for three different size industries based on the 10^{th} (3 firms), 50^{th} (8 firms), and 90^{th} (26 firms) percentiles of the industry size distribution. For ease of reference, the columns labeled ($\lambda \times \sigma_x$) and ($\gamma \times \sigma_x$) repeat the firm specific and peer firm average characteristics scaled parameter estimates from column (3) of Panel A in Table VI. We also present the unscaled peer firm average leverage coefficient (β).

There are several findings of particular interest. First, the amplification term, though noisily estimated, varies dramatically across industry size categories and is economically large. Changes in capital structure determinants are magnified by 70% in small industries, and 8% in large industries. Intuitively, each firm has a smaller effect on its peers, the larger is the peer group.

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

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

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

the firm-specific (λ) and peer firm average coefficients (γ). We hope that future theory will help to shed some light on the economic mechanism behind these relations.

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

V. Why do Firms Mimic One Another?

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

A. Theoretical Motivation

Peer effects in capital structure can arise for a variety of reasons. For example, interactions between financial structure and product market competition can lead to financial policy mimicking. Bolton and Scharfstein (1990) present a model in which high leverage invites predatory price competition from less-levered rivals. If the expected cost of this predatory behavior is severe enough, highly levered firms will mimic the capital structures of their less-levered rivals. Similarly, Chevalier and Scharfstein (1996) present a model in which firms with high leverage under-invest during an industry downturn and lose market share to more conservatively financed competitors. This loss can motivate firms to mimic the more conservative leverage policies of their peers.[18]

Additional motivation for mimicking behavior in capital structure comes from rational

[18]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 Zender (1991) also examine the interaction between product markets and financial policy. However, the implications of this study are geared more towards differential positioning within the industry, as opposed to mimicking behavior. See Phillips (1995) and Mackay and Phillips (2005) for empirical examination.

herding models (Devenow and Welch (1996)).[19] Zeckhauser, Patel and Hendricks (1991) suggest that free-riding in information acquisition or relative performance evaluation for managers may lead to herd behavior in capital structure policies. Both of these explanations have theoretical precedent in the finance literature. As shown by Banerjee (1992) and others, when a firm's own signal is noisy and optimization is costly or time-consuming (Conlisk, 1980), managers may rationally put more weight on the decisions of others than on their own information. This is especially likely when other firms in the industry are perceived as having greater expertise (Bikhchandani, Hirshleifer and Welch, 1998).

Indeed, Devenow and Welch (1996) note that informational cascades may explain the decisions of managers to assume debt because without a good model of why firms do so, managers may infer the best choice from peer companies. Additionally, managers need not completely ignore their own information, as occurs in the limit in sequential informational cascade models. Rather, it is sufficient that they update their priors in a Bayesian manner based on the observed actions of other firms (e.g., Romer (1993) and Tueman (1994)). As a result, their decisions will be pulled toward that of their peers, relative to what it would be if they relied solely on their own information.[20]

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

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

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

order to minimize the volatility of their relative performance.

B. Empirical Results

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

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

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 distribution of continuous interaction variables. The results show that smaller (market share), non-dividend paying, unrated firms tend to mimic their peers more strongly than their counterparts. Similarly, more financially constrained (Whited-Wu) firms tend to mimic more. These findings suggest that firms traditionally characterized as financially constrained are more likely to mimic their peers.

In Table X we examine which firms are mimicking and which firms are being mimicked. 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, incumbency, stock returns, and earnings growth. Followers are those firms in the bottom two thirds and leaders are those firms in the top third of the distribution. As suggested by their names, we seek to test whether smaller, less successful firms mimic the larger, more successful firms' financial policies.

