Industry Concentration and Average Stock Returns

Author(s): Kewei Hou and David T. Robinson

Source: *The Journal of Finance*, Aug., 2006, Vol. 61, No. 4 (Aug., 2006), pp. 1927-1956

Published by: Wiley for the American Finance Association

Stable URL: https://www.jstor.org/stable/3874731

THE JOURNAL OF FINANCE • VOL. LXI, NO. 4 • AUGUST 2006

Industry Concentration and Average Stock Returns

KEWEI HOU and DAVID T. ROBINSON*

ABSTRACT

Firms in more concentrated industries earn lower returns, even after controlling for size, book-to-market, momentum, and other return determinants. Explanations based on chance, measurement error, capital structure, and persistent in-sample cash flow shocks do not explain this finding. Drawing on work in industrial organization, we posit that either barriers to entry in highly concentrated industries insulate firms from undiversifiable distress risk, or firms in highly concentrated industries are less risky because they engage in less innovation, and thereby command lower expected returns. Additional time-series tests support these risk-based interpretations.

Firms generate cash flows through their actions in product markets. These risky cash flows are in turn priced in financial markets. Yet the economic link between product markets and asset prices remains relatively unexplored. This paper explores the link between industry concentration and average stock returns, offering the first empirical evidence of the asset pricing implications of industry market structure.

There are a number of potential reasons why the structure of product markets may affect stock returns. Firms take operating decisions that may affect the riskiness of their cash flows. These operating decisions arise from an equilibrium in the product market that potentially reflects strategic interactions among market participants. Therefore, the structure of product markets may affect the risk of a firm's cash flows, and hence a firm's equilibrium rate of return.

Take, for example, innovation. According to Schumpeter (1912), innovation is a form of creative destruction that is more likely to occur in competitive industries or on the fringes of established industries. If innovation is risky, and this risk is priced, then this predicts that competitive industries or firms on the competitive fringe of established industries earn higher returns, all else

*Kewei Hou is from the Fisher College of Business at The Ohio State University, and David T. Robinson is from the Fuqua School of Business at Duke University. We thank Alon Brav, Anne-Marie Knott, Robert Stambaugh (the editor), Lu Zhang, seminar participants at the 2005 WFA meetings, Ohio State, The University of Arizona, George Mason University, and an anonymous referee for many helpful comments. This paper is a significantly revised version of a paper entitled, "Market Structure, Firm Size, and Expected Stock Returns." Judith Chevalier, Eugene Fama, Peter Hecht, Owen Lamont, Toby Moskowitz, Per Olsson, Per Strömberg, and seminar participants at The University of Chicago and the Chicago Quantitative Alliance provided many helpful comments on this earlier draft. Any remaining errors are our own.

equal. Hence, innovation is one channel through which the structure of product markets has implications for stock returns.

Or consider distress. If barriers to entry in product markets insulate some firms from aggregate demand shocks, while exposing others, then we would expect distress risk to vary with market structure. This predicts that industries with high barriers to entry are associated with lower equilibrium stock returns. Thus, distress is another way that market structure can impact stock returns.

Regardless of whether the link between market structure and stock returns is better characterized by distress risk, innovation risk, or yet some other channel, our message is simple. It is well understood from industrial organization that the structure of product markets affects managers' equilibrium operating decisions. If these operating decisions affect the risk of a firm's cash flows, then these decisions should impact stock returns.

The main finding in this paper is that firms in highly concentrated industries earn lower returns, even after controlling for size, book-to-market, momentum, and other known return predictors. This finding is true both of industry portfolio returns and individual firm-level returns, and it is robust to a variety of empirical specifications. Moreover, the economic magnitude of these effects is large. Our results indicate that firms in the quintile of the most competitive industries earn annual returns that are nearly 4% higher than those of similar firms in the quintile of the most concentrated industries. This difference is highly statistically significant.

To rule out chance or spurious correlation as a potential explanation for these findings, we explore a wide range of robustness tests and alternative explanations. Using the Davis, Fama, and French (2000) files, we extend our main results back to 1927. In addition, the results hold across a wide range of industry concentration measures. Our sample selection criteria ensure that the results are driven neither by regulated industries, nor by the de-listing bias documented by Shumway (1997).

Another possible explanation is that we are simply documenting differences in unexpected returns that arise from persistent in-sample cash flow shocks: These shocks may be correlated with industry concentration in sample, but are unlikely to persist in the future. To control for this explanation, we examine the relation between concentration, profitability, and returns. Our analysis shows that on average, highly concentrated industries have experienced positive abnormal profitability, while abnormal profitability for competitive industries has been negative. Thus, not only does unexpected profitability fail to account for our findings, it works in the opposite direction. This suggests that we may be understating the true relation between concentration and *expected* returns.

Given that we cannot easily dismiss our findings as arising from chance, spurious correlation, persistent in-sample cash flow shocks, or correlation with other known determinants of returns, our next step is to explore potential explanations for our results. We study the time-series properties of the concentration premium to explore its relation to risk-based explanations such as distress or innovation risk. Spanning tests of the cross-sectional concentration premium reveal that it is statistically and economically significant and not well explained by existing asset pricing factors. Moreover, the concentration premium exhibits sensible business cycle variation and is related to future economic activity: The premium grows as the economy contracts and it is high when current and near-term GDP growth are low. This indicates that when future economic conditions look bleak, investors raise the required rate of return for firms in relatively more competitive industries.

Finally, our concentration premium largely subsumes the size and market factors, but the premium on book-to-market grows when we control for concentration. This leads us to examine the book-to-market spread in returns across concentration quintiles. We show that the premium associated with the book-to-market ratio is larger in more concentrated industries. Through double-sort portfolios, we find that most of the spread in returns across concentration quintiles occurs for low book-to-market firms. This finding supports a risk-based explanation, since it shows that returns are high for low book-to-market firms in competitive industries (where book-to-market is low because expected growth is high), while returns are low for low book-to-market firms in concentrated industries (where book-to-market is low because capitalized future profitability is high).

Although we cannot rule out behavioral explanations for our results, these time-series findings suggest that industry concentration proxies for a risk factor sensitivity. Our findings are consistent with the view that innovation/distress risk, which is more pronounced in competitive industries, is a priced source of risk in the context of the multifactor asset pricing models of Merton (1973) and Ross (1976).

This paper is part of a larger literature that links industrial organization to issues in financial economics. Earlier work such as Titman (1984) studies how capital structure and product markets interact through the liquidation decision. A number of recent papers examine the link between capital structure and industry characteristics; see, for example, Mackay and Phillips (2005) or Almazan and Molino (2001). In addition, a series of papers, including Asness and Stevens (1996), Moskowitz and Grinblatt (1999), Cohen, Polk, and Vuolteenaho (2003), and Hou (2003), demonstrate that a wide range of asset pricing phenomena have important industry components. To our knowledge, ours is the first paper to link expected stock returns to industry product market characteristics through the channel we propose.

The remainder of the paper is structured as follows. Section I motivates our hypotheses linking industry concentration to stock returns. Section II describes the data and how we construct industry concentration measures. In addition, this section illustrates the relation between industry concentration and industry-level characteristics. Section III examines how industry concentration affects the cross-section of stock returns. Section IV examines profitability surprises as a potential explanation for our results, while Section V presents the time-series evidence. We explore the relation between value, growth, and concentration in Section VI. Section VII concludes.

I. The Link between Market Structure and Stock Returns

If the structure of product markets affects asset prices, then either market structure affects risk directly, or else it is somehow correlated with investor perceptions in a way that links it to behavioral phenomena. In this section, we focus on risk-based channels through which market structure affects stock returns.

