# How Does Industry Affect Firm Financial Structure?

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We examine the importance of industry to firm-level financial and real decisions. We find that in addition to standard industry fixed effects, financial structure also depends on a firm's position within its industry. In competitive industries, a firm's financial leverage depends on its natural hedge (its proximity to the median industry capital–labor ratio), the actions of other firms in the industry, and its status as entrant, incumbent, or exiting firm. Financial leverage is higher and less dispersed in concentrated industries, where strategic debt interactions are also stronger, but a firm's natural hedge is not significant. Our results show that financial structure, technology, and risk are jointly determined within industries. These findings are consistent with recent industry equilibrium models of financial structure.

Despite extensive financial structure research since Myers (1984) and Harris and Raviv (1991) surveyed the literature, important questions remain about how financial structure is related to industry and about how real and financial decisions are related.[1] Although it is widely held that industry factors are important to firm financial structure, empirical evidence shows that there is wide variation in financial structure even after controlling for industries.[2] Researchers routinely remove industry fixed effects by including dummy variables or sweeping out industry

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[1] Recent empirical papers on financial structure examine static trade-off and pecking-order theories (Shyam-Sunder and Myers, 1999, Fama and French, 2002, Frank and Goyal, 2003), taxes (Graham, 1996, 2000), managerial fixed effects (Bertrand and Schoar, 2002), technology (MacKay, 2003), and stock returns (Welch, 2004).

[2] Bradley, Jarrell, and Kim (1984), Chaplinsky (1983), and Remmers et al. (1974).


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means and using the remaining variation to test how firm characteristics affect financial policy. Yet, this approach does not tell us *how* industry affects firm financial structure, nor *why* financial structure and real-side characteristics vary so widely across firms within a given industry. In addition, theoretical models such as Dammon and Senbet (1988) and Leland (1998) stress the jointness of real and financial decisions—yet little is known about the empirical relevance of the simultaneity of these decisions. We thus examine these two unresolved but related questions: How important are industry factors to firm financial structure? Can industry equilibrium forces explain how firms distribute within industries—both along real-side and financial dimensions?

We address these questions by examining how intra-industry variation in financial structure relates to industry factors and whether real and financial decisions are jointly determined within industries. We base our analysis on models of competitive-industry equilibrium (Maksimovic and Zechner, 1991, Williams, 1995, and Fries, Miller, and Perraudin, 1997).[3] Similar to Miller's (1977) irrelevance result, these models illustrate how conclusions reached in a partial-equilibrium framework are fundamentally altered, even reversed, as the equilibrium setting is aggregated to the level of an industry. Our research therefore goes beyond tests of static trade-off and pecking-order theories to examine whether the decisions of individual firms are related to those of industry peers. We also investigate the impact of endogeneity, both as an empirical matter and as an implication of recent theory, by contrasting single- and simultaneous-equation regressions for financial leverage, capital–labor ratios, and cash-flow volatility.

We precede our examination of industry equilibrium models with a broader investigation of inter- and intra-industry variation in financial structure. We document extensive cross-sectional variation in financial leverage in our sample of 315 competitive manufacturing industries. Regressing firm-level financial leverage on industry-level medians, we find that most of the variation in financial structure arises *within* industries rather than *between* industries. Specifically, we find that industry fixed effects account for only 13% of variation in financial structure. In contrast, firm fixed effects explain 54% of variation in financial structure, and the remaining 33% is within-firm variation.

Given the relative unimportance of industry fixed effects in explaining financial structure, we examine whether other industry-related factors can account for some of the wide variation observed within industries. Our empirical strategy is to construct various measures of a firm's industry position inspired from industry equilibrium models and test whether these

[3] Chevalier (1995), Phillips (1995), and Kovenock and Phillips (1995, 1997) show that financial structure conditions real decisions in *imperfectly* competitive industries. Opler and Titman (1994) show that highly leveraged firms lose market share in concentrated industries after negative industry shocks.

measures help explain firm financial structure. These include the similarity of a firm's capital–labor ratio to the industry median, the actions of its industry peers, and its status as an entrant, incumbent, or exiting firm. We focus on competitive industries but also examine concentrated industries to establish the general applicability of our findings.

Consistent with competitive-industry equilibrium models, we find that financial structure decisions are made simultaneously with technology and risk choices and that all three decisions are impacted by a firm's position within its industry. We find that firms near the industry median capital–labor ratio use less financial leverage than firms that deviate from the industry median capital–labor ratio. This is consistent with the idea of a natural hedge in Maksimovic and Zechner (1991) where firms at the technological core of an industry experience lower cash-flow risk and use less debt than firms at the technological fringe. We also find that changes to a firm's real and financial characteristics are inversely related to changes in the same variables made by other firms in its industry. These interactions are consistent with the adjustment patterns predicted by Maksimovic and Zechner, where the equilibrium process drives firms to react differently to common industry shocks.

We find contrasting results for concentrated industries. Our natural hedge proxy is neither statistically nor economically significant in concentrated industries, confirming that competitive-industry models perform poorly in concentrated industries. However, we find that the sensitivity of own-firm decisions to industry-peer decisions is much greater for firms in concentrated industries, consistent with the importance of strategic interaction in these industries.

We also investigate the dynamic industry equilibria developed by Williams (1995) and Fries, Miller, and Perraudin (1997), where entry and exit are endogeneized. First, we find that, although statistically significant, firm reversion to industry medians is economically unimportant. Second, we find that firm characteristics evolve slowly and that firms tend to retain their industry rankings. Indeed, we find high persistence in incumbents' industry position along real and financial dimensions, suggesting that industry equilibrium forces may act to sustain intra-industry diversity rather than smooth it away. However, our multivariate results show no important differences between incumbents and entrants. Thus, while there is some support for the *static* industry equilibrium modeled in Maksimovic and Zechner (1991), we find only limited support for the more intricate models of *dynamic* industry equilibrium represented by Williams (1995) and Fries, Miller, and Perraudin (1997).

This paper makes two contributions. First, we show that firm financial structure is determined by industry-related factors other than industry fixed effects. Consistent with competitive-industry equilibrium models, we find that proxies for a firm's position within its industry add both statistical and economic significance in explaining its real and financial decisions. This suggests that, although stylized, these models do provide a useful framework to explain individual firm behavior.

Second, we identify and account for the interactions between financial structure, technology, and risk choice. We find that accounting for the simultaneity of these decisions is important economically—not just econometrically. Accounting for this simultaneity impacts multiple relations, including the relations between financial leverage, capital–labor ratios, and cash-flow volatility.

Overall, our paper begins to bridge the gap between empirical studies of partial-equilibrium models, which simply use firm variation to test representative-firm behavior, and industry equilibrium models, which endogenize firm variation and link firm-level decisions to broader equilibrium forces. The remainder of the paper is organized as follows. Section 1 reviews the financial-structure literature and discusses the empirical implications of the industry equilibrium models. Section 2 describes our data sources, sample selection, and the variables we use to examine these implications. Section 3 discusses our univariate and multivariate results. Section 4 concludes.

## 1. The Importance of Industry to Financial Structure

This section reviews the theoretical models relevant to our analysis. Although our primary focus is on how financial structure is determined in perfectly competitive industries, we briefly discuss models of imperfect competition for comparison and to provide more background on how industry affects financial structure.

Early theory on the interaction of finance and product markets (Brander and Lewis, 1986, Maksimovic, 1988) deals with symmetric firms in concentrated industries and thus cannot explain why competing firms would choose different financial structures. Other theory examines how product-market competition is affected when firms have asymmetric financial structures (Bolton and Scharfstein, 1990, Rotemberg and Scharfstein, 1990). Neither this research nor partial-equilibrium theory can explain why real and financial firm characteristics vary so widely within industries.

A more recent line of theoretical research by Maksimovic and Zechner (1991), Williams (1995), and Fries, Miller, and Perraudin (1997) stresses equilibrium forces in the spirit of Miller (1977). These models show how real and financial decisions are jointly determined within *competitive* industries.[4] This approach offers additional insights relative to partial-equilibrium

[4] The jointness of real and financial decisions is also central to a number of partial-equilibrium models such as Dammon and Senbet (1988), Mauer and Triantis (1994), and Leland (1998). MacKay (2003) finds significant empirical interactions between real-side flexibility and financial structure.

models, namely, that firms make their individual real and financial decisions in reference to the collective decisions of industry peers, and that equilibrium outcomes imply intra-industry diversity rather than industry-wide targets.[5]

Maksimovic and Zechner (1991) assume that firms can choose between a "safe" technology with a certain marginal cost, and a "risky" technology with an uncertain cost. In partial equilibrium, no debt is issued since shareholders would expropriate bondholder wealth by picking the risky technology. However, each firm has an incentive to finance with debt and adopt the risky technology because by allowing firms to raise (lower) output in good (bad) states, the risky technology initially has greater expected profits and risk than the safe technology. As more firms pick the risky technology, the price of output more closely tracks that technology's marginal cost; the risky technology becomes less risky and less profitable. Equilibrium obtains when the expected value of the *ex-ante* safe and risky technologies is equal and firms are indifferent between high-debt/high-risk and low-debt/low-risk configurations. Thus, what Maksimovic and Zechner (1991) show is that in *industry* equilibrium, firm financial structure is irrelevant because a technology's risk and profitability depend not only on *ex-ante* characteristics but also on how many firms adopt that technology.

Two implications follow from Maksimovic and Zechner's analysis. First, firms near the median industry technology benefit from a risk-reducing "natural hedge". Such firms will use less financial leverage than firms whose technology departs from the industry norm. Second, to preserve equilibrium, firms within an industry make offsetting adjustments to their debt and technology.

Williams (1995) extends Maksimovic and Zechner's (1991) model by endogenizing entry and exit and adding exogenous perks consumption. Williams assumes that firms produce a homogeneous good using either a high variable-cost, labor-intensive technology with no capital outlay, or a low variable-cost, capital-intensive technology requiring capital-market financing. Because managers cannot credibly commit to forego their perks, capital is rationed in equilibrium even though the capital market is perfectly competitive. Even as the cost of entry converges to zero, a core of capital-intensive firms earns positive profits because managerial agency prevents the fringe of labor-intensive firms from raising capital and dissipating the core firms' monopoly rents.

Like Maksimovic and Zechner (1991), Williams (1995) characterizes the equilibrium industry distribution of debt and firm characteristics and

[5] Almazan and Molina (2002) contrast multiple explanations for the dispersion in financial structure within industries. Their analysis complements ours in that they focus on explaining the variation in financial structure while we test implications of industry equilibrium models for firm-level financial and real-side decisions.

explains firm heterogeneity within industries. By allowing for entry, Williams predicts an asymmetric equilibrium industry structure characterized by a core of large, stable, profitable, capital-intensive, financially-leveraged firms flanked by a competitive fringe of small, risky, non-profitable, labor-intensive firms.

Fries, Miller, and Perraudin (1997) use a contingent-claims approach to analyze optimal financial structure in a competitive-industry equilibrium that combines features of the previous models. Like Williams (1995), they allow for endogenous firm entry and exit. Like Maksimovic and Zechner (1991), they incorporate shareholder–bondholder conflicts and corporate debt tax-shields. Fries, Miller, and Perraudin (1997) find that as a result of a trade-off between tax advantages and agency costs, a firm optimally adjusts its financial leverage upward after it enters the industry.