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

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

The results provide a useful interpretation of the findings in Table IX. Those results suggest that financially constrained firms are more likley to mimic than unconstrained firms. This finding may be odd since it is precisely those firms for which mimicing is more costly since the cost of external financing is higher for financially constrained firms. However, the results here suggest that this cost may be swamped by the perceived benefit associated with mimicing 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 mimic followers. The results are reported in Panel B. Despite several statistically significant first stage estimates, the second stage estimates are all statistically insignificant. In other words, leader firms' financial policies appear insensitive to the financial policies 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 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)). Likewise, Ross, Westerfield, and Jaffe (2010) 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.[21]

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 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. Further, an open empirical question is whether or not this mimicking behavior is optimal in a value enhancing sense. Finally, we hope that the findings of this study shift the direction of capital structure research towards models, both theory and empirical, that explicitly recognize the interactions among firms.

[21]We also perform two additional sets of analysis examining in which industries does mimicking occur and which CEOs mimic. The results from this analysis are largely inconclusive and sensitive to sample selection and measurement issues. To conserve space, these results are contained in the accompanying internet appendix.

Appendix A: Variable Definitions

Corporate accounting data come from the merged CRSP-Compustat database available on the Wharton Research Data Services server. We draw a sample of firm-year observations during the period 1965 to 2008. We choose 1965 as the start year to mitigate the selection bias toward large, successful firms that exist in the early part of the Compustat sample. To maintain consistency with previous empirical studies and to avoid capital structures dictated by regulatory considerations, we exclude financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999), as well as government entities (SIC codes greater than or equal to 9000).[22] Stock return data for our sample of firms come from the Center for Research in Security Prices (CRSP) monthly stock price database.

To ensure consistency throughout our primary analysis, we require each firm-year observation to have nonmissing data for the levels and first differences of the following variables: net equity issuances, net debt issuances, book leverage, market leverage, sales, market-to-book ratio, profitability, tangibility, 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** - **prstkc**(t) / **at**(t-1).

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

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

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

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

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

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

Common Dividends = **dvc**.

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

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

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

Capital Expenditures = **capx**.

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

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

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

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

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

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

Appendix B: Exogenous Variable Derivatives

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

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

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

Solving equation (9) for y yields

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

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

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

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

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

where we used the equality

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

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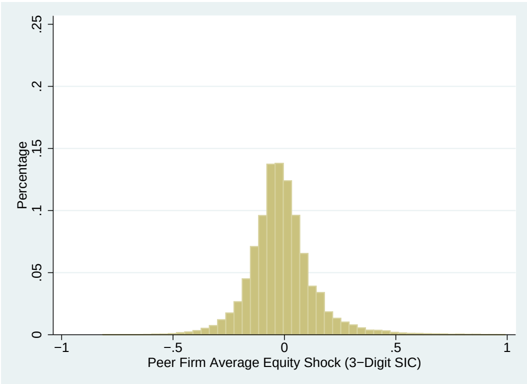
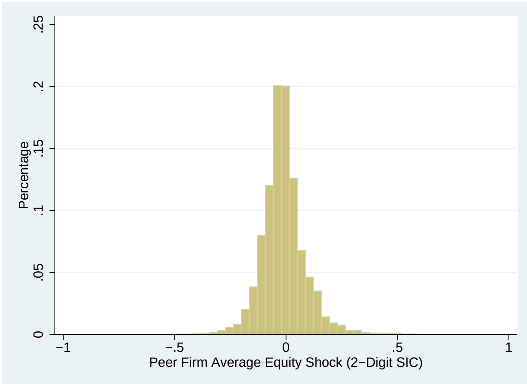
Figure 1
Industry Average Idiosyncratic Stock Returns Distribution

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (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 has been truncated at -1 and +1 to ease the presentation.