For market structure to affect equilibrium stock returns through a risk-based channel, it must be that equilibrium operating decisions induced by a particular market structure are related to expected returns. While it is well understood that market structure affects equilibrium firm behavior, the industrial organization literature stops short of making predictions for stock returns. Our purpose in this section is to conjecture a possible mechanism through which industrial organization affects equilibrium stock returns.

Of course, whether or not existing asset pricing factors capture the risks brought about by market structure is an empirical question—one that we address later in this paper. Our goal in this section is not to argue whether a certain number of priced factors is correct for explaining stock returns, and thus whether existing asset pricing factors should or should not capture the risks associated with market structure (for more on this see Fama (1998)). Rather, our purpose here is to close the gap between industrial organization and asset pricing by generating testable predictions for stock returns based on theories from industrial organization.

We focus on two channels through which industry concentration can potentially affect stock returns. The first draws on Schumpeter's (1912) concept of creative destruction. The second, closely related, channel is through barriers to entry.

Creative destruction is the idea that innovation occurs in small firms on the fringes of established industries, and that these small challengers ultimately overturn the existing status quo and usher in a new technological paradigm. In short, innovation and technological progress involve unseating incumbent firms in industries.[1]

Recently this view has received renewed support in industrial organization. Knott and Posen (2003) show empirically that innovation increases with the degree of industry competition. He, Mørck, and Yeung (2003) present complementary evidence relating turnover in firm dominance to differences in economic growth across countries. They find that economic growth correlates positively

[1] Schumpeter is associated with two influential and opposing views of the link between market structure and innovation. His later view, discussed in Schumpeter (1942), argues that monopolistic firms have stronger incentives to innovate than firms in competitive industries, since monopolistic firms can enjoy the economic profits arising from their innovation, rather than have their supernormal profits competed away. This later view has received criticism. For instance, work by Geroski (1990) finds evidence against the hypothesis that competitive rivalry diminishes innovation, and Reinganum (1985) models an industry with a single incumbent and multiple challengers and shows that the challengers have stronger innovation incentives, suggesting that the level of innovation varies non-monotonically with the number of firms in the industry.

with firm turnover, suggesting that creative destruction is an important element of long-run growth.

If creative destruction describes the relation between market structure and risky innovative activities, then this predicts that more concentrated industries have lower average returns, all else equal, because firms in more concentrated industries engage in less innovation. We label this the *creative destruction hypothesis for stock returns*.

An alternative, but related, way to link market structure to stock returns is based on an old and influential paradigm in industrial organization known as the Structure/Conduct/Performance (S/C/P) paradigm. This work originates with Bain (1954), who links the exogenous production characteristics of an industry to a firm's pricing behavior, which in turn determines firm performance.

The observational starting point for the S/C/P paradigm is the nature of the production technology in an industry, which is taken to be exogenous. For example, the computer chip manufacturing industry has high fixed costs, since large, expensive plants must be built and customized to each new chip that is designed. The S/C/P paradigm would view these high fixed costs as a natural barrier that restricts competitive entry (*structure*). Since entry to this industry would be limited, the number of incumbent firms would be few, and each would be able to price significantly above marginal cost without fear of arousing entry (*conduct*). As a result, firms in this industry would earn supernormal economic profits (*performance*).

The S/C/P paradigm suggests that barriers to entry affect expected returns whenever differences in the number of competitors in an industry, or in the pricing practices they observe, change the risk characteristics of the firms in question. For example, barriers to entry may affect how firms optimally respond to aggregate demand shocks. Firms in high barriers-to-entry industries can respond to positive demand shocks by increasing prices or raising output without fearing competitive entry. All else equal, this raises their expected future profitability, giving them deeper pockets that help them weather downturns without facing industry exit. Thus, if exit in response to aggregate demand shocks is associated with priced distress risk, we would expect these firms to face less distress risk.[2]

Looking across industries, we would expect firms in high barriers-to-entry industries to earn lower average returns since the average distress risk would be lower in these industries. To test this prediction, one empirical approach is to measure barriers to entry directly and relate them with stock returns. However, recent work in industrial organization focuses on the fact that barriers to entry reflect the strategic choices of incumbent firms in addition to the inherent production characteristics of the industry. This is illustrated in a large body of work including Schmalensee (1978), Salop (1979), Schmalensee (1981),

[2] Industry exit could be priced if it changed the production possibilities of the economy and hence the investment opportunity set faced by investors. This would be the case if, for example, exit involved abandoning investments that are costly to reverse, or redeploying assets and human capital to production processes for which they were not originally specialized.

Sutton (1991), and Sutton (1998). The fact that barriers to entry reflect strategic choices of incumbent firms as well as the primitives of industry production technology makes it impractical to link stock returns directly to barriers to entry. In particular, the strategic nature of barriers to entry not only makes them difficult to measure, but introduces potential endogeneity with stock returns. For a variety of reasons, direct measures of barriers to entry are unattractive or incomplete.

Instead, we focus on industry concentration as a measure of barriers to entry, since it is a natural consequence of these barriers no matter how the barriers came to exist. Under the *barriers-to-entry hypothesis*, we hypothesize that firms in highly concentrated industries earn lower returns because, all else equal, they are better insulated from undiversifiable, aggregate demand shocks.

II. Data and Measures of Industry Concentration

A. Sample Selection

Our sample includes all NYSE-, AMEX-, and NASDAQ-listed securities with share codes 10 or 11 that are contained in the intersection of the CRSP monthly returns file and the COMPUSTAT industrial annual file between July 1963 and December 2001. Prior to January 1973, industry coverage is more sparse, since the CRSP sample includes NYSE and AMEX firms only. However, all of our findings hold for the 1963 to 2001 sample period as well as the 1973 to 2001 sample period. Throughout our analysis, we employ the corrections suggested in Shumway (1997) for the de-listing bias; however, these adjustments have no effect on our results.

To ensure that accounting information is already impounded into stock prices, we match CRSP stock return data from July of year t to June of year $t + 1$ with accounting information for fiscal year ending in year $t - 1$, as in Fama and French (1992). To be included in our return tests, a firm must have CRSP stock price, shares outstanding and three-digit SIC classification data for June of year t.[3] Many of our tests require the presence of COMPUSTAT data on earnings, sales, book equity, market equity, and total assets for fiscal year $t - 1$. This data requirement probably biases our sample toward larger firms, which may in turn diminish the overall variation in the concentration measures.

Book equity is stockholder's equity plus balance sheet deferred taxes and investment tax credits minus the book value of preferred stock and post-retirement assets. The book-to-market ratio is calculated by dividing book equity by COMPUSTAT market equity, which is COMPUSTAT stock price times shares outstanding at fiscal year-end. Earnings is measured before interest, and equals income before extraordinary items plus interest expense plus income statement deferred tax. Leverage is defined as the ratio of book liabilities (total assets minus book equity) to total market value of firm (COMPUSTAT market

[3] Kahle and Walkling (1996) report problems between CRSP and COMPUSTAT with regard to SIC industry classifications. To minimize any impact this may have on our results, and to maintain internal consistency with our variable construction, we disregard COMPUSTAT SIC classifications.

equity plus total assets minus book equity). For size we use CRSP market equity for June of year t. We follow Fama and French (1992) to estimate market β by computing full-period βs for portfolios sorted by size and pre-ranking β and then assigning portfolios βs to stocks in those portfolios. The pre-ranking β is estimated as the sum of the coefficients of regressions of individual monthly stock returns on contemporaneous and lagged market returns over the past 3 years.