The overarching implication of these models is that own-firm decisions are partly determined by the position a firm occupies within its industry. In Maksimovic and Zechner (1991), industry position refers to how closely a firm's technology compares to the rest of its industry. In Williams (1995) and Fries, Miller, and Perraudin (1997), industry position refers to whether a firm belongs to the core or fringe of its industry or its status as entrant, incumbent, or exiting firm. These models also show that firm decisions within an industry are interdependent and that firm heterogeneity arises as an equilibrium outcome. Section 2 describes the specific empirical strategies we employ to test these implications.

On a broader level, our contribution is in examining the central *theme* of these models—that firms' debt, technology, and risk decisions are jointly determined within industries—not in testing one model against the others. Note that we do not conduct structural tests of these models but rather test the implications that industry position and peer actions matter, and the central theme that real and financial decisions are simultaneously determined as result of industry equilibrium forces.

To examine this central theme, we estimate simultaneous-equation regression models for financial leverage, capital–labor ratios, and cash-flow volatility. Empirically, as well as theoretically, we allow the financial-structure decision to depend on technology and risk choice and vice versa. We account for interactions between these dependent variables by including each of the remaining two variables as regressors for the dependent variables featured in each equation. We use generalized method of moments (GMM) to reflect the correlation of the residuals across these equations and to instrument endogenous right-hand-side variables. We include measures of a firm's industry position, such as the similarity of its capital–labor ratio to the industry median capital–labor ratio, the actions of firms inside and outside its industry-year peer group, and its status as entrant, incumbent, or exiting firm, to test the idea that firms' decisions are affected by those of their industry peers.

## 2. Data, variable construction, and methodology

We examine active and inactive firms from the merged COMPUSTAT-CRSP set produced by Wharton Research Data Services (WRDS). We use COMPUSTAT for the financial accounting and operating variables. We use CRSP for historical industry classifications because COMPUSTAT only reports current industry classifications. We merge in COMPUSTAT's business-segment files to compute diversification Herfindahls. Using these segment files limits the sample to 1981–2000.

COMPUSTAT codifies why firms drop out from the sample (note 35, "reason for deletion"). We use this variable to distinguish between true firm exit (Chapter 11 bankruptcy and Chapter 7 liquidation) and firms whose CUSIP changes because of corporate restructuring. This allows us to examine the behavior of firms that enter, stay, or leave their industry as a test of the dynamic industry models developed by Williams (1995), Fries, Miller, and Perraudin (1997) and Poitevin (1989).

We collect four-digit SIC industry concentration ratios (Herfindahl–Hirschman Index, HHI) from the Census of Manufacturers for 1982, 1987, 1992, and 1997. The Census of Manufacturers reports the results of the U.S. Census Bureau's Economic Census held every 5 years. This provides us with an independent and reasonably timely measure of industry concentration. An independent measure of industry concentration is preferable for two reasons. First, rather than rely on the availability of COMPUSTAT data, the Census of Manufacturers offers the broadest coverage available and thus helps minimize selection bias and classification error. Second, the Department of Justice (DOJ) and other regulatory agencies use the HHI to set and enforce competition policy. Thus, the HHI is appropriate because it affects both government and firm behavior and is observable to all.[6]

### 2.1 Sample selection

The models we discussed earlier make different assumptions regarding industry competition. Motivated by the predictions of Maksimovic and Zechner (1991), Williams (1995), and Fries, Miller, and Perraudin (1997) under perfect competition, we form a sample of firms operating in competitive industries by retaining industries with a HHI under 1000.[7] To benchmark our results and investigate models of imperfect competition (Brander and Lewis, 1986, 1988, Maksimovic, 1988, 1990, etc.), we also form a sample of firms operating in concentrated industries by retaining

[6] We thank the referee for this suggestion. The previous version of the paper relied on the number of firms on COMPUSTAT operating in each industry.

[7] This follows the industry classification scheme used by the U.S. Department of Justice and Federal Trade Commission (1997): Unconcentrated industries (HHI under 1000), moderately concentrated industries (HHI from 1000 to 1800), and highly concentrated industries (HHI over 1800).

industries with a HHI over 1800. For a sharper contrast between competitive and concentrated industries, we exclude industries with a HHI between 1000 and 1800, which the DOJ considers "moderately concentrated".

Because the models we consider build on classical notions of industry and technology, such as capital–labor ratios, we limit our sample to firms operating in manufacturing industries, namely, SIC 2000 to 3990. We exclude firms in industries classified as miscellaneous by dropping industries where the last two digits of the four-digit SIC code end in ninety-nine.

In addition to dropping observations with incomplete data, we delete observations with negative sales or assets, and those with a CRSP permanent number or capital–labor ratio equal to zero. To prevent influential observations from skewing our results, we delete outliers as follows. We drop observations where Tobin's $q$ is over ten, earnings before interest and taxes divided by assets is less (more) than negative (positive) two, or financial leverage lies outside the [0,1] interval.[8]

The regressions presented in Section 3 control for firm fixed effects by first-differencing the firm-level variables (we also control for interacted industry-year fixed effects). The GMM regressions appearing in that section use the second lags in levels as instruments. Hence, observations without at least two lags of data ultimately fall out of the sample.[9] The final sample forms an unbalanced panel of 3074 firms (17,140 firm-years) operating in 315 competitive industries and 309 firms (1630 firm-years) operating in 46 concentrated industries.

### 2.2 Proxies and variable construction

We measure financial leverage as total debt divided by total assets (book leverage). Using book values may be justified by a recent survey by Graham and Harvey (2001) who report that managers focus on book values when setting financial structure. Furthermore, Barclay, Morellec, and Smith (2003) show how book leverage is theoretically preferable in regressions of financial leverage, arguing that using market values in the denominator might spuriously correlate with explanatory variables such as Tobin's $q$. However, Welch (2004) argues against book leverage in favor of market leverage, and Fama and French (2002) find strikingly different results for book leverage and market leverage. In light of this recent controversy, we rerun our regressions using total debt divided by the market value of equity plus the book value of debt and preferred stock minus deferred taxes (market leverage).

[8] Our base results use the book value of equity to compute financial leverage. As a robustness check, we rerun our regressions using the market value of equity and relax the screening interval on financial leverage to [0,2].

[9] Because the sample is highly unbalanced, with some firms appearing only a few years and others remaining throughout the entire panel, this number of lags reflects a trade-off between reducing endogeneity bias, losing observations and statistical power, and introducing large-firm and survivor biases.

We use fixed-capital stock (net property, plant, and equipment, in millions of dollars) divided by the number of employees as a proxy for capital intensity (the capital–labor ratio, $K/L$).[10] To measure risk, we use the standard deviation of operating cash flow divided by total assets using up to ten (minimum four) annual observations.[11] Profitability is earnings before interest expense and taxes (EBIT) (data item 13 minus 14) divided by total assets. We measure diversification as one minus the Herfindahl of output calculated across a firm's four-digit SIC industries (computed from segment data). This measure equals zero for single-segment firms and tends toward one for multi-segment firms. We control for diversification directly and for robustness, repeat our tests for single-segment firms only. Following Barclay, Morellec, and Smith (2003) and others, we control for the investment opportunity set with Tobin's $q$ (market value of equity plus the book value of debt and preferred stock minus deferred taxes, divided by book assets).

**2.2.1 Industry position variables.** We construct two measures of a firm's position within its industry. First, we develop a proxy that captures Maksimovic and Zechner's (1991) natural hedge idea. The natural hedge proxy must possess three properties: (1) it must reflect a firm's production technology; (2) it must measure the distance between a firm's technology and the typical technology in the firm's industry, and (3) it must be comparable across industries. We use the capital–labor ratio to measure technology. This variable is specifically modeled in Williams (1995) and is true to the spirit of the safe-versus-risky cost structure discussed by Maksimovic and Zechner. We define the typical technology as the median capital–labor ratio for a given industry and year. This industry-year median is weighted by each firm's market share of sales and excludes the firm itself. We use the absolute value of the difference between firm's capital–labor ratio and the industry-year median capital–labor ratio because natural hedge should only measure how similar or dissimilar a firm is to the rest of its industry, not whether the firm has a

[10] COMPUSTAT's employment number (data item #29) is rarely used in the empirical finance literature, so we test the quality of this variable on three fronts: coverage, reliability, and stickiness. Coverage: Keeping only observations where the fixed-capital stock is neither missing nor zero, we find that only about 6% of observations are missing the number of employees. This percentage is even lower if we screen on the availability of other variables used in the study. Reliability: We randomly picked ten firms in 1997 and cross-checked the COMPUSTAT number against what the firms report in their 10-Ks. All concurred 100%. Stickiness: We count how many times we observe employment changes of exactly zero. This happens about five percent of the time. We exclude these observations from our sample. However, including them makes no material difference to our main conclusions.

[11] We also tried using twenty quarterly data points to compute risk. Although this should increase sample size by requiring fewer consecutive years of firm data, in practice, going to quarterly data results in a smaller sample because the coverage of the quarterly dataset is poor. Results using quarterly data to compute risk (deseasonalized or not) are substantially the same as those presented here.

high or low industry-adjusted capital–labor ratio.[12] We then divide this deviation by the range of capital–labor ratio deviations in each industry-year; this bounds the natural hedge proxy between zero and one and makes it comparable across industries. For ease of interpretation, we subtract this value from one. A natural hedge value of one indicates that the firm's capital–labor ratio is identical to the industry-year median capital–labor ratio. A natural hedge value of zero indicates that the firm's capital–labor ratio is the furthest from the industry-year median capital–labor ratio.

Thus, our natural hedge measure can be expressed algebraically as follows

$$NH_{f,i,y} = \frac{\left|(K/L)_{f,i,y} - \text{median}_{i,y,-f}(K/L)\right|}{\text{range}\left\{\left|(K/L)_{f,i,y} - \text{median}_{i,y,-f}(K/L)\right| \forall f \in i,y\right\}} \in [0,1]$$

where $f$ stands for firm, $i$ for industry, and $y$ for year.

Because our natural hedge is built solely around the capital–labor ratio, it might fail to reflect other dimensions of a firm's position in its industry. To address this issue, our regressions control for the mean change in the dependent variables (financial leverage, capital–labor ratios, and cash-flow volatility) inside and outside a firm's industry-year quantile (intra- and extra-quantile). Intra-quantile change is the mean change in the dependent variable within the industry half to which a firm belongs. To avoid hardwiring a spurious correlation into the analysis, the mean change for each firm's own quantile excludes that firm itself. Extra-quantile change is the mean change in the other half of the industry. We construct the quantiles themselves from the lagged levels of the dependent variables.

### 2.3 Regression model specification

Our main regressions are simultaneous-equation regressions where financial leverage, capital–labor ratios, and cash-flow volatility appear both as dependent variables and as regressors in the other two equations. We include the measures of a firm's industry position described above, namely, natural hedge, intra- and extra-quantile change, and dummy variables for firm entry and exit. These are the main variables of interest in this study. To ensure that these measures of industry position do not simply reflect static trade-off and pecking-order theories, we also include standard control variables such as profitability, firm size (log of total assets), diversification, and Tobin's $q$.