Panel A: Three-Digit SIC Code Peer Groups



Panel B: Two-Digit SIC Code Peer Groups



Panel C: One-Digit SIC Code Peer Groups

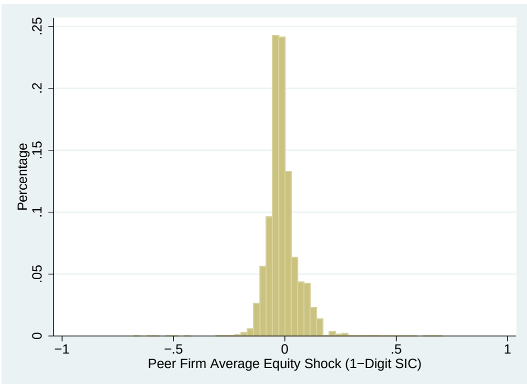


Table I
Summary Statistics

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

	Levels			First Differences		
	Mean	Median	SD	Mean	Median	SD
Peer Firm Averages						
Book Leverage (Total Debt / Book Assets)	0.238	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						
# of Firms per Industry-Year	13.217	8.000	18.344			
Total # of Industries	217					
Sample Characteristics						
Observations	80,279					
Firms	9,126					

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-squares 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 industry is defined by three-digit SIC code. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data from the CRSP database. We require at least 24 months of historical data and use up to 60 months of data in the estimation. Expected returns are computed using the estimated factor loadings and realized factor returns one year hence. Idiosyncratic returns are computed as the difference between realized and expected returns.

	Mean	Median	SD
α_{it}	0.008	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

Table III
Instrument Properties

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents OLS estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. The dependent variable is our instrument, peer firm average idiosyncratic equity returns. All independent variables are in levels and are either contemporaneous with or a one-period lead relative to the dependent variable. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. 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. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

	Peer Firm Average Equity Shock	
	Contemporaneous Independent Vars	1-Period Lead Independent Vars.
Firm Specific Factors		
Log(Sales)	-0.000	-0.000
	(-0.565)	(-0.334)
Market-to-Book	-0.001	0.000
	(-1.444)	(0.104)
EBITDA / Assets	-0.001*	-0.000
	(-2.336)	(-0.048)
Net PPE / Assets	0.002	0.001
	(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

Table IV
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 one 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 5% and 1% levels are denoted by "*" and "**", respectively.

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	

Table V
Peer Effects in Financial Policy

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients scaled by the corresponding variable's standard deviation, and t-statistics robust to heteroskedasticity and within firm dependence in parentheses. The method of estimation and dependent variable are indicated at the top of columns. The endogenous variable is the peer firm average leverage ratio, and, for the 2SLS estimations, the instrument is the one period lagged peer firm average equity return shock. Peer firm averages denote variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All variables are in levels or first differences as indicated at the top of the columns. All right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable unless otherwise specified. Issue Stock (Debt) is an indicator variable equal to one if Net Stock (Debt) Issuances normalized by lagged book assets is greater than 1%. Column (3) isolates the subsample of observations in which either an equity or debt issuance, but not both, occurred. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Panel A: Leverage Regressions

	OLS		2SLS			
	Market Leverage	Book Leverage	Market Leverage	Book Leverage	Δ Market Leverage	Δ Book Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Firm Averages						
Leverage	0.066**	0.047**	0.100**	0.100**	0.077**	0.045*
	(30.124)	(25.517)	(4.803)	(3.573)	(5.431)	(2.566)
Log(Sales)			-0.011**	-0.015**	-0.004*	-0.001
			(-2.719)	(-3.111)	(-2.440)	(-0.777)
Market-to-Book			0.032**	0.011**	0.001	0.002
			(4.403)	(2.791)	(1.463)	(1.602)
EBITDA / Assets			0.021**	0.020**	0.002*	0.001
			(4.618)	(4.949)	(2.416)	(1.151)
Net PPE / Assets			-0.013	-0.033**	-0.001	-0.001
			(-1.659)	(-2.858)	(-1.788)	(-1.251)
Firm Specific Factors						
Log(Sales)	0.022**	0.020**	0.021**	0.021**	0.005**	0.002**
	(10.375)	(10.859)	(9.113)	(10.435)	(6.541)	(2.640)
Market-to-Book	-0.069**	-0.018**	-0.067**	-0.018**	-0.002**	-0.002**
	(-45.709)	(-13.153)	(-42.570)	(-11.257)	(-3.661)	(-3.081)
EBITDA / Assets	-0.047**	-0.034**	-0.048**	-0.037**	-0.003**	-0.002**
	(-29.189)	(-19.929)	(-28.700)	(-20.769)	(-5.128)	(-3.280)
Net PPE / Assets	0.028**	0.033**	0.034**	0.042**	0.004**	0.003**
	(13.178)	(17.421)	(11.281)	(15.105)	(5.955)	(4.680)
Equity Shock			-0.003**	-0.000	0.002**	-0.000
			(-4.468)	(-0.484)	(3.030)	(-0.713)
First Stage Instrument						
Peer Firm Avg Equity Shock			-0.033**	-0.015**	-0.015**	-0.005**
			(-13.126)	(-7.350)	(-8.713)	(-4.383)
Industry Fixed Effects	No	No	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	80,279	80,279	80,279	80,279	80,279	80,279