Throughout the paper, we use three-digit SIC classifications to define industry membership. This choice balances two offsetting concerns. On the one hand, we wish to use fine-grained industry classifications so that firms in unrelated lines of business are not grouped together. On the other hand, using too fine an industry classification results in portfolios that are statistically unreliable, with firms being grouped into distinct industries arbitrarily. Choosing three-digit classifications strikes a balance between these two concerns. Although all of the results in the paper are presented with three-digit SIC classifications, in unreported tables we replicate our findings at the two- and four-digit level, and the results are qualitatively identical.

Finally, we remove regulated industries from our sample.[4] Regulated industries may face lower costs of capital either because they have lower operating risks (due to regulated entry and exit), or because their capital structure and/or capital charges are legally constrained. If regulation is correlated with industry concentration, then this could potentially explain our findings without offering any fresh insights into the structure of asset prices. Removing these industries has no material effect on our findings.

B. Measuring Industry Concentration

We measure industry concentration using the Herfindahl index, which is defined as

$$\text{Herfindahl}_j = \sum_{i=1}^{I} s_{ij}^2, \tag{1}$$

where s_{ij} is the market share of firm i in industry j. We perform the above calculations each year for each industry, and then average the values over the past 3 years. This ensures that potential data errors do not have undue influence on our Herfindahl measure.[5]

The Herfindahl measure uses the entire distribution of industry market share information to obtain a complete picture of industry concentration. Small

[4] The industries are taken from Barclay and Smith (1995).

[5] In unreported robustness tests, we vary the averaging horizon of the Herfindahl calculation from 1 year (i.e., no averaging) to 10 years. We also skip multiple years between the Herfindahl calculation and the returns, and we relate Herfindahl in the beginning of the sample to late-sample returns. These robustness checks ensure that our results are not affected by industries with large swings in Herfindahl. Our findings hold under all of these alternative specifications.

values of the Herfindahl index imply that the market is shared by many competing firms, while large values imply that market share is concentrated in the hands of a few large firms.

A common way to measure Herfindahl is to use net sales to calculate market share. We call this variable H(Sales) in our analysis. We also define H(Assets) and H(Equity) using total assets and book equity, respectively, to compute market share. The H(Equity) measure allows us to use Davis et al. (2000) data and extend our results to time periods before net sales and asset data became widely available. The measures are only imperfectly correlated with true market share, but to ensure that they produce reasonable values, we compare the three measures over the 1963 to 2001 interval, during which time all three measures are available. As Panel A of Table I shows, they are highly correlated.

C. Characteristics of Concentration-Sorted Portfolios

In Panel B, we report characteristics averaged across concentration quintiles. The spread in H(Sales) is large: The most competitive quintile has an average H(Sales) of 0.133, while the most concentrated quintile has an average of 0.982. In addition, the production, risk, and profitability characteristics of the industry quintiles tell us much about the nature of industry concentration.

Average sales and assets are significantly larger for the most concentrated quintiles, but size is smaller for the most concentrated quintile. (Skewness in the within-industry size distribution of firms is responsible for the latter result.) Firm turnover, as proxied by the number of new listings and de-listings in an industry, is significantly higher in the quintile of the most competitive industries, which suggests that barriers to entry are higher in more concentrated industries.

Measures of risk and leverage are largely flat across concentration quintiles. The average book-to-market ratio is roughly constant, as is the average β. Leverage is roughly flat across the quintiles as well.

Unlike risk and leverage, profitability shows considerable variation across quintiles. We summarize profitability with four measures. Earnings to assets (E/A in Table I) averages 1.3% for the lowest concentration quintile, jumps to 2.9% for the second lowest quintile, and is above 3% for the remaining three quintiles. Similarly, earnings to sales (E/S) ranges from 11% for the lowest concentration quintile to 13.6% for the highest concentration quintile. More concentrated industries have higher profitability on average; this is consistent with the view that industry concentration is an indirect measure of barriers to entry.

The variable labeled V/A is our proxy for Tobin's Q, and is simply market value of assets over book value of assets. It exhibits behavior similar to that above, ranging from 1.29 for the lowest concentration quintile to 1.70 for the highest concentration quintile. The positive correlation between Tobin's Q and industry concentration suggests that high industry-concentration firms not only have higher current profitability, but expect this profitability to persist in the future.

Table I

Summary Statistics

The sample includes all NYSE/AMEX/NASDAQ-listed securities with share codes 10 or 11 that are contained in the intersection of the CRSP monthly returns file and the COMPUSTAT industrial annual file between July 1963 and December 2001. Panel A reports summary statistics of industry concentration measures for three-digit SIC industries. The H(Sales) for an industry is formed by first calculating the sum of squared sales-based market shares of all firms in that industry in a given year and then averaging over the past 3 years. H(Assets) and H(Equity) are computed analogously, using total assets and book equity in place of sales. The right-most columns present Spearman and Pearson correlations between industry concentration measures. Spearman (rank) correlations are presented below the main diagonal, Pearson above. Panel B reports average characteristics of quintile portfolios sorted by H(Sales). Quintile 1 corresponds to the 20% of industries with the lowest concentration, while Quintile 5 corresponds to the 20% of industries with the highest concentration. Newlist is the average number of newly listed firms per year in each quintile. Delists is the average number of de-listed firms per year. Size (market equity) is CRSP price times shares outstanding (in millions of dollars). Asset is COMPUSTAT Total Assets. Sales is COMPUSTAT Net Sales. E/A is earnings before interest (income before extraordinary items + interest expense + income statement deferred tax) divided by assets; E/S is earnings divided by sales. V/A is market value of firm (market equity + total assets − book equity) divided by total assets. D/B is the ratio of dividends to book equity. Book equity is stockholder's equity (or common equity + preferred stock par value, or asset − liabilities) plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock and post-retirement asset. R&D/A is the ratio of R&D expenditure to total assets. Lev. is the ratio of book liabilities (total assets − book equity) to total market value of firm. B/M is the ratio of book equity to market equity. Beta is post-ranking beta as in Fama and French (1992). Each of these characteristics is calculated at the firm level and then averaged within each H(Sales) quintile.

Panel A: Summary of Industry Concentration Measures

										Spearman–Pearson Correlation		
	Mean	Median	*SD*	Max	Min	20%	40%	60%	80%	H(Sales)	H(Assets)	H(Equity)
H(Sales)	0.544	0.490	0.310	1.000	0.025	0.231	0.385	0.611	0.944	1.000	0.976	0.951
H(Assets)	0.549	0.499	0.307	1.000	0.024	0.233	0.397	0.618	0.936	0.976	1.000	0.964
H(Equity)	0.546	0.502	0.308	1.000	0.024	0.230	0.405	0.609	0.931	0.953	0.966	1.000

Panel B: Characteristics of H(Sales) Sorted Quintile Portfolios

Rank	H(Sales)	Newlist	Delists	Size	Asset	Sales	E/A	E/S	V/A	D/B	R&D	R&D/A	Lev.	B/M	Beta
Low	0.133	267.40	214.60	531.3	1200.4	582.5	0.013	0.110	1.293	0.026	35.293	0.075	0.437	0.798	1.579
2	0.287	126.21	84.70	527.8	645.1	509.6	0.029	0.111	1.257	0.024	21.226	0.060	0.399	0.742	1.632
3	0.470	60.47	42.70	607.4	1204.8	786.7	0.036	0.116	1.327	0.031	21.759	0.040	0.432	0.809	1.595
4	0.745	41.51	23.82	606.4	1087.9	629.3	0.038	0.124	1.558	0.041	17.164	0.037	0.428	0.787	1.606
High	0.982	20.13	8.68	431.3	1604.9	717.6	0.037	0.136	1.695	0.036	13.059	0.027	0.421	0.767	1.609

The dividend payout ratio (D/B) also increases with industry concentration. Since Fama and French (2000) and many others relate dividend policy to expected profitability, we take this as further evidence that firms in high concentration industries are more profitable. We discuss this issue in further detail in Section IV.