[12] Note that natural hedge is distinct from firm-level operating leverage. We focus separately on operating leverage by including the capital–labor ratio both as an explanatory variable in our regressions and as a dependent variable for one of the regression equations.

Our identification strategy reflects two objectives, namely, to control for firm fixed effects and to address endogeneity bias. Whited (1992) shows how both these objectives can be achieved in the context of GMM estimation with panel data. Specifically, we use year-to-year changes in the variables (first differences) rather than the levels of the variables to control for firm fixed effects. Using year-to-year changes rather than regular firm fixed effects enables us to use twice-lagged levels of the same variables as instruments. We also adjust the variables for interacted industry-year fixed effects in order to isolate intra-industry variation.[13] We estimate the following system of simultaneous equations using GMM:

$$\begin{aligned}
\Delta\text{Leverage} &= f(\Delta\text{capital/labor},\ \Delta\text{risk};\ \Delta\text{industry position},\\
&\qquad \Delta\text{controls, fixed effects}) + \tilde{\mu}\\
\Delta\text{Capital/labor} &= g(\Delta\text{leverage},\ \Delta\text{risk};\ \Delta\text{industry position},\\
&\qquad \Delta\text{controls, fixed effects}) + \tilde{\varepsilon}\\
\Delta\text{Risk} &= g(\Delta\text{leverage},\ \Delta\text{capital/labor};\ \Delta\text{industry position},\\
&\qquad \Delta\text{controls, fixed effects}) + \tilde{\omega}
\end{aligned}$$

where $\Delta$ is the first-difference operator, $\tilde{\mu}$, $\tilde{\varepsilon}$, and $\tilde{\omega}$ are random error terms, and the endogenous right-hand side variables (financial leverage, capital–labor ratio, or cash-flow volatility, and natural hedge, profitability, size, diversification, and Tobin's $q$) are instrumented using their twice-lagged values and other instruments discussed later. For comparability with prior studies and to show the impact of controlling for endogeneity and simultaneity, we also estimate the equations separately using ordinary least squares (OLS).

## 3. Results

We begin by examining how much variation in financial structure arises between and within industries. After a graphical examination of the extent of variation in financial structure, our research design is then to present summary statistics, univariate regressions, transition frequencies, and multivariate regressions—all examining the importance of industry to firm decisions.

### 3.1 Variation in financial structure between and within industries

Figure 1 shows how financial structure varies between and within industries. We construct these figures as follows. First, we average each firm's debt-to-asset ratio over all years it appears in the panel. Next, we calculate the standard deviation of these firm averages across firms within each

[13] From this point on we refer to these adjustments as "industry-year adjusted".

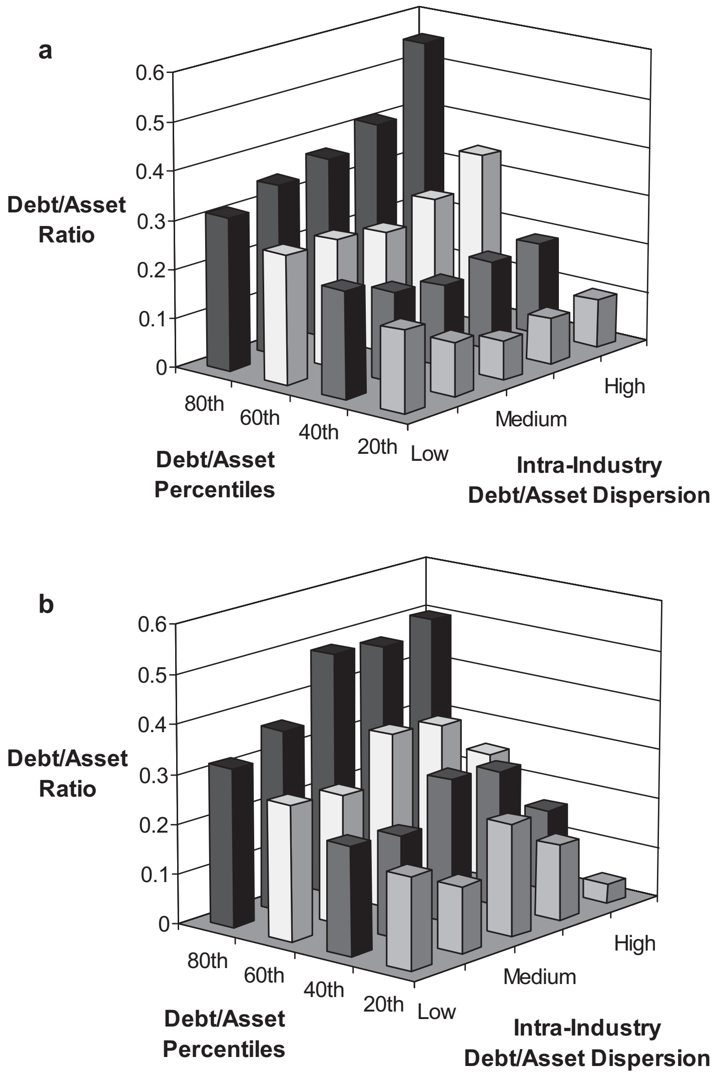


**Figure 1**
(a) Dispersion in financial leverage for competitive industries. (b) Dispersion in financial leverage for concentrated industries.

four-digit SIC industry. We use these standard deviations to examine variation *between* industries by grouping industries into industry-dispersion quintiles. We examine variation *within* industries by forming financial-leverage quintiles within each of these industry-dispersion quintiles.

Figure 1*a* and 1*b* plot financial-leverage quintile medians by industry-dispersion quintile, for competitive industries (HHI under 1000) and concentrated (HHI over 1800) industries. Both figures clearly show that there is substantial financial-structure dispersion within four-digit SIC industries, even within industries with the least dispersion. However, firms in concentrated industries cluster around higher financial leverage ratios than firms in competitive industries, where we also observe broader dispersion in financial leverage within industries. We interpret these patterns in light of the summary statistics presented in the next section.

### 3.2 Summary statistics

Table 1 reports summary statistics for six key variables: financial leverage, capital–labor ratios, cash-flow volatility, natural hedge, profitability, and asset size. The top panel presents results for competitive industries and the bottom panel presents results for concentrated industries. The bottom panel also shows tests of differences between competitive and concentrated industries. We report industry-year-adjusted statistics in *italics* since we are primarily interested in within-industry patterns. We also report unadjusted values to facilitate interpretation. The industry-year-adjusted means differ from zero because we demean the variables individually but construct the final sample based on data availability for all variables.[14]

Table 1 shows that there is wide variation in financial leverage and all the other variables, whether we adjust for industry-year or not. Several differences arise between competitive and concentrated industries. These differences are economically significant. Mean (median) financial leverage is about 15% (20%) higher in concentrated industries [0.275 (0.256)] than in competitive industries [0.239 (0.212)]. This finding is consistent with evidence by Spence (1985) and predictions by Brander and Lewis (1986, 1988) and Maksimovic (1988). We also find that *dispersion* in financial leverage is slightly greater in competitive industries.[15] In other words, firms in concentrated industries cluster around higher leverage levels, whereas firms in competitive industries carry less leverage and are more widely dispersed. This is consistent with recent theory and evidence by Lyandres (2001). Lipson (1993) also predicts lower intra-industry dispersion but lower *levels* of leverage for concentrated industries.

Competitive and concentrated industries also differ significantly along the real-side variables. Competitive industries exhibit greater risk levels and more dispersion in risk. Profitability and asset size are both substantially higher for concentrated industries. These findings suggest that concentrated industries are collusive, exhibiting higher and more stable profitability and

[14] The fact that industry-year adjusted profitability and asset size means and medians are substantially above zero indicates that the data-availability requirement primarily causes small, unprofitable firms to fall out of the sample.

[15] Except for capital-labor ratios and mean natural hedge, differences in means, medians, and dispersion between competitive and concentrated industries for all variables are significant at the 10% confidence level or better.

**Table 1**
**Summary statistics**

| | Firm-years | Mean | Median | Standard deviation | Robust dispersion | Range (maximum–minimum) |
|---|---|---|---|---|---|---|
| | | | **Competitive industries** | | | |
| Leverage | 17,140 | 0.239 | 0.212 | 0.194 | 0.203 | 1.000 |
| | | *−0.005* | *−0.028* | *0.176* | *0.165* | *1.427* |
| Capital/Labor | 17,140 | 0.047 | 0.024 | 0.085 | 0.022 | 1.375 |
| | | *−0.004* | *−0.004* | *0.078* | *0.015* | *4.164* |
| Risk | 17,140 | 0.091 | 0.062 | 0.089 | 0.049 | 0.878 |
| | | *−0.007* | *−0.014* | *0.079* | *0.042* | *1.014* |
| Natural hedge | 17,140 | 0.669 | 0.790 | 0.330 | 0.311 | 1.000 |
| | | *n/a* | *n/a* | *n/a* | *n/a* | *n/a* |
| Profitability | 17,140 | 0.041 | 0.076 | 0.186 | 0.083 | 2.618 |
| | | *0.026* | *0.029* | *0.175* | *0.099* | *2.819* |
| Size (log of assets) | 17,140 | 4.406 | 4.239 | 2.081 | 2.115 | 12.280 |
| | | *0.243* | *0.106* | *1.704* | *1.617* | *13.317* |
| | | | **Concentrated industries** | | | |
| Leverage | 1630 | 0.275[a] | 0.256[a] | 0.182[a] | 0.169[a] | 0.955 |
| | | *−0.005* | *−0.025* | *0.171*[c] | *0.163*[c] | *1.077* |
| Capital/labor | 1630 | 0.048[-] | 0.027[a] | 0.070[a] | 0.027[c] | 1.170 |
| | | *−0.003* | *−0.005* | *0.058*[a] | *0.017*[-] | *1.180* |
| Risk | 1630 | 0.074[a] | 0.049[a] | 0.081[a] | 0.038[a] | 0.632 |
| | | *−0.009* | *−0.010* | *0.071*[a] | *0.028*[a] | *0.795* |
| Natural hedge | 1630 | 0.665[-] | 0.810[b] | 0.350[a] | 0.352[a] | 1.000 |
| | | *n/a* | *n/a* | *n/a* | *n/a* | *n/a* |
| Profitability | 1630 | 0.072[a] | 0.085[a] | 0.135[a] | 0.066[a] | 1.940 |
| | | *0.015* | *0.016* | *0.128*[a] | *0.081*[a] | *1.737* |
| Size (log of assets) | 1630 | 5.826[a] | 5.599[a] | 2.645[a] | 3.051[a] | 11.777 |
| | | *0.374* | *0.159* | *2.147*[a] | *2.094*[a] | *14.929* |

Summary statistics for manufacturing firms operating in 315 competitive industries and 46 concentrated industries between 1981 and 2000. Superscripts show tests of differences between competitive and concentrated industries where a, b, c denote statistical significance at the 1, 5, and 10% confidence levels. Following the U.S. Department of Justice, we define competitive industries as those with a Herfindahl–Hirschman Index under 1000 and concentrated industries as those with a Herfindahl–Hirschman Index over 1800. Values in *italics* (the second row for each variable) are adjusted for industry-year. Robust dispersion is a nonparametric measure of dispersion, calculated as the range between the 69th and 31st percentiles, which is comparable to one standard deviation under normality. Leverage is total debt divided by total assets (book values). Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by assets. Natural hedge is one minus the absolute value of the difference between the firm's capital–labor ratio and the market-share weighted industry-year median (own firm excluded), normalized by the industry-year range. We do not demean natural hedge because it is industry-year adjusted by construction. Profitability is EBIT divided by assets.

less dispersion in profitability than competitive industries. These findings also concur with previous empirical research (Chevalier, 1995, Phillips, 1995, and Kovenock and Phillips, 1997) that shows that product-market competition is less aggressive when leading firms have high financial leverage.[16]

[16] In contrast, Lipson (1993) shows that debt-coordinated collusion implies *lower* financial leverage in concentrated industries. Bolton and Scharfstein (1990) argue that rivals prey more aggressively on financially vulnerable firms as the value of predation increases; this, too, would imply lower financial leverage in concentrated industries. Finally, Rotemberg and Scharfstein (1990) show that depending on what investors infer from rivals' profitability, financial leverage can either facilitate or hinder collusion, and therefore rise or fall with industry concentration.