Panel B: Security Issuance Regressions

	Issue Stock	Issue Debt	Subsample of Issuances: Issue Debt
	(1)	(2)	(3)
Peer Firm Averages			
Dependent Variable	0.046*	-0.631	0.105*
	(2.423)	(-1.249)	(2.230)
Log(Sales)	-0.003	0.095	0.001
	(-0.599)	(1.387)	(0.120)
Market-to-Book	-0.002	0.092	0.017
	(-0.278)	(1.555)	(1.410)
EBITDA / Assets	0.008*	0.102	0.006
	(2.244)	(1.632)	(0.744)
Net PPE / Assets	0.007	0.083	-0.001
	(1.095)	(1.200)	(-0.144)
Firm Specific Factors			
Log(Sales)	-0.026**	0.035**	0.051**
	(-9.161)	(7.432)	(12.410)
Market-to-Book	0.095**	0.015	-0.097**
	(34.880)	(1.871)	(-27.751)
EBITDA / Assets	-0.040**	0.005	0.026**
	(-17.645)	(0.514)	(7.661)
Net PPE / Assets	0.009**	0.040**	0.018**
	(2.940)	(8.654)	(4.137)
Equity Shock	0.032**	0.007	-0.028**
	(21.071)	(1.535)	(-12.039)
First Stage Instrument			
Peer Firm Avg Equity Shock	0.074**	0.009	-0.091**
	(19.430)	(1.530)	(-8.146)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	80,279	80,279	34,578

Table VI
Robustness 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). All specifications include firm specific and peer firm averages for firm size, profitability, tangibility, and the market-to-book ratio. The models are all estimated via 2SLS. Stock return controls includes firm i's lagged and contemporaneous total stock return. Additional control variables include lagged firm specific and peer firm averages for cash flow volatility, a dividend payer indicator, Altman's Z-score, Graham's marginal tax rate, capital expenditures divided by the capital stock as of the previous period, R&D expenditures divided by sales, and SG&A expenditures divided by sales as well as the intra-industry standard deviation of leverage. Bank × Market Return effects include fixed effects for the primary or lead underwriter for the firm's past security issuances, debt or equity, and these same fixed effects interacted with the market equity return. Polynomials of control variables (Vars) include quadratic and cubic terms of all right hand side variables other than industry average leverage. Contemporaneous controls replace the lagged firm specific and peer firm averages control variables with contemporaneous values. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

	Δ Market Leverage					
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage Estimate						
Peer Firm Avg Leverage Change	0.055**	0.073**	0.048**	0.075**	0.048**	0.076**
	(4.343)	(4.797)	(3.002)	(5.336)	(4.966)	(5.646)
First Stage Instrument						
Peer Firm Avg Equity Shock	-0.014**	-0.015**	-0.017**	-0.015**	-0.018**	-0.016**
	(-8.410)	(-7.897)	(-5.931)	(-8.737)	(-12.118)	(-9.427)
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Return Controls	Yes	No	No	No	No	No
Additional Control Variables	No	Yes	No	No	No	No
Bank × 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