To get a sense of how Schumpeter's prediction squares with our data, we also report two measures of R&D intensiveness. The first is simply gross R&D expenditure, which declines substantially as concentration increases, falling from an average of $35 million per firm-year for the least concentrated quintile to $13 million for the highest concentration quintile. When we scale by total assets, we see the same pattern, with the R&D to asset ratio falling from 7.5% for the lowest concentration quintile to 2.7% for the most concentrated quintile.

In Table II, we report Fama and Macbeth (1973, henceforth FM) regressions of the cross section of industry concentration measures on industry average characteristics. We estimate equations of the following form:

$$H(Sales)_{jt} = \alpha_t + \sum_{n=1}^{N} \lambda_{nt} X_{jt} + \varepsilon_{jt}, \tag{2}$$

where the X_{jt} are industry average characteristics. Regressions are run for every year t from 1963 to 2001, and the time-series means of annual cross-sectional coefficient estimates are reported along with the time-series t-statistics. This procedure allows for multivariate correlation analysis, and it is robust to cross-correlated error terms. Thus, the resulting coefficients can be interpreted as simple or conditional correlations between concentration and industry-average characteristics, and appropriate statistical inferences can be drawn about the magnitude of these relations.

The row labeled "Simple" reports results from FM regressions of concentration on each characteristic in isolation. (Thus, there are eleven separate univariate regressions reported in a single row.) Each row under the panel labeled "Multiple" reports a single regression in which multiple characteristics are included as independent variables simultaneously. This provides conditional correlations of H(Sales) on industry characteristics.

When we combine the correlations reported here with the descriptive statistics from Table I, a picture of industry concentration emerges that is consistent with the prior literature discussed in Section I and that is important for the interpretation of our findings. Measures of profitability are positively correlated with industry concentration. Earnings to assets, earnings to sales, and market-to-book ratios are all highly positively correlated with industry concentration, both unconditionally, and conditional on other industry characteristics.

Concentrated industries have large asset bases and high unit profitability. In addition, R&D to assets is much lower for these industries. Thus, highly concentrated industries have high capitalized future profitability but they do not engage in risky innovation (they do not have high levels of R&D). These descriptive statistics paint a picture of concentrated industries as innovation-poor, profit-rich industries with high barriers to entry.

Table II

Fama–MacBeth Regressions of H(Sales) on Industry Average Characteristics

This table presents Fama–MacBeth regressions of the H(Sales) index with other industry average characteristics. The variables are defined according to Table I. Every year, a cross-sectional regression is estimated. The time-series mean of the annual regression coefficients and the time-series *t*-statistics (appearing below) are reported. In Panel A, each coefficient is obtained from a simple (univariate) regression of H(Sales) on each characteristic alone. Panel B reports the results of multiple (multivariate) regressions of H(Sales) on a series of industry characteristics.

ln(Size)	ln(Assets)	ln(Sales)	E/A	E/S	V/A	D/B	R&D/A	Leverage	ln(B/M)	Beta
Panel A: Simple Regressions										
−0.040	−0.032	−0.043	0.179	0.213	0.014	−0.002	−0.984	−0.033	−0.028	0.091
−13.45	−17.97	−22.81	4.77	7.15	3.71	−0.02	−4.97	−1.73	−5.34	4.92
Panel B: Multiple Regressions										
−0.034			0.522				−1.443	−0.056	−0.057	−0.011
−3.89			3.28				−6.99	−0.84	−6.08	−0.23
	−0.027		0.525				−1.527	0.026	−0.044	0.021
	−3.26		3.32				−7.22	0.44	−3.75	0.46
		−0.027	0.489				−1.514	0.012	−0.036	0.021
		−4.09	2.50				−7.26	0.20	−3.35	0.55
−0.039				0.580			−1.399	−0.017	−0.056	−0.016
−4.36				7.57			−6.81	−0.24	−5.80	−0.38
−0.023					0.024		−1.487	−0.114		0.019
−1.91					4.23		−7.05	−1.80		0.36
−0.034			0.542			0.570	−1.361	−0.043	−0.044	0.011
−3.84			3.21			2.97	−6.75	−0.64	−3.83	0.22

III. Concentration and the Cross-Section of Returns

A. The Concentration Spread

Table III relates industry concentration to the cross section of average stock returns, measured both at the industry and firm level. In June of each year, industries are sorted into quintiles based on their Herfindahl index. We then report average monthly returns and t-statistics for these portfolios, as well as the difference between Quintile 5 (most concentrated) and Quintile 1 (least concentrated).

The first row in the left panel presents raw average returns computed by equally weighting firms within each concentration portfolio. Looking across Herfindahl quintiles, firms in the least concentrated (most competitive) industries earn an average return of 1.52% per month. This declines to 1.26% per month for firms in the most concentrated quintile. The spread between the two is −0.26% per month, which carries a statistically significant t-statistic of 2.14.

Because concentration is an attribute of an industry, not a firm, there is flexibility in how quintile returns are measured. The right panel reports returns calculated by first forming industry portfolios, and then equally weighting industry returns within each concentration quintile. These industry-level returns mirror the firm-level results. In each case, we see a large and statistically significant spread between the most concentrated and the most competitive quintiles.

Since Table I shows that industry concentration is associated with a number of known determinants of average returns, we also report characteristics-adjusted returns. We use the procedure in Daniel et al. (1997) to adjust individual stock returns for size, book-to-market, and momentum. All firms in our sample are first sorted each month into size quintiles, and then within each size quintile we further sort firms into book-to-market quintiles. Within each of these 25 portfolios, firms are again sorted into quintiles based on the firm's past 12-month return, skipping the most recent month. Stocks are averaged within each of these 125 portfolios to form a benchmark that is subtracted from each individual stock's return. The expected value of this excess return is zero if size, book-to-market, and past one-year return completely describe the cross section of expected returns.

The characteristic-adjusted average returns of the above quintile portfolios as well as the average spread between Quintile 5 and Quintile 1 are reported in the second row of each panel. Even after adjusting for these characteristics, we still see a significant spread in average returns across concentration quintiles. Interestingly, adjusted returns for the quintile of the most competitive industries (Q1) are positive and statistically significant, and they decrease monotonically to negative and statistically significant for the quintile of the most concentrated industries (Q5). However, the adjustments only serve to increase the spread in returns. The spread for the Herfindahl index jumps to −0.36% per month, 10 basis points higher in absolute value than the raw returns figure. Similarly, the spread for industry portfolios grows two basis points

Table III
Industry Concentration and the Cross-Section of Average Stock Returns

In June of each year, industries are grouped into quintiles based on their H(Sales) value. The average monthly returns (in percent) of the quintile portfolios are reported, as well as the difference between Quintile 5 (most concentrated) and Quintile 1 (least concentrated). We report t-statistics below average returns. Firm-level raw returns are unadjusted returns averaged across firms within the same concentration quintile. Firm-level adjusted returns are calculated by subtracting the return on a characteristic-based benchmark from each firm's return, then averaging within the same concentration quintile. Characteristic-based benchmarks are constructed following Daniel et al. (1997) to account for the premia associated with size, book-to-market, and momentum. Industry-level raw and adjusted returns are computed similarly, except that individual stock raw and adjusted returns are first averaged within each industry, and then averaged across industries within the same concentration quintile. During the 1927 to 1951 sample period, H(Sales) is replaced by H(Equity). This is constructed from Davis et al. (2000) data.