Our finding that financial structure, capital–labor ratios, and risk are more dispersed within competitive industries is consistent with models of perfect competition, where firm diversity arises endogenously within competitive industries (Maksimovic and Zechner, 1991, Williams, 1995, and Fries, Miller, and Perraudin, 1997) and models of imperfect competition, where dispersion decreases with industry concentration (Lipson, 1993, Lyandres, 2001). This finding also challenges the heuristic that competition in competitive industries drives firms to similar financial structure and cost structures.

In sum, we find that competitive and concentrated industries differ in many important respects. The statistical and economic differences we find in both the level and the dispersion of real and financial variables suggest that industry structure reflects distinct equilibrium forces that lead to diverse outcomes. These base results confirm that understanding the effect of industry on firm decisions requires a richer treatment than simply accounting for industry fixed effects.

### 3.3 Entry and exit in competitive and concentrated industries

To examine the dynamic predictions formulated by Williams (1995) and Fries, Miller, and Perraudin (1997) for competitive industries, and by Poitevin (1989) for concentrated industries, Table 2 presents subsample means for entrants, incumbents, and exiters. Entrants are firms that appear in the sample between 1991 and 2000 but not between 1981 and 1990. We distinguish these firms from those that enter an industry simply by changing the nature of their operations ("switchers"). Exiters are firms that appear in the sample between 1981 and 1990 period but not between 1991 and 2000. We distinguish these firms from those that leave an industry through asset sales ("sellers").[17] Table 2 also reports subsample means for the years following entry ("post entry") and preceding exit ("pre-exit").

Several patterns emerge for competitive industries, both in industry-year adjusted and unadjusted terms.[18] First, entrants start off with high financial leverage ratios compared to incumbents, suggesting a greater

[17] Data limitations prevent us from precisely determining the type of firm entry. For instance, we cannot distinguish between privately-held incumbents that go public and new firms that actually add productive capacity to their industry. We should point out that by tracking firms by their CRSP permanent number (permno) rather than by their COMPUSTAT CUSIP, we avoid miss-classifying firms that undergo mergers and acquisitions or name changes as entrants. By using the historical SIC from CRSP rather than the current SIC from COMPUSTAT, we can identify incumbent firms that change industry. Thus, we refer to firms that change two-digit SIC industry between the 1981–1990 and 1991–2000 subperiods as "switchers". Finally, thanks to COMPUSTAT's "reason for deletion" variable (note 35), we are able to distinguish between firms that exit through Chapter 11 bankruptcy or Chapter 7 liquidation and those whose assets are simply redeployed through corporate restructuring ("sellers").

[18] Similar patterns appear in concentrated industries, however, most of the differences between the entrant, post entry, incumbent, pre exit, and exit categories are statistically insignificant because of the small sample count.

**Table 2**
**Subsample means for entrants, incumbents, and exiters**

| | Entrants | Post Entry | Incumbents | Pre Exit | Exiters |
|---|---|---|---|---|---|
| | | **Competitive industries** | | | |
| Leverage | 0.296 | $0.218^{a}$ | $0.229^{a,-,a,a}$ | $0.413^{-}$ | $0.470^{a}$ |
| | *0.033* | *0.002*$^{b}$ | *−0.013*$^{a,b,a,a}$ | *0.119*$^{-}$ | *0.167*$^{a}$ |
| Capital/labor | 0.031 | $0.046^{a}$ | $0.050^{a,c,b,b}$ | $0.028^{-}$ | $0.025^{-}$ |
| | *−0.014* | *−0.010*$^{-}$ | *−0.003*$^{a,b,-,-}$ | *−0.008*$^{-}$ | *−0.001*$^{b}$ |
| Risk | n/a | $0.133^{n/a}$ | $0.086^{n/a,a,a,a}$ | $0.122^{-}$ | $0.126^{n/a}$ |
| | *n/a* | *0.002*$^{n/a}$ | *−0.010*$^{n/a,a,a,a}$ | *0.027*$^{-}$ | *0.025*$^{n/a}$ |
| Natural hedge | 0.753 | $0.750^{-}$ | $0.662^{a,a,-,-}$ | $0.680^{-}$ | $0.656^{c}$ |
| | *n/a* | *n/a* | *n/a* | *n/a* | *n/a* |
| Profitability | 0.017 | $-0.052^{a}$ | $0.049^{a,a,a,a}$ | $-0.055^{a}$ | $-0.153^{a}$ |
| | *0.002* | *0.003*$^{-}$ | *0.032*$^{a,a,a,a}$ | *−0.072*$^{a}$ | *−0.155*$^{a}$ |
| Size (log of assets) | 3.025 | $4.069^{a}$ | $4.558^{a,a,a,a}$ | $3.032^{-}$ | $2.779^{-}$ |
| | *−0.515* | *0.173*$^{a}$ | *0.304*$^{a,b,a,a}$ | *−0.596*$^{c}$ | *−0.959*$^{b}$ |
| Observations (firm-years) | 349 | 636 | 13,661 | 95 | 44 |
| | | **Concentrated industries** | | | |
| Leverage | 0.313 | $0.316^{-}$ | $0.261^{-,c,b,b}$ | $0.466^{c}$ | $0.731^{b}$ |
| | *0.031* | *0.017*$^{-}$ | *−0.017*$^{-,-,b,c}$ | *0.156*$^{-}$ | *0.375*$^{-}$ |
| Capital/labor | 0.031 | $0.047^{-}$ | $0.051^{b,-,c,c}$ | $0.022^{-}$ | $0.017^{-}$ |
| | *−0.004* | *−0.023*$^{-}$ | *−0.003*$^{-,b,-,-}$ | *−0.005*$^{-}$ | *−0.004*$^{-}$ |
| Risk | n/a | $0.083^{n/a}$ | $0.069^{n/a,-,-,-}$ | $0.080^{-}$ | $0.094^{n/a}$ |
| | *n/a* | *0.005*$^{n/a}$ | *−0.011*$^{n/a,c,-,-}$ | *−0.012*$^{-}$ | *0.014*$^{n/a}$ |
| Natural hedge | 0.736 | $0.767^{-}$ | $0.650^{-,b,-,-}$ | $0.777^{-}$ | $0.948^{-}$ |
| | *n/a* | *n/a* | *n/a* | *n/a* | *n/a* |
| Profitability | 0.027 | $0.037^{-}$ | $0.081^{c,b,a,-}$ | $-0.041^{-}$ | $-0.023^{-}$ |
| | *−0.006* | *−0.015*$^{-}$ | *0.021*$^{-,c,c,-}$ | *−0.042*$^{-}$ | *−0.058*$^{-}$ |
| Size (log of assets) | 3.140 | $4.766^{a}$ | $6.067^{a,a,a,-}$ | $3.800^{-}$ | $3.876^{-}$ |
| | *−1.947* | *−0.553*$^{a}$ | *0.500*$^{a,a,-,-}$ | *0.028*$^{-}$ | *−0.689*$^{-}$ |
| Observations (firm-years) | 19 | 48 | 1,319 | 8 | 2 |

Subsample means for manufacturing firms operating in 315 competitive industries and 46 concentrated industries between 1981 and 2000. Superscripts in column 2 show tests of differences in means between entrants and post entry. Superscripts in column 3 show tests of differences between incumbents and all other groups. Superscripts in column 4 show tests of differences between pre exit and exiters, and in column 5 between entrants and exiters—where a, b, and c denote statistical significance at the 1, 5, and 10% confidence levels. Following the U.S. Department of Justice, we define competitive industries as those with a Herfindahl–Hirschman Index under 1000 and concentrated industries as those with a Herfindahl–Hirschman Index over 1800. Values in *italics* are adjusted for industry-year. Entrants are firms that enter the panel in the last ten years of the sample period (1991–2000). Exiters are firms that leave the panel in 1991–2000 through bankruptcy (Chapter 11) or liquidation (Chapter 7). Incumbents are firms present in both subperiods, though not necessarily in every year of the panel. Means for entrants (exiters) pertain to their first (last) year in the sample. Means for post-entry (pre-exit) pertain to the years after (before) entry (exit). Leverage is total debt divided by total assets (book values). Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by assets. Natural hedge is one minus the absolute value of the difference between the firm's capital–labor ratio and the market-share weighted industry-year median (own firm excluded), normalized by the industry-year range. We do not demean natural hedge because it is industry-year adjusted by construction. Profitability is EBIT divided by assets.

reliance on debt at inception. This finding is consistent with costlier equity finance for little-known entrants. Second, entrants begin less capital-intensive and less profitable than incumbents but trend toward incumbent levels. These findings suggest that because of limited access to capital markets, entering firms must first rely on less efficient, labor-intensive technologies, as predicted by Williams (1995). Third, exiters leave their industries much more leveraged, risky, and unprofitable than incumbents, consistent with received ideas on financial and economic distress. Lastly, asset size and capital intensity rise and fall following entry and upon exit.

Fries, Miller, and Perraudin (1997) predict that, in competitive industries, entrants are slightly less financially leveraged than incumbents and increase their leverage ratios following entry; our findings support neither of these predictions—in fact, we find just the opposite. While we do find that entrants are less capital intensive than incumbents, our evidence does not support Williams' (1995) prediction that entrants begin their existence substantially less financially leveraged than incumbents. However, our finding that entrants start off with high financial leverage ratios does fit Poitevin's (1989) prediction that "high-value" entrants issue debt to signal type and enter the industry with a high level of financial leverage relative to incumbents.