Table VII
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 2SLS regression results 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. The instrument in these specifications is the average equity return shock to the customers of the peer firms. Panel B presents placebo results in which we replace each customer from the analysis in Panel A with a randomly selected non-customer in the same industry as the customer. The average shock to the randomly selected non-customers is then used as an instrument for firm i's peer group outcome variable. We perform the random selection and 2SLS regression analysis 100 times to obtain a distribution of estimated peer effects and their t-statistics. All specifications include firm specific and peer firm averages for firm size, profitability, tangibility, and the market-to-book ratio. All specifications include firm specific factors and peer firm averages for firm size, profitability, tangibility, and the market-to-book ratio. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Panel A: Customer Return Shocks

			Subsample of Issuances
	Market Leverage	Δ Market Leverage	Issue Debt
Second Stage Estimate			
Peer Firm Average	0.057*	0.029**	0.142
	(2.315)	(3.340)	(1.907)
First Stage Instrument			
Peer Firm Customers' Avg Equity Shock	-0.036**	-0.032**	-0.080**
	(-9.385)	(-12.355)	(-5.075)
Control Variables			
Peer Firm Averages	Yes	Yes	Yes
Firm Specifc Factors	Yes	Yes	Yes
Firm i Stock Return	Yes	Yes	Yes
Firm i Industry Average Stock Return	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes
Obs	54,599	52,222	21,410

Panel B: Placebo Tests

		Percentiles				
	Mean	5	25	50	75	95
Peer Effect Marginal Effects						
Market Leverage	-0.050	-1.026	-0.078	0.032	0.130	0.401
Δ Market Leverage	0.014	-0.190	-0.005	0.020	0.045	0.165
Issue Debt	0.069	-0.626	-0.105	0.013	0.197	0.836
Peer Effect t-stats						
Market Leverage	0.468	-2.015	-0.740	0.216	1.533	3.499
Δ Market Leverage	0.732	-1.179	-0.222	0.596	1.535	3.224
Issue Debt	0.124	-1.173	-0.455	0.043	0.697	1.496

Table VIII

Exogenous Variable Derivatives, Marginal Effects, and Leverage Multipliers

The sample consists of all nonfinancial, nonutility firms in the annual Compustat database between 1965 and 2008 with nonmissing data for all analysis variables (see Appendix A). The table presents estimated coefficients and derivatives, both scaled by the corresponding variable standard deviation, from a regression of market leverage on peer firm leverage, peer firm characteristics, and firm specific factors. All variables are in levels. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. Derivatives are computed for three peer groups differing in their size: small (10th percentile = 3 firms), medium (50th percentile = 8 firms), and large (90th percentile = 25 firms). The derivative $\partial y_i/\partial x_{im}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation i (x_{im}). The derivative $\partial y_i/\partial x_{km}$ shows the change to the outcome of observation i (y_i) following a one unit change to variable x_m for observation k (x_{km}). Both derivatives are scaled by the standard deviation of the corresponding x variable, (σ_x). Amplification term is the multiplicative factor due to the peer effect action variable and is equal to $\left(1 + \frac{\beta^2}{(N-1+\beta)(1-\beta)}\right)$. The terms Spillover 1 and Spillover 2 are the additive factors due to both the peer firm actions and characteristics, and are equal to $\left(\frac{\beta}{(N-1+\beta)(1-\beta)}\right)$ and $\left(\frac{1}{(N-1+\beta)(1-\beta)}\right)$, respectively. In parentheses are t-statistics robust to heteroskedasticity and within firm dependence. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively.