	Firm-Level Returns						Industry-Level Returns					
	Quintile						Quintile					
	1	2	3	4	5	5 − 1	1	2	3	4	5	5 − 1
Raw and adjusted returns, 63/07–01/12												
Raw	1.52	1.28	1.38	1.26	1.26	−0.26	1.35	1.29	1.30	1.24	1.09	−0.26
	5.02	4.37	4.55	4.3	4.43	−2.14	4.71	4.39	4.58	4.2	3.74	−2.35
Adjusted	0.26	0.00	0.02	−0.03	−0.10	−0.36	0.09	−0.02	−0.09	−0.15	−0.18	−0.28
	3.81	0.07	0.34	−0.76	−2.60	−3.8	2.59	−0.55	−1.77	−2.61	−1.80	−2.34
Adjusted returns, alternative sample periods												
27/01–01/12	0.11	−0.01	0.05	−0.02	−0.04	−0.15	0.06	0.00	−0.08	−0.07	−0.12	−0.17
	2.18	−0.26	1.21	−0.59	−1.33	−2.43	2.16	−0.03	−2.19	−1.74	−1.69	−2.18
51/07–01/12	0.21	0.00	−0.01	−0.03	−0.07	−0.28	0.07	−0.02	−0.08	−0.09	−0.13	−0.20
	3.94	−0.05	−0.21	−0.78	−2.29	−3.83	2.57	−0.64	−2.15	−2.05	−1.71	−2.29
74/01–01/12	0.31	0.02	0.01	−0.03	−0.13	−0.44	0.05	−0.05	−0.06	−0.15	−0.30	−0.35
	3.75	0.29	0.10	−0.62	−2.79	−3.8	2.56	−1.13	−0.97	−2.32	−2.62	−2.88
Adjusted returns, alternative concentration measures, 63/07–01/12												
H(Assets)	0.09	0.17	0.01	−0.02	−0.12	−0.20	0.10	−0.03	−0.13	−0.08	−0.16	−0.26
	1.19	2.64	0.39	−0.44	−2.95	−2.12	2.95	−0.75	−2.72	−1.42	−1.49	−2.12
H(Equity)	0.16	0.12	0.05	−0.10	−0.08	−0.24	0.11	−0.09	−0.09	−0.11	−0.16	−0.27
	2.30	2.20	0.95	−2.19	−2.09	−2.52	3.24	−2.16	−1.85	−1.80	−1.54	−2.28
Segment-level	0.18	−0.14	−0.26	−0.44	−0.45	−0.63	0.47	0.09	0.07	−0.20	−0.27	−0.74
H(Sales)	2.54	−1.83	−2.66	−3.83	−2.27	−2.75	2.89	0.94	0.86	−2.56	−3.40	−3.32

to −28 basis points. Together, this suggests that the return premium associated with industry concentration is independent from those of size, book-to-market, and momentum, and that controlling for industry concentration is important for understanding the cross section of stock returns.

In the second set of numbers, we take a number of steps to control for a variety of potential explanations of our results. We extend our results back to 1927 by using an H(Equity) concentration measure constructed from the Davis–Fama–French files. The row reporting results from 1951 to 2001 uses the entire length of the Compustat sample to compute Herfindahl indices, in spite of the fact that only NYSE-listed firms are present until 1963. Data from 1974 to 2001 provide our results for the subsample in which we have Nasdaq-, AMEX-, and NYSE-listed stocks. The concentration spread is robust to each of these specification choices.

The third set of numbers pushes the robustness question further with results from quintiles formed on alternative concentration measures.[6] The concentration premium is robust to using H(Assets) or H(Equity) to form concentration quintiles. The concentration premium also shows up significantly when we use net sales from the Compustat Business Segment file (available 1985 to 2001) to attribute sales of conglomerate firms to their respective industries.

B. Fama–MacBeth Cross-Sectional Regressions

To further examine the relation between industry concentration and average stock returns, we conduct Fama–MacBeth (FM) regressions of monthly stock returns on industry concentration and other characteristics. In Panel A of Table IV, we report regressions of industry portfolio returns regressed on industry characteristics and the H(Sales) measure. The time-series average of each cross-sectional regression loading is reported along with its time-series t-statistic. These regressions provide a robustness check of the relationship between industry concentration and average returns without imposing quintile breakpoints, and they allow us to control for additional alternative explanations.

The first column of Panel A shows that more concentrated industries earn lower average returns, consistent with our previous results from quintile portfolios. The cross-sectional regression coefficient on the H(Sales) index is negative and statistically significant at the 5% level. The next seven rows demonstrate that industry average returns are positively related to industry average book-to-market, leverage and momentum (past 1-year's industry return), negatively associated with industry average size, and insignificantly related to industry average market β.

The last two rows reexamine the industry concentration effect, controlling for the above characteristics. These rows show that taking these variables into

[6] In tables available from the authors, we also replicate our findings on the much smaller sample of observations for which Census of Manufactures definitions of industry concentration are available. In addition, we repeat our findings using the ratio of the sales of the top five firms in an industry to total industry sales (the five-firm ratio).

Table IV

Fama–MacBeth Cross-Sectional Regressions of Industry-Level and Firm-Level Returns

This table presents results from industry-level (Panel A) and firm-level (Panel B) Fama–MacBeth cross-sectional regressions estimated monthly between July 1963 and December 2001. In Panel A, industry average returns are regressed on industry H(Sales) measure, industry average values of ln(Size), ln(B/M), Leverage, Beta, and the past 1-year return on the industry portfolio (Momentum). In Panel B, individual stock returns are regressed on H(Sales) value of the industry to which each stock belongs, firm-level ln(Size), ln(B/M), Leverage, Beta, and the past 1-year stock return (Momentum). Time-series average values of the monthly regression coefficients are reported with time-series *t*-statistics appearing below.

H(Sales)	ln(Size)	ln(B/M)	Momentum	Beta	Leverage
		Panel A: Industry-Level Regressions			
−0.30					
−2.41					
	−0.12				
	−1.54				
		0.39			
		4.16			
			1.03		
			4.21		
				−0.18	
				−0.43	
					0.98
					2.96
	−0.24	0.28	0.95	−0.95	0.08
	−2.81	2.77	4.40	−2.56	0.24
−0.30	−0.12	0.29	0.90		
−2.58	−1.57	3.07	3.93		
−0.31	−0.25	0.27	0.94	−1.00	0.04
−2.85	−2.98	2.68	4.36	−2.73	0.12
		Panel B: Firm-Level Regressions			
−0.35					
−2.41					
	−0.14	0.35	0.56		
	−2.62	4.55	3.34		
−0.44	−0.14	0.35	0.55		
−3.75	−2.63	4.62	3.32		
				0.26	
				0.90	
					0.76
					2.81
	−0.18	0.38	0.60	−0.39	−0.30
	−3.78	6.41	3.81	−1.87	−1.56
−0.42	−0.18	0.39	0.59	−0.41	−0.33
−3.42	−3.81	6.62	3.78	−1.95	−1.70

account does not destroy the significance of the industry concentration effect. By including leverage in our regressions, we control for another possible explanation for our findings, namely, that competitive industries have higher leverage, thereby raising the required return on equity mechanically. In the univariate

FM regression, leverage works in the predicted direction, but controlling for other characteristics weakens leverage.