### 3.4 Importance of industry to firm characteristics

Table 3 examines the importance of industry to firm decisions in a general manner by regressing firm-level financial leverage, capital–labor ratios, and cash-flow volatility on industry medians and changes in medians. First, we regress in levels to determine the importance of industry and firm effects. Second, we regress in changes to determine if firms respond to industry-wide changes. Finally, we examine whether firm-level variables

**Table 3**
**Industry effects and reversion in financial structure for competitive industries**

| | Industry financial structure | | | | | |
|---|---|---|---|---|---|---|
| | 2-SIC | 3-SIC | 4-SIC | Adjusted $R^2$ | Adjusted $R^2$ with firm fixed effects | Firm-years |
| | | **A. Importance of industry levels** | | | | |
| Leverage | 0.048 (1.37) | 0.013 (0.54) | 0.186 (12.40)[a] | 13.0% | 67.0% | 15,719 |
| Capital/Labor | 0.350 (14.00)[a] | 0.198 (6.83)[a] | 0.158 (7.90)[a] | 45.0% | 85.0% | 15,707 |
| Risk | 0.068 (1.84)[c] | 0.003 (0.13) | 0.141 (10.07)[a] | 3.8% | 87.6% | 15,553 |
| | | **B. Importance of industry changes** | | | | |
| ΔLeverage | 0.026 (0.81) | 0.076 (4.22)[a] | 0.277 (25.65)[a] | 5.0% | | 15,719 |
| ΔCapital/labor | −0.002 (−0.08) | 0.031 (1.82)[c] | 0.119 (9.92)[a] | 1.0% | | 15,707 |
| ΔRisk | −0.012 (−0.41) | 0.059 (4.21)[a] | 0.038 (4.75)[a] | 0.4% | | 15,553 |
| | | **C. Reversion to industry levels** | | | | |
| ΔLeverage | −0.032 (−2.91)[a] | −0.031 (−2.07)[b] | −0.104 (−8.00)[a] | 8.0% | | 15,719 |
| ΔCapital/Labor | 0.030 (1.88)[c] | −0.045 (−3.46)[a] | −0.035 (−3.89)[a] | 1.0% | | 15,707 |
| ΔRisk | −0.006 (−0.75) | −0.013 (−1.39) | −0.041 (−5.91)[a] | 4.0% | | 15,553 |

Ordinary least squares regressions of firm-level variables on industry-level variables for firms in competitively-structured industries between 1981 and 2000. (*t*-statistics in parentheses). a, b, c denote statistical significance at the 1, 5, and 10% confidence levels. Leverage is total debt divided by total assets (book values). Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by assets. Panel A regresses the firm-level variables on lagged industry-year medians. Panel B regresses changes in firm-level variables on concurrent changes in industry-year medians. For leverage we estimate: $\Delta firm\ leverage_{\ t,t-1} = \beta^{*}\Delta industry\ median\ leverage_{\ t,t-1}$. Panel C regresses changes in firm-level variables on lagged deviations from industry-year medians - for leverage we estimate: $\Delta firm\ leverage_{t,t-1} = \beta^{*}(firm\ leverage_{t-1}$ - $industry\ medians\ leverage_{t-1})$. Industry medians exclude the firm itself, and the three (two)-digit SIC medians exclude firms in the finer four (three)-digit SIC industries.

revert back to industry benchmarks by regressing changes in firm characteristics on lagged firm-level deviations from industry medians.

The industry fixed effects in Table 3 are nested in the sense that firms and industries used in narrowly-defined industry medians are excluded from the calculation of more broadly-defined industry medians. For instance, median four-digit SIC industry financial leverage for a given firm in SIC 3561 excludes that firm. Median three-digit SIC industry financial leverage for all firms in SIC 3561 excludes these firms but includes all other firms in the 356 SIC. Finally, median two-digit SIC industry financial leverage for all firms in SIC 356 excludes these firms but includes all other firms in the 35 SIC.[19] We only analyze competitive industries because the distinction between "firm" and "industry" is lost if each firm represents a significant part of the industry itself.

Panel A regresses the firm-level variables on lagged industry-year median levels, first without firm fixed effects (reported coefficients), then including firm fixed effects. We lag the industry medians to avoid endogeneity problems.[20] This is essentially an analysis of variance where the adjusted R-square indicates the importance of industry in explaining firm-level characteristics. We find that industry is relatively unimportant in explaining firm financial structure, at least in our sample of competitive manufacturing industries, where the adjusted R-square is only 13%. The adjusted R-square rises sharply if we add firm fixed effects (67%), which shows that most of the variation in financial leverage arises *within* industries rather than *between* industries.[21]

In contrast, industry effects explain much of the variation in capital–labor ratios (45%). Firm fixed effects explain another 40% of the variation in capital–labor ratios while 15% is within-firm. This shows that capital intensity is highly industry-specific, with some variation across firms within industries but little firm-level change over time. These findings are consistent with capital intensity being essentially fixed once technology is chosen. They also suggest that industry dummies are reasonable proxies for capital intensity. Finally, industry explains little of the variation in cash-flow volatility (4%), most of it being within-industry. Together, these findings make the strong but simple case that firms in a given industry differ widely with respect to their real and financial characteristics.

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[19] This causes the degrees of freedom to drop from the 17,140 observations reported in Table 1. This is because some three-digit SIC industries contain a single four-digit SIC industry.

[20] The adjusted R-squares only increase about two percentage points if we use contemporaneous industry medians.

[21] Bradley, Jarrell, and Kim (1984) regress firms' average debt ratios for 1962-1981 on two-digit SIC dummies for a broad set of industries. They report that industry fixed effects explain 23.6% of the variation in financial structure. We examine firms in a time-panel of manufacturing industries (not panel averages), and over a different time period, which explains why our R-square is somewhat lower than theirs.

Panel B examines how firms respond to industry-wide changes by regressing changes in firm-level variables on concurrent changes in industry-year medians. Although we find statistical significance, the low R-squares (5% and under) and point estimates that are far away from one suggest that firms adjust their financial structures little in response to overall industry trends.[22] Similar results obtain for capital–labor ratios and cash-flow volatility. We conclude that changes in firm characteristics bear a small to moderate relation to industry-level changes.

Finally, we consider whether the observed diversity within industries reverses over time by investigating whether firms drift back to their industry medians. Panel C examines this question by regressing changes in firm characteristics on lagged firm-level deviations from industry-year medians. We find that firms do revert to industry norms, though very slowly. We find annual financial-leverage industry-median reversion rates of 3.2% for two-digit, 3.1% for three-digit, and 10.4% for four-digit industries, not unlike Fama and French (2002) who report that firms revert to their *own* leverage targets at rates of 7% to 18% per year. This evidence of slow reversion is consistent with Fischer, Heinkel, and Zechner (1989) in suggesting that there are substantial transaction costs in adjusting firm financial structure. However, it is also consistent with industry equilibrium outcomes where firms do not trend toward the industry norm but rather adopt differential finance-technology-risk configurations that persist over time. Since slow industry reversion could equally reflect transaction costs or equilibrium forces, we next look more closely at how firms evolve within their industries.

### 3.5 Evolution of entrants, exiters, switchers, sellers, and incumbents within industries

To expand on our findings of Table 3 and investigate the dynamic properties of the competitive-industry equilibrium models (Williams, 1995, and Fries, Miller, and Perraudin, 1997), Table 4 presents transition frequencies for firms that enter, stay, or leave their industries. For each variable presented, the table panels show the percentage of incumbent firms that stay in the same industry-year quintile or move to other quintiles between the first half of the empirical period (1981–1990) and the second half (1990–2000). Each panel also shows the 1990–2000 quintile distribution of firms that enter an industry in the 1990–2000 time period, either through new entry (enter) or by changing two-digit SIC industry (switch). Finally, the panels show the 1981–1990 quintile distribution of firms that leave an industry in the 1990–2000 time period, either through bankruptcy or liquidation (exit) or by selling assets through corporate mergers

[22] This finding is consistent with Roberts (2002) who reports that firms do not adjust their financial structure to industry targets, but rather adjust to a firm-specific target financial structure.

**Table 4**
**Transition frequencies for competitive industries**

| | Firm status in 1991–2000 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Exit | Sell | Total |
| | | | | **Leverage** | | | | |
| Enter | 25 | 18 | 18 | 20 | 18[b] | | | 17[-] |
| Switch | 12 | 19 | 21 | 25 | 23[a] | | | 11[b] |
| Q1 | 32[a] | 18 | 9 | 4 | 2 | 3 | 32 | 10[a] |
| Q2 | 10 | 28[a] | 19 | 9 | 3 | 1 | 30 | 18[a] |
| Q3 | 4 | 17 | 22[a] | 18 | 7 | 2 | 32 | 17[a] |
| Q4 | 2 | 9 | 17 | 23[a] | 15 | 4 | 31 | 17[a] |
| Q5 | 1 | 5 | 7 | 17 | 30[a] | 9[a] | 31[-] | 12[a] |
| Total | 11 | 17 | 17 | 17 | 13 | 3[a] | 22[a] | 100 |
| | | | | **Capital/Labor** | | | | |
| Enter | 14 | 22 | 22 | 21 | 22[b] | | | 17[c] |
| Switch | 19 | 25 | 23 | 15 | 18[-] | | | 11[-] |
| Q1 | 30[a] | 21 | 5 | 0 | 0 | 8 | 36 | 10[a] |
| Q2 | 12 | 27[a] | 15 | 7 | 1 | 3 | 35 | 17[a] |
| Q3 | 5 | 19 | 21[a] | 14 | 5 | 3 | 33 | 16[a] |
| Q4 | 2 | 8 | 18 | 29[a] | 13 | 2 | 27 | 17[a] |
| Q5 | 2 | 2 | 11 | 28 | 32[a] | 3[-] | 23[-] | 12[a] |
| Total | 11 | 18 | 17 | 17 | 13 | 3[-] | 22[a] | 100 |
| | | | | **Risk** | | | | |
| Enter | 18 | 19 | 20 | 23 | 20[-] | | | 17[-] |
| Switch | 13 | 21 | 21 | 27 | 18[-] | | | 11[b] |
| Q1 | 30[a] | 27 | 11 | 5 | 0 | 0 | 27 | 10[a] |
| Q2 | 16 | 29[a] | 17 | 8 | 2 | 1 | 27 | 17[a] |
| Q3 | 6 | 18 | 19[a] | 18 | 3 | 4 | 32 | 17[a] |
| Q4 | 3 | 9 | 18 | 24[a] | 8 | 5 | 33 | 17[a] |
| Q5 | 0 | 3 | 10 | 16 | 28[a] | 8[a] | 35[b] | 11[a] |
| Total | 12 | 18 | 17 | 17 | 11 | 3[a] | 22[a] | 100 |
| | | | | **Natural hedge** | | | | |
| Enter | 16 | 20 | 19 | 23 | 22[c] | | | 17[-] |
| Switch | 18 | 15 | 19 | 25 | 22[-] | | | 11[-] |
| Q1 | 33[a] | 23 | 8 | 1 | 2 | 5 | 27 | 10[a] |
| Q2 | 12 | 30[a] | 16 | 8 | 2 | 3 | 30 | 17[a] |
| Q3 | 5 | 18 | 24[a] | 15 | 4 | 2 | 32 | 16[a] |
| Q4 | 2 | 7 | 16 | 28[a] | 12 | 3 | 32 | 17[a] |
| Q5 | 0 | 1 | 8 | 20 | 31[a] | 6[-] | 33[b] | 12[a] |
| Total | 11 | 17 | 17 | 18 | 13 | 3[-] | 22[a] | 100 |
| | | | | **Profitability** | | | | |
| Enter | 21 | 21 | 20 | 20 | 18[-] | | | 17[-] |
| Switch | 17 | 24 | 20 | 24 | 15[-] | | | 11[-] |
| Q1 | 17[a] | 19 | 6 | 6 | 3 | 12 | 36 | 10[a] |
| Q2 | 12 | 23[a] | 16 | 11 | 5 | 4 | 29 | 17[a] |
| Q3 | 6 | 17 | 22[a] | 16 | 7 | 2 | 30 | 17[a] |
| Q4 | 2 | 10 | 18 | 23[a] | 14 | 2 | 31 | 17[a] |
| Q5 | 2 | 7 | 14 | 18 | 28[a] | 0[a] | 31[-] | 12[a] |
| Total | 11 | 17 | 17 | 17 | 13 | 3[a] | 22[b] | 100 |
| | | | | **Size (log of assets)** | | | | |
| Enter | 12 | 17 | 25 | 28 | 18[b] | | | 17[a] |
| Switch | 19 | 30 | 19 | 16 | 16[-] | | | 11[a] |
| Q1 | 36[a] | 18 | 3 | 0 | 0 | 8 | 34 | 9[a] |
| Q2 | 13 | 26[a] | 15 | 3 | 1 | 4 | 38 | 17[a] |