Variable	Firm-Specific Factor Scaled Coefs ($\lambda \times \sigma_x$)	Peer Firm Average Scaled Coefs ($\gamma \times \sigma_x$)	Peer Group Size - Small $\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	Peer Group Size - Small $\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	Peer Group Size - Medium $\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	Peer Group Size - Medium $\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$	Peer Group Size - Large $\frac{\partial y_i}{\partial x_{im}} \times \sigma_x$	Peer Group Size - Large $\frac{\partial y_i}{\partial x_{km}} \times \sigma_x$
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)	

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 estimates for the peer firm average market leverage change interacted with indicator variables identifying the lower and upper third of the within industry-year distribution of lagged values for firm specific measures of whether the firm has a credit rating, whether the firm paid a dividend in year $t-1$, market share, profitability, market-to-book ratio, and the Whited-Wu Index of financial constraints. We exclude the middle third of the distribution for each of these regressions. The coefficient estimates are scaled by the corresponding variable standard deviation. The dependent variable is the change in market leverage ratio. All models are estimated by linear 2SLS where the endogenous variables are the peer firm average leverage ratio changes interacted with indicator variables, and the instruments are the one period lagged peer firm average idiosyncratic component of stock returns interacted with the same indicator variables. The table also presents the heteroskedasticity corrected Cragg-Donald statistic testing for weak instruments (First Stage Multivariate F-stat). Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All variables are in first differences except the instrument. All right hand side variables, including the instrument but excluding the endogenous variable, are lagged one year relative to the dependent variable unless otherwise specified. All test statistics are computed using standard errors that are robust to within firm correlation and heteroskedasticity. Statistical significance at the 5% and 1% levels are denoted by "*" and "**", respectively. F-stat statistical significance implying less than 15% or 10% size distortion is denoted by "*" and "**", respectively.

	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	Yes	Yes	Yes	Yes	Yes	Yes
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. Peer firm averages denotes variables constructed as the average of all firms within an industry-year combination, excluding the i^{th} observation. Industry is defined by three-digit SIC code. Firm specific factors denotes variables corresponding to firm i's value in year t. All specifications include one-period lagged peer firm averages and firm specific effects for the following characteristics: firm size, profitability, tangibility, and the market-to-book ratio. Firms are classified as either "Leaders" or "Followers" based on their within industry-year ranking by: age, profitability, market share (sales as a fraction of industry sales), stock returns, and earnings growth. The table restricts attention to the subsample of firms in the middle and lower thirds of the within industry-year distribution (i.e., Followers) of each classification variable and regresses their change in market leverage ratio on the average change in market leverage of firms in the upper third (i.e., Leaders), as well as the control variables indicated towards the bottom of the table. F-stat statistical significance implying less than 10% or 15% size distortion is denoted by "*" and "**", respectively.

Panel A: Do Follower Firms Respond to Leaders?

	Change in Market Leverage				
	Age	Profitability	Market Share	Stock Return	Earnings Growth
Peer Firm Average					
Leader Firm Avg Leverage Change	0.074**	0.076**	0.084**	0.087**	0.120**
	(3.475)	(5.055)	(5.312)	(3.830)	(3.423)
First Stage Univariate F-stat	36.300**	62.913**	55.665**	34.530**	17.716**
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes
Industry Effects	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	49,287	51,588	43,677	51,590	37,184

Panel B: Do Leader Firms Respond to Followers?

	Change in Market Leverage				
	Age	Profitability	Market Share	Stock Return	Earnings Growth
Follower Firm Avg Leverage Change	0.103	-0.019	0.018	-0.088	-0.049
	(1.772)	(-0.890)	(0.745)	(-1.711)	(-0.956)
First Stage Univariate F-stat	4.804*	17.688**	13.788**	6.021*	4.856*
Peer Firm Average Characteristics	Yes	Yes	Yes	Yes	Yes
Firm Specific Factors	Yes	Yes	Yes	Yes	Yes
Industry Effects	No	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	49,726	53,554	45,529	53,552	38,918