Thus, while the results of Table I suggest that industry concentration is correlated with other industry characteristics that describe average returns, the results from the top of Table IV suggest that those correlations are not the driving forces behind the inverse relationship between industry concentration and average stock returns.

Panel B of Table IV repeats the analysis described above, but replaces industry portfolio returns with firm-level stock returns and replaces industry characteristics with firm-level measures of size, book-to-market, leverage, and market β. These results mirror those obtained in the industry portfolio regressions. FM regressions of individual stock returns on the Herfindahl index alone produce an average slope coefficient of -0.35% with a t-statistic of -2.41. Accounting for the premia associated with known return predictors strengthens these results. Introducing size, book-to-market, past 1-year return, leverage and market β to the cross-sectional regressions raises both the point estimates and the t-statistics for industry concentration.

The conclusion that emerges from this section is that not only do industry returns vary with industry concentration, but so do individual stock returns: Firms in concentrated industries earn lower stock returns than firms in more competitive industries. The results hold under a variety of different empirical strategies, and are robust to whether or not we control for characteristics such as size, book-to-market ratio, and past returns, both at the firm and industry levels. These controls suggest that the industry concentration effect that we identify is not being driven by correlations with other determinants of expected returns, or through capital structure choice.

IV. Industry Concentration and Profitability Surprises

The preceding analysis demonstrates a statistically reliable and economically meaningful link between market structure and average stock returns. However, from a standard Campbell and Shiller (1988) decomposition we know that returns must, by their very definition, equal the sum of expected returns, shocks to cash flows, and shocks to discount rates. Thus, persistent differences in cash flow surprises across industries with different market structures could be responsible for our findings.

This section explores this issue. If differences in average returns across concentration quintiles are due to persistent in-sample cash flow shocks that need not persist in the future, then while industry concentration may happen to explain average returns during the period of our analysis, concentration would still be unrelated to true expected returns.

We extend the Fama and French (2000) profitability model by adding lagged profitability, following Vuolteenaho (2002). Specifically, we are interested in models of the form

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_t}{A_t} + \alpha_2 DD_t + \alpha_3 \frac{D_t}{B_t} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \varepsilon_t, \tag{3}$$

where E/A is earnings scaled by total assets, V/A is the ratio of market value of assets to book assets, DD is a dummy variable for non-dividend-paying firms, and D/B is the ratio of dividend payments to book equity. Expected profitability is the fitted value from this regression, and unexpected profitability is regression error. To estimate this model, we follow Fama and French (2000), and estimate cross-sectional regressions each year.

Panel A of Table V presents average coefficients from the cross-sectional regressions for three profitability specifications. The first row, labeled "Firm-Level," reports FM regressions of firm-level profitability on firm-level characteristics. The row labelled "Industry Total" computes a single-earnings measure for each industry, scales this by total industry assets, and then regresses it on the four independent variables that are constructed similarly. Finally, the row labeled "Industry Average" reports regressions of the industry average profitability on industry average values of the variables described above.

Our numbers closely match those reported in Fama and French (2000). Specifically, we obtain statistically positive loadings on D/B and statistically negative loadings on the dividend dummy. Profitability loads positively and significantly on V/A, suggesting that V/A captures differences across firms in expected profitability that are missed by the two dividend variables. Our regression R^2 values, ranging from 42% to 50%, are about twice as high as those reported in Fama and French (2000), due largely to the inclusion of lagged profitability as suggested in Vuolteenaho (2002).

In the rest of Table V we take the regression errors from Panel A and relate them to industry concentration. We do this for two measures of unexpected profitability. The variable UP_t is the in-sample regression error from the FM regression reported in Panel A. The variable UP_{t+1} is the one-period-ahead regression error: This is the error obtained by using the FM coefficients from a regression in year $t-1$ to forecast the profitability in year t, and treating this forecast error as unexpected profitability.

In Panel B, Quintiles 1 to 5 report the average unexpected profitability by concentration quintile. As in previous tables, Quintile 1 is the least concentrated and Quintile 5 the most concentrated quintile. If our results were driven by cash flow shocks, then we should expect to see large positive average profitability shocks for Quintile 1 and large negative shocks for Quintile 5.

Instead, we see the opposite. Concentrated industries have experienced better-than-expected profitability over the 1963 to 2001 period, while competitive industries have experienced poorer-than-expected profitability. Unexpected profitability is increasing as we move toward more concentrated quintiles. With firm-level UP_t and UP_{t+1}, and with industry-level UP_t measures, we can reject the null hypothesis that profitability is the same across all five concentration quintiles.

In the far-right column of Panel B, labeled "FM," we report FM regressions of UP on industry concentration. These results mirror the findings obtained by quintile breakdowns. In all but one specification, there is a statistically positive relation between unexpected profitability and industry concentration. In one case (industry average UP_{t+1}) we cannot reject the null of zero correlation;

Table V
Industry Concentration and Profitability Surprises

This table examines the relation between profitability surprises and industry concentration. Firm-level E/A is firm-level earnings to assets. Industry total (E/A) is the total earnings in the industry divided by total assets of the industry. Industry average E/A is the industry average earnings-to-assets ratio. Expected profitability is obtained from Fama–MacBeth regressions of the form

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_t}{A_t} + \alpha_2 DD_t + \alpha_3 \frac{D_t}{B_t} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \varepsilon_t,$$

following Fama and French (2000) and Vuolteenaho (2002). Unexpected profitability is the regression error from this regression. In Panel B, we group industries according to concentration quintiles and report average unexpected profitability. The variable UP_t is the unexpected profitability from in-sample regressions, while UP_{t+1} is the regression error obtained by predicting next year's profitability using next year's regressors but parameter values obtained from year t. The two "Tests" columns report the F-statistic for the joint equality of Quintiles 1 through 5, as well as the t-statistic for the equality of Quintiles 1 and 5. The final column reports the Fama–MacBeth coefficient from a regression of unexpected profitability on the H(Sales) index.

Panel A: Expected Profitability Regressions

Profitability Measure	α_0	V/A	DD	D/B	ROA_{t-1}	Avg. R^2
Firm-level E/A	0.0187	0.0120	−0.0164	0.0679	0.5341	0.4267
	11.91	7.46	−8.19	7.12	34.38	
Industry total E/A	0.0089	0.0136	−0.0027	0.0890	0.5684	0.5099
	5.69	9.53	−0.69	5.13	25.95	
Industry average E/A	0.0196	0.0139	−0.0132	0.0801	0.5130	0.4600
	10.69	7.34	−6.02	4.05	27.88	

Panel B: Unexpected Profitability by Concentration Quintile

	Quintiles					Tests		
Profitability:	1	2	3	4	5	$F\ (1 = 2 = 3 = 4 = 5)$	$t\ (1 = 5)$	FM
Firm-level								
UP_t	−0.0017	0.0014	0.0041	0.0025	0.0023	5.95	3.07	0.0101
	−4.14	2.45	3.96	2.90	1.88	0.0002	0.0036	4.49
UP_{t+1}	−0.0043	−0.0013	0.0029	0.0024	0.0002	2.81	1.65	0.0124
	−1.98	−0.76	1.97	1.47	0.14	0.0268	0.1035	2.85
Industry total								
UP_t	−0.0013	−0.0007	0.0007	0.0004	0.0025	3.06	2.58	0.0043
	−2.48	−1.25	1.06	0.49	1.81	0.0179	0.0131	2.66
UP_{t+1}	−0.0015	−0.0014	0.0004	−0.0008	0.0014	0.65	1.27	0.0038
	−1.07	−0.83	0.30	−0.61	0.77	0.6268	0.2065	2.01
Industry average								
UP_t	−0.0018	0.0002	0.0015	−0.0004	0.0013	2.95	2.31	0.0031
	−3.70	0.32	2.10	−0.60	1.05	0.0214	0.0254	2.21
UP_{t+1}	−0.0030	−0.0005	0.0001	−0.0015	0.0007	1.08	1.79	0.0026
	−2.19	−0.39	0.04	−1.16	0.47	0.3699	0.0773	1.36

however, we never see results going in the direction that would be required to support cash flow shocks as an explanation for our findings. In short, differences in unexpected profitability cannot explain our findings. In fact, since the shocks go in the opposite direction of the return spread, this suggests that the true spread in expected returns is more pronounced than the spread that we observe in the data.