**Table 4**
**(continued)**

| | Firm status in 1991–2000 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q5 | Exit | Sell | Total |
| Q3 | 5 | 19 | 26[a] | 10 | 2 | 3 | 35 | 17[a] |
| Q4 | 1 | 7 | 19 | 35[a] | 11 | 2 | 25 | 18[a] |
| Q5 | 0 | 1 | 3 | 22 | 51[a] | 2[a] | 22[-] | 12[a] |
| Total | 11 | 17 | 17 | 17 | 13 | 3[c] | 22[a] | 100 |

Quintile transition frequencies for firm-period means between 1981–1990 and 1991–2000 for firms that enter or switch industries, incumbents, and firms that leave the panel through exit or sale. Each panel shows percentages relative to row totals. Superscripts in the last column and bottom row of each panel show Chi-square tests that industry demographics follow a uniform distribution. Superscripts in quintile five test whether the percentages in quintiles one and five are equal. Superscripts on the diagonal quintiles test whether adjacent quintiles are equal. a, b, c denote statistical significance at the 1, 5, and 10% confidence levels. Leverage is total debt divided by total assets (book values). Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by assets. Natural hedge is one minus the absolute value of the difference between the firm's capital–labor ratio and the market-share weighted industry-year median (own firm excluded), normalized by the industry-year range. Profitability is EBIT divided by assets.

or acquisitions (sell). The quintiles are formed using firm means for each time period (1981–1990 and 1990–2000). The table also reports statistical tests of differences in proportions between quintiles and goodness-of-fit tests that industry transition patterns follow a uniform distribution. As in Table 3, we only run this analysis for competitive industries.

We note several transition patterns for incumbent firms and for firms that enter or leave their industries. First, the top-left panel of Table 4 shows that 25% of entrants fall in the lowest financial-leverage quintile. This percentage is a significantly lower 18% in quintile five. In contrast, switchers tend to enter an industry in the higher financial-leverage quintiles, with 23% (12%) of switchers in the fifth (first) quintile. Among exiters, three times more firms belong to the top financial-leverage quintile than the bottom quintile. This pattern does not obtain for sellers, where firms are roughly equally distributed across financial-leverage quintiles. Since most of the transition frequencies pertaining to entrants, switchers, sellers, and exiters concur with the Section 3.3 discussion of firm means reported in Table 2, we now turn our attention to the behavior of incumbent firms over time.

The diagonal elements of each panel represent incumbent persistence rates, namely, the percentage of firms that remain in their industry quintile between the period 1981–1990 and the period 1990–2000. For all variables, we find that persistence is greatest for quintiles one, five, or both. This may simply reflect the fact that these quintiles contain the tails of the distribution for each variable: Firms in these quintiles must change substantially to transit to the inner quintiles. The highest persistence rates are 32, 31, and 51% for the fifth quintiles for capital–labor ratios, natural hedge, and asset size, and 36, 33, and 32% for the first asset-size, natural-hedge, and leverage quintiles. These results suggest that large, capital-intensive, profitable, and stable incumbent firms tend to maintain their dominant industry position over time and represent a Williams-style industry core. Higher turnover rates and lower persistence rates arise as capital intensity, profitability, and asset size decrease and as financial leverage and cash-flow volatility increase. These results suggest that small, labor-intensive, unprofitable, risky, marginal firms tend to move in, around, and out of their industries over time and represent a Williams-style industry fringe.

For all variables, we find persistence rates that significantly diverge from 20%, the rate expected if incumbents were uniformly randomly redistributed across quintiles between 1981–1990 and the 1990–2000 time period.[23] Consistent with our industry-median reversion analysis (Table 3), this finding suggests that firm characteristics evolve slowly and that firms maintain their relative industry position, even within competitively-structured industries. Table 4 also highlights the high attrition rate among small firms (fully 34% of firms in the lowest asset-size quintile sell out, 8% exit, and 36% remain in the lowest asset-size quintile) and the staying power of large firms (51% of firms in the highest asset-size quintile remain in that quintile, 2% exit, and 22% sell out).

What Tables 3 and 4 demonstrate is that the traditional, fixed-effects view of industry is of limited use in explaining firm financial structure. Yet, we find high persistence in incumbents' industry position along real and financial dimensions, suggesting that, as recent theories contend, industry equilibrium forces may act to sustain intra-industry diversity rather than smooth it away. An alternative explanation is that the observed diversity reflects firm-level hysteresis caused by transaction costs and financial constraints. While such frictions might explain persistence in the *absolute* level of firm characteristics, it cannot account for the persistence in a firm's industry ranking unless we (unrealistically) assume that all firms in an industry share very similar adjustment paths.

### 3.6 Multivariate analysis

Although informative, the evidence uncovered so far on the role of industry factors relies on univariate analyses. In this section, we investigate whether this evidence holds up in a simultaneous-equation instrumental-variable estimation framework that deals with endogeneity in the regressors and simultaneity between three dependent variables featured in the industry equilibrium models: financial leverage, capital–labor ratios, and cash-flow volatility.

[23] True persistence rates are even higher because the percentages shown are relative to all firms, not just incumbents. For a narrower test of persistence, we test whether the percentage of incumbents that remain in the same quintile is different than the percentage of incumbents that move up or down one quintile. For every quintile and for every variable, we reject the null hypothesis that these percentages are equal at the 1% confidence level or better.

**3.6.1 Econometric Approach.** Table 5 presents OLS and GMM regression results for competitive industries. In contrast to OLS, GMM allows for simultaneity among the dependent variables by incorporating the correlation of residuals across the three equations. This improves the efficiency and consistency of the estimates. As an instrumental-variable estimation method, GMM also mitigates simultaneity bias.[24] However, we also present OLS results for comparison with prior work that uses non-IV methods (e.g., Titman and Wessels, 1988, Rajan and Zingales, 1995, Barclay, Morellec, and Smith, 2003).

For our GMM regressions, we instrument all variables except for the entry/exit dummy variables and the quantile changes by their second lags in levels. The instrument set includes the four dummy variables (enter, switch, sell, and exit), current and lagged intra- and extra-quantile changes for the three dependent variables (twelve variables), and a constant term, resulting in ten over-identifying restrictions per equation.

We use Hansen's (1982) J-statistic to jointly test whether the model is well-specified and the instruments are valid, that is, uncorrelated with the residuals. Except for the risk equation, Table 5 shows that the over-identifying restrictions are not rejected at conventional statistical levels, indicating that the financial leverage and capital–labor equations are well-specified and that the instrument set is valid, that is, that the instruments are sufficiently orthogonal to the residuals.

The instruments must also be relevant, that is, correlated with the endogenous variables. We test the relevance of the instrument set using the procedure outlined in Shea (1997) for multivariate models.[25] Table 5 shows instrument relevance values of about 8% for financial leverage, 10% for capital–labor, and 18% for risk. Although there is no accepted norm on what constitutes a relevant set of instruments, these values (interpretable as R-squares) are statistically significant and consistent with the level of explanatory power generally found in corporate finance studies.[26]

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[24] Despite these advantages over OLS, Ferson and Foerster (1994) show that GMM can understate the coefficient standard errors. They find that this problem mainly arises in the small samples they study (60 observations) and tends to vanish as their sample size grows to 720 observations.

[25] First, regress each endogenous variable on the set of instruments; save the fitted values. Second, regress each endogenous variable on the remaining endogenous variables; save the residuals. Third, regress each fitted endogenous variable on the remaining fitted endogenous variables; save the residuals. Fourth, regress the residuals from the second step on the residuals from the third step; save the R-squares. Finally, adjust the R-squares for the number of observations and instruments. These R-squares are reported at the bottom of Table 5.

[26] We experimented with several other sets of instruments, such as adding the third lags in levels, the first and second leading values in levels (as suggested by Hayashi and Inoue, 1991), or the squared and cubed values of the second lags in levels, none of which materially improved the relevance measures without also causing a rejection of the over-identifying restrictions or a substantial drop in sample size. Another reason to limit the number of instruments is that, as Angrist and Krueger (2001) discuss, adding weak instruments (poorly correlated to the endogenous variables) can bias IV estimates and this bias increases in proportion to the number of over-identifying restrictions.

**Table 5**
**Ordinary least squares and generalized method of moments regressions for competitive industries**

| | Ordinary least squares | | | General method of moments | | |
|---|---|---|---|---|---|---|
| Dependent variables | Leverage | *K/L* | Risk | Leverage | *K/L* | Risk |
| Leverage | | 0.014 (5.83)[a] | −0.001 (−0.44) | | 0.005 (0.27) | 0.196 (5.56)[a] |
| Capital/Labor | 0.139 (6.27)[a] | | −0.002 (−0.48) | −1.049 (−3.62)[a] | | 0.218 (2.76)[a] |
| Risk | −0.019 (−0.51) | −0.002 (−0.17) | | | 2.786 (9.89)[a] | 0.034 (0.86) |
| *Industry Variables* | | | | | | |
| Natural hedge | −0.021 (−5.74)[a] | −0.025 (−21.00)[a] | 0.000 (−0.58) | −0.727 (−7.14)[a] | −0.004 (−0.26) | 0.153 (4.52)[a] |
| (Natural hedge)$^2$ | 0.013 (2.38)[b] | 0.001 (0.39) | −0.004 (−3.39)[a] | 0.917 (8.40)[a] | 0.010 (0.58) | −0.201 (−5.09)[a] |
| Intra-quantile change | −0.303 (−21.23)[a] | −0.434 (−40.17)[a] | −0.498 (−31.08)[a] | −0.105 (−2.75)[a] | −0.419 (−5.00a) | −0.246 (−3.04)[a] |
| Extra-quantile change | −0.023 (−26.40)[a] | −0.071 (−36.37)[a] | −0.040 (−33.86)[a] | −0.006 (−2.57)[b] | −0.069 (−5.53)[a] | −0.015 (−2.56)[b] |
| *Control Variables* | | | | | | |
| Profitability | −0.163 (−26.30)[a] | −0.001 (−0.71) | −0.046 (−36.88)[a] | −0.054 (−0.34) | 0.009 (0.66) | 0.060 (1.05) |
| (Profitability)$^2$ | 0.072 (7.84)[a] | −0.007 (−2.15)[b] | 0.087 (49.50)[a] | 0.440 (2.76)[a] | 0.005 (0.30) | −0.107 (−2.05)[b] |
| Size (log of assets) | 0.081 (25.82)[a] | 0.005 (4.76)[a] | −0.005 (−7.20)[a] | 1.146 (9.42)[a] | 0.013 (0.58) | −0.242 (−5.24)[a] |
| Diversification | 0.012 (1.36) | 0.001 (0.44) | 0.004 (2.45)[b] | −0.874 (−4.02)[a] | 0.027 (1.16) | 0.175 (2.71)[a] |
| Tobin's $q$ | −0.005 (−5.04)[a] | −0.001 (−4.16)[a] | 0.002 (8.09)[a] | 0.271 (6.41)[a] | −0.001 (−0.17) | −0.061 (−3.98)[a] |
| *Entry/Exit Dummies* | | | | | | |
| Entrant | 0.005 (1.24) | −0.001 (−0.97) | 0.000 (0.32) | −0.003 (−0.18) | −0.002 (−1.62) | 0.002 (0.42) |
| Switcher | 0.009 (3.37)[a] | −0.001 (−0.63) | −0.003 (−5.73)[a] | 0.021 (1.89)[c] | −0.001 (−0.85) | −0.004 (−1.29) |
| Exiter | 0.033 (3.87)[a] | −0.004 (−1.48) | −0.004 (−2.07)[b] | 0.053 (1.73)[c] | −0.003 (−0.74) | −0.008 (−0.94) |
| Seller | 0.006 (2.20)[b] | −0.001 (−0.73) | −0.002 (−3.88)[a] | −0.021 (−1.98)[b] | −0.001 (−1.07) | 0.006 (1.86)[c] |
| Adjusted $R^2$ | 12.54% | 12.89% | 28.16% | n/a | n/a | n/a |
| Degrees of freedom | 17,125 | 17,125 | 17,125 | 17,125 | 17,125 | 17,125 |
| Wald test, $H_0$: all coefficients = 0 | 2,482[a] | 2,551[a] | 6,756[a] | 191[a] | 62[a] | 54[a] |
| Hansen $J$-statistic (10 dof) | n/a | n/a | n/a | 7[-] | 10[-] | 21[b] |
| Instrument relevance | n/a | n/a | n/a | 8.49% | 9.60% | 17.78% |

The continuous variables are first-differenced to control for firm fixed effects. The regressions also control for four-digit SIC industry-year fixed effects. For our GMM regressions, we instrument all variables except for the entry/exit dummy variables and quantile changes by their second lags in levels. We also include the four dummy variables, current and lagged quantile changes (twelve variables), and a constant term in the instrument set, resulting in ten over-identifying restrictions per equation. Leverage is total debt divided by total assets (book values). Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by assets. Natural hedge is one minus the absolute value of the difference between the firm's capital–labor ratio and the market-share weighted industry-year median (own firm excluded), normalized by the industry-year range. Intra-quantile change is the mean change in the dependent variable within the industry half to which a firm belongs (own firm excluded). Extra-quantile change is the mean change in the other half of the industry. These quantiles are based on the lagged levels of the dependent variables. Profitability is EBIT divided by assets. Diversification is one minus the Herfindahl of output across the firm's four-digit SIC industries. Tobin's $q$ is the market value of equity plus the book value of debt and preferred stock minus deferred taxes, divided by the book value of assets. For GMM, we use the Newey–West procedure to address heteroscedasticity and the autocorrelation introduced by first-differencing. Asymptotic $t$-values in parentheses. a, b, c denote statistical significance at the 1, 5, and 10% confidence levels.

The panel nature of our sample allows us to control for unobserved firm-specific factors. Instead of the usual deviation-from-means approach, which is invalid when using lagged variables as instruments, we control for firm fixed effects by first-differencing the variables. However, first-differencing introduces first-order moving-average autocorrelation. Our GMM estimation uses the Newey–West (Newey and West, 1987) procedure to address this issue and adjust for heteroscedasticity. We also include four-digit SIC interacted industry-year fixed effects to focus on variation within industries.

**3.6.2 Regression results.** Table 5 shows several differences between the OLS and GMM coefficient estimates. Several of the coefficient signs change as we go from OLS, which uses realized values of the variables, to GMM, which uses predicted (instrumented) values of the variables. For instance, we find that the relation between financial leverage and the capital–labor ratio is positive and significant for OLS but negative and significant for GMM.[27,28] The coefficient signs for risk and Tobin's *q* also change across the two estimation methods. These differences show that the simultaneity of financial leverage and its determinants is a real concern requiring proper econometric treatment. Since the GMM estimates address this issue directly, inasmuch as the chosen instrument set is both valid and relevant, we emphasize the GMM results over the OLS estimates. In any case, results for the industry position variables—natural hedge and intra- and extra-quantile change—are similar across estimation methods.

The first industry position variable we examine is a firm's natural hedge, which measures how close a firm's capital–labor ratio is to the industry-year median. We find a significant inverse relation between this variable and financial leverage, supporting Maksimovic and Zechner's (1991) prediction that firms that depart from the median industry technology choose high financial leverage.

[27] We have traced the cause of this sign switch to an endogeneity problem in the OLS estimation. We hypothesized that the relation between financial leverage and the capital-labor ratio reflects two offsetting factors: a collateral effect (more fixed capital, more debt capacity) and a substitution effect (more operating leverage, less financial leverage). As an indirect test of the collateral effect, we drop asset size from the model. We find that this has no qualitative effect on the capital-labor coefficient in the OLS estimation but changes the sign from negative to positive in the GMM estimation, confirming that asset size and the capital-labor ratio are interdependent. As a more direct proxy of the collateral effect, we add the capital-to-assets ratio to the model (along with assets). Doing so lowers the statistical significance of capital-labor in the OLS but raises its statistical significance in the GMM estimation. Thus, we conclude that as an IV estimator that addresses simultaneity bias by using predicted rather than realized values of endogenous variables, GMM does a better job than OLS in picking up both the collateral effect (through assets) and the substitution effect (through instrumented capital-labor ratios).

[28] The interacted industry-year fixed effects are also key to having GMM pick up this substitution effect, since without them the coefficient on the capital-labor ratio in the financial leverage GMM regression is insignificant.

We also include two other industry position variables to capture the central idea that, even in competitive industries, decisions made by individual firms are related to the decisions made by other firms in their industry. We include the change in financial structure, technology, and risk of industry firms both above and below the industry median. For instance, if a firm's financial leverage is less than or equal to the median financial leverage for its industry-year, then we define "intra-quantile change" as the mean change in financial leverage of all other firms whose financial leverage is less than or equal to the median for that particular industry and year; "extra-quantile change" is the mean change in financial leverage of all firms above the median in that industry-year. A similar procedure is used for firms whose financial leverage lies above the industry-year median. The same is done for the other two dependent variables (capital–labor ratios and cash-flow volatility).

Regardless of estimation method (OLS or GMM), we find negative and significant coefficients for these intra- and extra-quantile changes in each of the three equations we consider. In other words, we find that changes in own-firm financial leverage, capital-intensity, and cash-flow volatility are inversely related to changes made by other firms within the same industry. This finding supports the asymmetric adjustment patterns predicted by Maksimovic and Zechner (1991) where the equilibrium process drives firms to react differently to common industry shocks. These relations are stronger (weaker) inside (outside) a firm's industry-year quantile, indicating that firms pay most attention to industry peers with similar characteristics. Thus, we conclude that firm interdependence, usually associated with imperfect competition, arises even within competitively-structured industries.

Maksimovic and Zechner also show how debt, technology, and risk are jointly determined, which motivates our use of simultaneous equation methods. Our results confirm that this approach is justified as capital-intensity and cash-flow volatility explain financial leverage, and financial leverage and capital-intensity explain cash-flow volatility. However, causation does not run both ways: We find no significant relation between capital-intensity and financial leverage or cash-flow volatility.

Our GMM results show that firms with riskier cash flows tend to use more financial leverage. This finding is of particular interest since past empirical work has in turn found the relation between financial leverage and cash-flow volatility to be positive (Kim and Sorensen, 1986), negative (Bradley, Jarrell, and Kim, 1984), and insignificant (Titman and Wessels, 1988). Besides lending credence to Maksimovic and Zechner's (1991) prediction of a positive relation between financial leverage and risk, this finding also suggests that the mixed results in the literature might depend on the econometric treatment of simultaneous decision variables and endogenous explanatory variables.

Our regressions include squared values for natural hedge and profitability because an unreported analysis of how variables distribute across industry quintiles shows significant non-monotonic relations between these variables and the dependent variables. We find a significant positive coefficient for the squared value of natural hedge, indicating a U-shaped relation between this variable and financial leverage. This non-monotonic relation is not predicted by Maksimovic and Zechner (1991) and suggests that factors besides those analyzed in their model induce firms at the technological core of the industry to assume more debt than firms whose capital–labor ratios lie between the core and fringe of the industry. However, as we show next (Table 6), the combined impact of the squared and unsquared values of natural hedge is negative, as per their prediction.[29]

One possibility is that our natural hedge measure acts as a proxy for financial distress. As shown in Table 2, we observe a drop in capital intensity in years prior to exit, causing natural hedge to drop as well (although neither of these variables differ significantly from incumbent levels once we adjust for industry-year). We use two methods to avoid confusing financial distress with a *bona fide* natural-hedge effect. First, we include (instrumented) capital–labor ratios themselves in the financial leverage regressions; we also control for risk, profitability, and size, which Table 2 showed to correlate with financial distress and exit. Second, we include dummy variables for exiting firms.

Since our univariate results showed significant differences between firms that enter, stay, or leave their industries, our regressions also include indicator variables for entrants, switchers, sellers, and exiters (incumbents are the omitted category). These dummy variables allow us to contrast Maksimovic and Zechner's (1991) static industry equilibrium model, where entry and exit play no role because the number of firms in the industry is held constant, and dynamic industry equilibrium models by Williams (1995) and Fries, Miller, and Perraudin (1997), where entry and exit are endogenized.

Table 2 showed that entering and exiting firms carry more leverage than incumbents. However, our multivariate results show that only firms that switch into an industry or exit through bankruptcy or liquidation carry significantly more leverage than incumbents. Our GMM regressions also show no evidence that entrants or exiters differ from incumbents in terms of capital-intensity or cash-flow volatility.[30] Thus, we find no multivariate evidence to support the Williams (1995) and Fries, Miller, and Perraudin's (1997) prediction that entrants carry less debt than incumbents.

[29] Excluding the squared term from the regressions does not change this conclusion.

[30] Firms that exit by selling assets are statistically riskier, although only at the 10% confidence level.

As an indirect test and benchmark for our results, we run the same regressions for the sample of concentrated industries presented earlier (Tables 1 and 2). We do so to examine whether the measures of a firm's industry position we develop to test competitive-industry equilibrium models also help explain firm financial structure in concentrated industries. If these variables are also significant for concentrated industries, then we would conclude that the forces modeled in the context of competitive-industry equilibrium extend to concentrated industries. Otherwise, we would conclude that the forces captured in these models are indeed specific to competitive industries. Since this is essentially a robustness check, we do not present regressions for the concentrated industry sample.