V. Concentration and Time-Series Variation in Returns

A. Time-Series Variation of the Industry Concentration Premium

This subsection links changes in the concentration premium to various risk factors and business cycle indicators. This allows us to examine the question of whether the concentration premium remains significant after taking existing risk factors into account, and also whether it exhibits variation over the business cycle that is consistent with the risk-based explanations we argue are responsible for its existence.

In Table VI, we report results from the following time-series regressions of monthly concentration premia on risk factors and economic indicators:

$$\lambda_t^H = \alpha + \sum_{i=1}^{I} \beta_i F_{it} + \sum_{j=1}^{J} \gamma_j X_{jt} + \varepsilon_t, \tag{4}$$

where F_{it} are returns to factor-mimicking portfolios in month t, and X_{jt} are month-t values of the business cycle indicators. The dependent variable, λ_t^H, is the time series of H(Sales) risk premia generated from the FM regressions reported in Panel B of Table IV, in which the cross section of individual stock returns is regressed on industry concentration, controlling for other characteristics.

In the first row, the monthly concentration premium is regressed against the market excess return. The next row adds the factor-mimicking portfolios associated with the size effect (SMB) and book-to-market effect (HML). The following row adds a momentum factor-mimicking portfolio to the Fama–French factors as in Carhart (1997) to estimate a four-factor model. As the table indicates, the regression intercepts are both economically and statistically significant in the presence of various risk factors. The H(Sales) premium drops slightly (in absolute value) from −42 basis points (Table IV, Panel B, last row) to −40 per month when regressed on the market excess return. The adjusted R^2 from this regression is close to zero. Controlling for the Fama and French (1993) factors actually increases the premium to −0.46%, whereas the R^2 goes up to 16.1%. Adding the momentum factor decreases the premium to −0.33% (still significant), and there is a slight increase in the R^2 to 19%.

These three sets of regressions show that the concentration premium cannot be explained by known risk factors, which reinforces the finding in Section III that industry concentration contains independent information about the cross section of average returns.

Table VI

Time-Series Variation of the Concentration Premium

This table presents results from time-series regressions of the H(Sales) premium on various asset pricing factors and business cycle indicators. The H(Sales) premium is obtained from monthly Fama–MacBeth cross-sectional regressions of stock returns on industry H(Sales) index, controlling for other characteristics (see the last row of Table IV, Panel B). RMRF is the market excess return. SMB and HML are size and B/M factor-mimicking returns (see Fama and French (1993) for description). MOM is the momentum factor as in Carhart (1997). The factor data come from Ken French's website. INF is the monthly rate of inflation, obtained from the St. Louis Federal Reserve Economic Database (FRED). Term is the term spread, the difference between 10-year and 1-year treasury constant maturity rates. T-bill is the 30-day T-bill rate. g_t and g_{t+1} are the current and next four quarters' growth rates in GDP, also obtained from FRED. Alpha is the intercept from time-series regression. t-statistics are reported below parameter estimates.

Alpha	RMRF	SMB	HML	MOM	INF	Term	T-Bill	g_t	g_{t+1}	Adj. R^2
−0.40	−0.049									0.0072
−3.87	−1.99									
−0.46	0.0416	−0.2171	0.1729							0.1608
−4.27	1.32	−3.13	2.74							
−0.33	0.0341	−0.217	0.1225	−0.1129						0.1904
−3.4	1.14	−3.41	2.49	−2.83						
−1.02					1.44					0.0263
−4.37					3.75					
−0.59						−0.9313				0.0406
−4.49						−4.56				
−1.08							0.1011			0.0106
−4.16							3.27			
−2.02								0.0661	0.1324	0.0449
−3.79								0.71	3.15	
−0.84	0.0435	−0.2149	0.1202	−0.1118	1.2163					0.2086
−4.43	1.45	−3.46	2.48	−2.85	3.53					
−0.49	0.042	−0.2253	0.1078	−0.1118		−0.8871				0.227
−4.33	1.44	−3.63	2.3	−2.89		−4.82				
−0.90	0.0403	−0.216	0.1219	−0.1135			0.0877			0.1981
−3.63	1.35	−3.41	2.49	−2.86			2.61			
−2.04	0.0374	−0.2348	0.1069	−0.1106				0.1109	0.1358	0.2419
−5.33	1.27	−3.89	2.38	−3.02				1.15	4.47	
−0.50	0.0435	−0.2239	0.1081	−0.1111	0.6036	−0.8156	−0.0349			0.2263
2.47	1.48	−3.64	2.31	−2.89	1.55	−3.82	−0.88			
−2.36	0.0426	−0.2325	0.1064	−0.1108	0.2096	−0.0303	0.0576	0.0775	0.1282	0.2433
−3.36	1.45	−3.85	2.34	−3.01	0.54	−0.1	1.19	0.77	2.87	

In the next three rows we regress the concentration premium on the inflation rate, term spread, and T-bill rate. Inflation is measured by the growth rate of the consumer price index (CPI). The term spread is the difference between 10-year and 1-year treasury constant maturity rates. These variables are obtained from the Federal Reserve Bank of St. Louis, and are shown elsewhere in the literature to track business cycle fluctuations (see, e.g., Fama and French (1989)). The results indicate that the H(Sales) premium carries positive and statistically significant loadings on the inflation rate and the T-bill rate. Since the H(Sales) premium has a negative mean value, this means that the concentration premium grows (in absolute value) as the business cycle declines, since both the inflation rate and the T-bill rate rise during economic expansion and fall during economic contraction. The concentration premium also loads negatively on the term spread. Since the term spread tends to decrease as the business cycle moves from trough to peak, this finding is consistent with the loadings on the inflation rate and the T-bill rate, which indicates that the concentration premium diminishes as the economy takes an upturn. This is again consistent with a risk interpretation: The spread in returns between firms that are insulated from economic distress and those that are not grows as economic conditions deteriorate.[7]

In addition to examining inflation, the T-bill rate, and the term premium, we also include current and future GDP growth rates to directly examine the relation between the concentration premium and economic activities. The variable g_t is the current quarterly GDP growth rate, while g_{t+1} is the GDP growth rate over the next four quarters. There is a positive correlation with current GDP growth, but this correlation is not statistically significant. There is a much larger, and highly significant, correlation with GDP growth over the next year. This is in line with the result that short-horizon stock returns contain forward-looking information about the strength of economic activities over many future periods (see, e.g., Fama (1990), Kothari and Shanken (1992)). This supports a risk-based interpretation of the industry concentration effect, since it indicates that the magnitude of the concentration premium grows as the economic outlook deteriorates. Replacing GDP growth with industry production growth produces qualitatively similar, but slightly weaker, results.