Comparing GMM results across industry types, we find that most of the variables that are statistically significant determinants of financial leverage and cash-flow volatility in competitive industries are not significant in concentrated industries. Focusing on the industry position variables, we find that none of the natural hedge or entry/exit dummy variables are significant in concentrated industries. However, changes inside and outside a firm's industry-year quantile continue to be highly significant for all three dependent variables. As we later show, these variables are also more economically significant in concentrated industries than they are in competitive industries.

To summarize, regardless of estimation method (OLS or GMM), we find empirical evidence consistent with many of the predictions deriving from the static industry equilibrium model presented in Maksimovic and Zechner (1991). For instance, we find an inverse relation between financial leverage and natural hedge. We also find that firms tend to adjust away from their industry peers. In contrast, we find no multivariate support for the predictions deriving from the dynamic industry equilibrium models presented by Williams (1995) and Fries, Miller, and Perraudin (1997).

**3.6.3 Economic significance.** Table 6 reports the economic significance of our multivariate regression results. The table presents predicted percentage changes in the dependent variables as each regressor varies from the 25th to 75th percentile, holding all other regressors at their sample mean levels (statistically insignificant relations are omitted). The percentages we report are relative to the mean and are normalized by the sample range (maximum minus minimum). The top (bottom) panel pertains to competitive (concentrated) industries. Both panels use the GMM regression coefficient estimates.[31]

[31] Because the GMM coefficient estimates are obtained from predicted (instrumented) values of the variables rather than their realized values, we compute economic significance using predicted rather than realized values of the variables. The economic impact that natural hedge and profitability have on financial leverage is complicated by the non-monotonic relations between these variables and financial leverage. Indeed, Table 5 shows negative coefficients for both variables and positive coefficients for their squared values. Table 6 combines these offsetting relations and presents the total effect each of these variables has on the dependent variables.

**Table 6**
**Economic significance of the determinants of financial leverage, capital intensity, and risk**

| | 25th percentile | | | 50th percentile | | | 75th percentile | | |
|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | Debt | *K/L* | Risk | Debt | *K/L* | Risk | Debt | *K/L* | Risk |
| **Competitive industries** | | | | | | | | | |
| Leverage | n/a | | −1.32 | n/a | | 0.25 | n/a | | 1.68 |
| Capital/labor | 0.03 | n/a | −0.05 | −0.28 | n/a | 0.09 | −0.60 | n/a | 0.22 |
| Risk | −1.68 | | n/a | 0.12 | | n/a | 1.92 | | n/a |
| *Industry Variables* | | | | | | | | | |
| Natural hedge | 3.37 | | −1.51 | 0.79 | | −0.38 | −3.28 | | 1.39 |
| Intra-quantile change | 0.34 | 0.08 | 0.40 | −0.27 | 0.00 | 0.08 | −0.87 | −0.08 | −0.26 |
| Extra-quantile change | 0.01 | 0.09 | 0.16 | −0.23 | 0.00 | 0.07 | −0.51 | −0.09 | −0.03 |
| *Control Variables* | | | | | | | | | |
| Profitability | −0.14 | | −0.18 | −0.26 | | 0.10 | −0.37 | | 0.35 |
| Size (log of assets) | −6.26 | | 2.69 | −0.61 | | 0.23 | 5.46 | | −2.42 |
| Diversification | 1.07 | | −0.48 | −0.15 | | 0.03 | −1.25 | | 0.49 |
| Tobin's q | −2.67 | | 1.20 | 0.90 | | −0.46 | 4.03 | | −1.92 |
| **Concentrated industries** | | | | | | | | | |
| Leverage | n/a | | −0.26 | n/a | | 0.01 | n/a | | 0.27 |
| Capital/labor | | n/a | | | n/a | | | n/a | |
| Risk | −0.40 | | n/a | 0.01 | | n/a | 0.45 | | n/a |
| *Industry Variables* | | | | | | | | | |
| Natural hedge | | | | | | | | | |
| Intra-quintile change | 2.39 | 0.29 | 0.91 | −0.08 | −0.01 | 0.03 | −2.38 | −0.26 | −0.92 |
| Extra-quintile change | 2.06 | 0.16 | 0.97 | −0.05 | 0.01 | 0.02 | −2.25 | −0.18 | −0.98 |
| *Control Variables* | | | | | | | | | |
| Profitability | | | −0.24 | | | 0.01 | | | 0.25 |
| Size (log of assets) | −1.13 | | | 0.09 | | | 1.23 | | |
| Diversification | | | 0.05 | | | 0.00 | | | −0.06 |
| Tobin's *q* | | | 0.40 | | | −0.06 | | | −0.50 |

Predicted changes in the dependent variables (using generalized method of moments estimates) as each regressor varies from the 25th to 75th sample percentile, holding all other regressors at their sample mean levels (statistically insignificant relations omitted). Reported are percentages relative to the sample mean and normalized by the sample range (maximum minus minimum). Leverage is total debt divided by total assets. Capital/labor is net property, plant and equipment (in millions of dollars) per employee. Risk is the standard deviation of operating cash flow divided by sales. Natural hedge is one minus the absolute value of the difference between the firm's capital–labor ratio and the market-share weighted industry-year median (own firm excluded), normalized by the industry-year range. Intra-quantile change is the mean change in the dependent variable within the industry half to which a firm belongs (own firm excluded). Extra-quantile change is the mean change in the other half of the industry. These quantiles are based on the lagged levels of the dependent variables. Profitability is EBIT divided by assets. Diversification is one minus the Herfindahl of output across the firm's four-digit SIC industries. Tobin's $q$ is the market value of equity plus the book value of debt and preferred stock minus deferred taxes, divided by the book value of assets

The top panel of Table 6 shows that in competitive industries, the economic importance of natural hedge is similar to that of explanatory variables such as asset size and Tobin's $q$. For instance, going from the 50th to the 25th (75th) size percentile, we see a 6.26% (5.46%) drop (rise) in financial leverage, a difference of over eleven percentage points; going from the 50th to the 25th (75th) natural-hedge percentile coincides with a 3.37% (3.28%) rise (drop) in financial leverage, a difference of well over six percentage points. This shows that an economically significant fraction of within-firm variation in financial structure is tied to industry factors *other* than standard industry fixed effects. However, although statistically significant, changes in financial leverage by other firms inside and outside a firm's industry-year quantile are only weakly economically significant: Going from the 25th to the 75th intra- and extra-quantile change percentiles causes changes in financial leverage of only about one percentage point. Similar patterns obtain for capital–labor ratios and cash-flow volatility.

We find contrasting results for concentrated industries. As the bottom panel shows, the natural hedge variable is neither statistically nor economically significant in concentrated industries, confirming that competitive-industry models perform poorly in concentrated industries. However, we do find economic significance for intra- and extra-quantile change. Going from the 50th to the 25th (75th) intra- and extra-quantile change percentiles causes changes in financial leverage of over four percentage points. This suggests that although we document firm interdependence in competitive industries, strategic substitution is much stronger in concentrated industries, as one might expect.

### 3.7 Robustness checks

Since our analysis depends heavily on industry classification, it is important to check whether our results hinge on how finely we define industry. Up to this point, we have used firms' four-digit SIC to compute natural hedge, measure intra- and extra-quantile changes, and control for industry-year fixed effects. We rerun our GMM regressions for the competitive-industry sample with industry redefined at the two- and three-digit SIC level. Although we hold no strong priors, we would expect the importance of industry position variables to fall as we broaden the industry definition. This is in fact what happens. The main qualitative difference is in the industry quantile changes, which become statistically insignificant in the two-digit SIC regressions. However, natural hedge is significant even in the two-digit SIC regressions and the entry/exit dummies are mostly insignificant.

Thus, these findings provide some assurance that our main results are robust to industry definition. However, there are econometric grounds to favor results with industry defined at the four-digit SIC level. First, the over-identifying restrictions for the financial-leverage equation are rejected when industry is defined at the two- or three-digit SIC (J-statistics statistically greater than zero). The over-identifying restrictions are not rejected when industry is defined at the four-digit SIC level. Second, instrument relevance falls when industry is defined at the two- or three-digit SIC. Third, unreported likelihood ratio tests show a better fit when industry is defined at the four-digit SIC level.

As mentioned earlier, we use diversification as a control but also to screen out multi-segment firms as a robustness check of our results. The downside to *including* multi-segment firms is that the models on which we base our hypotheses concern single-segment firms in well-defined industries. The downside to *excluding* multi-segment firms is that we might omit important competitive aspects. Keeping only undiversified single-segment firms reduces the competitive-industry sample to 6673 firm-years. Our results pertaining to industry position still hold and, unlike Table 5 but as in Table 2, we find that firms that enter, sell, or exit carry significantly more leverage than incumbents.

Finally, recent papers report that results change if financial leverage is measured relative to the book value or the market value of assets. For instance, Fama and French (2002) report a negative relation between market leverage and Tobin's $q$ but a positive relation for book leverage. Barclay, Morellec, and Smith (2003) find a significant negative OLS relation between book leverage and Tobin's $q$, which we find as well. However, our GMM estimates show this relation to be *positive* and significant. We therefore rerun our OLS and GMM regressions for competitive and concentrated industries using market leverage instead of book leverage. Using market leverage produces no notable changes.[32]

## 4. Conclusions

In this paper, we examine the importance of industry to firms' real and financial decisions. We find that industry fixed effects explain far less of the variation in financial structure than do firm fixed effects. However, we find that industry-related factors other than industry fixed effects can explain part of this wide intra-industry variation in financial structure in competitive industries.

Our findings support the idea that industry factors affect not only individual firm decisions but also the joint distribution of real-side and financial characteristics within industries. We find that accounting for a firm's position within its industry is important both economically and statistically. Our finding that own-firm financial structure depends on changes made by industry peers shows the importance of industry interdependence—even in competitive industries.

In competitive industries, we find that firms with capital–labor ratios close to the industry median (high natural hedge) use less financial leverage than firms that depart from the industry median capital–labor ratio (low natural hedge), as predicted by Maksimovic and Zechner (1991). We also find that real and financial variables are more dispersed in competitive industries, consistent with the intra-industry diversity predicted in models of competitive-industry equilibrium.

[32] Likelihood ratio tests show no difference in the explanatory power of the equations when estimated using book leverage or market leverage.

Also consistent with industry equilibrium models—and certain partial-equilibrium models—we find that financial structure, technology, and risk are simultaneously determined. Accounting for this simultaneity affects the economic significance and nature of the relations we document between financial leverage, capital–labor ratios, cash-flow volatility, and the determinants of these variables.

Our research has practical implications for future research. First, we show that simple measures of a firm's position within its industry help us understand how firms choose financial structure. These measures are easy to construct and economically significant. Second, our research supports the proposition that benchmarks should be created on multiple within-industry measures—along both real and financial variables—rather than just relying on single measures such as industry dummies, or industry means or medians.

Overall, our evidence shows that industry factors help explain firm financial structure, the diversity of firms that populate industries, and the simultaneity of real and financial decisions. We conclude that departures from the mean industry financial structure are systematically related to technology and risk choices relative to the industry. When firms depart from industry norms for financial structure, they also systematically depart along technology and risk dimensions.

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