In the remaining rows of this table, we regress the concentration premium on risk factors and business cycle indicators. Controlling for business cycle movement in addition to factor returns raises the regression intercept and R^2, but weakens the loading on the inflation rate, the term spread, and the T-bill rate. The loading on 1-year-ahead GDP growth remains highly significant. Nevertheless, the message remains largely unaltered: The premium associated with industry concentration is not spanned by existing factors and it exhibits sensible business cycle variation. The fact that the concentration premium grows during downturns, when economic distress is relatively greater, speaks in favor of the hypothesis that industry concentration is a mechanism through which aggregate shocks are propagated through the equity market.[8]

In an efficient market in which assets are priced rationally, industry concentration must proxy for sensitivity to a systematic risk factor in stock returns.

[7] The predictive power of these business cycle variables for the concentration premium is low. At most they explain 4% of the total variation in monthly concentration premium. However, this is not unusual given previous studies (e.g., Fama and French (1989), Lewellen (1999)), which show that ex ante instruments can only account for a small portion of the time-series variation in monthly stock returns.

[8] In unreported tables, we also include cash flow and discount rate news factors from Campbell and Vuolteenaho (2004). The concentration premium loads on them in a manner that is consistent with the interpretation offered above.

In unreported tables, we follow the logic offered in Fama and French (1993) and employ time-series regressions to explore this question. We find that a mimicking concentration factor captures substantial common variation in stock returns that is left unexplained by existing asset pricing factors. In addition, spread in returns across concentration portfolios is related to the spread in loadings on the concentration factor. Moreover, while existing factor models fail to price these concentration portfolios, including the concentration mimicking factor completely explains the industry concentration effect in average returns. The regression intercepts are all within 10 basis points of 0 and a Gibbons–Ross–Shanken (1989) test cannot reject the null that the constant terms are jointly 0.

B. Can the Concentration Premium Explain Existing Factors?

Since we show in Table VI that the concentration premium is not spanned by existing asset pricing factors, we now turn the tables and examine how much of existing asset pricing factors can be explained by the concentration premium. This is presented in Table VII, where we report time-series regressions of existing asset pricing factors on the conditional H(Sales) premium.

First we regress returns from a number of factor-mimicking portfolios on the conditional H(Sales) premium. This is presented in Panel A of Table VII. The first column, labeled "Mean," reports the unconditional mean of the mimicking factor returns over the 1963 to 2001 period. The remaining three columns report the conditional mean, the loading on the conditional H(Sales) premium, and the regression R^2.

The first row examines the excess market return. The unconditional mean of the excess market return is 47 basis points per month in our sample, but this drops to a statistically insignificant 36 basis points when we account for comovement with the H(Sales) premium. The regression R^2, however, reveals that very little of the variation in the market premium is explained by the concentration premium.

The concentration premium does a better job explaining the size factor, SMB. The size factor loads negatively and highly negatively significantly on the conditional H(Sales) premium, leaving a constant term that is statistically zero. The adjusted R^2 indicates that we explain 13% of the variation in the size premium with the conditional H(Sales) premium. This is only a modest success, however, as the unconditional size premium is a statistically insignificant 21 basis points in our sample.

The concentration premium does less well at explaining the book-to-market and momentum factors. The momentum factor does not load statistically significantly on the concentration premium, and its conditional mean is only slightly different from its unconditional mean.

Interestingly, controlling for the concentration premium actually strengthens the book-to-market factor. HML loads significantly positively on the conditional H(Sales) premium, and the concentration premium explains 12% of the variation in HML. But the mean of HML increases from 42 basis points per

Table VII

Can the Concentration Premium Explain Existing Factors?

This table reports results from time-series regressions of mimicking portfolio returns and cross-sectional premia of asset-pricing factors on the conditional H(Sales) premium. In Panel A, the dependent variables are factor mimicking returns obtained from Ken French's website. RMRF is the market excess return. SMB and HML are size and B/M factor mimicking returns (see Fama and French (1993) for description). MOM is the momentum factor as in Carhart (1997). In Panel B, the dependent variables are cross-sectional premia obtained from monthly Fama–MacBeth regressions of stock returns on ln(Size), ln(B/M), and Momentum. The column labeled "Mean" is the average value of the factor mimicking return or premium. Alpha is the regression intercept from regressing factor return/premium on H(Sales) Premium. The column labeled "H(Sales) Premium" reports the loading of the factor/premium on H(Sales) premium. The final column reports the adjusted R^2 of the regression. Point estimates are reported with t-statistics appearing below.

LHS	Mean	Alpha	H(Sales) Premium	Adj. R^2
	Panel A: Explaining Factor Returns			
RMRF	0.47	0.36	−0.2827	0.02
	2.26	1.66	−3.31	
SMB	0.21	0.00	−0.5055	0.13
	1.35	0.00	−4.56	
HML	0.42	0.59	0.4410	0.12
	2.98	4.31	6.23	
MOM	0.87	0.82	−0.1430	0.01
	4.75	4.69	−0.82	
	Panel B: Explaining Cross-Sectional Factor Premia			
Size premium	−0.13	−0.09	0.1194	0.07
	−2.65	−1.77	3.38	
B/M premium	0.35	0.44	0.2331	0.13
	4.83	6.48	5.41	
Momentum premium	0.56	0.58	0.0400	0.00
	3.54	3.81	0.42	

month unconditionally to 59 basis points per month conditionally. This conditional mean HML value is highly statistically significant (and different from the unconditional value).

In Panel B of Table VII we replace the asset pricing factors with the factor premia obtained from cross-sectional FM regressions. We focus on size, book-to-market, and a firm's lagged 1-year return. The results largely mirror those obtained in Panel A; namely, the size premium disappears, the momentum premium remains unexplained, and book-to-market premium increases. This points to an interesting interaction between concentration and the book-to-market premium, which we take up in more detail in the next section.

VI. Value, Growth, and Industry Concentration

Based on the fact that the book-to-market premium grows in magnitude when we control for industry concentration, we turn next to FM regressions that explore the interaction of book-to-market and concentration. These are presented in Panel A of Table VIII. Returns are at the firm level (as in Panel B of Table IV) and the final column is an interaction term between industry concentration and firm-level book-to-market. The coefficient on the interaction term is positive and statistically significant, suggesting that the premium associated with being a high book-to-market firm grows as industry concentration increases.

To get a sense of the economic magnitude involved here, next we examine returns to book-to-market portfolios for different levels of industry concentration in a five-by-five grid. At the end of June of each year, we sort industries into concentration quintiles according to their concentration (H(Sales)) value. Then within each industry, we calculate quintile breakpoints for book-to-market and place firms into five portfolios.[9] Finally, within each concentration group, we pool firms with the same book-to-market ranking into one portfolio and calculate the average returns from July to June of the following year. Our sorting approach also guarantees that one industry with particularly large variation in book-to-market does not dominate the tail portfolios of the five-by-five grid; instead, there is equal representation across industries in each book-to-market quintile. Panel B of Table VIII reports the average value-weighted monthly returns of the five book-to-market portfolios as well as the difference in returns between Quintile 5 and Quintile 1 for each H(Sales) group; Panel C reports equally weighted returns. Each row demonstrates the prevalence of the book-to-market effect within each concentration group.

As the table indicates, the spread in returns associated with the book-to-market ratio is largest among the most concentrated industries. For example, high book-to-market stocks outperform low book-to-market stocks by 47 basis points per month in the lowest Herfindahl quintile, and this number grows to 76 basis points per month for the highest Herfindahl quintile. These double-sorted portfolio results reinforce the findings from the cross-sectional regressions, which show that the book-to-market premium grows as industry concentration increases.

These double-sort portfolios yield insights into the relations among market structure, value, and growth. Prior research examines the book-to-market ratio as a risk proxy related to relative profitability or distress and yields mixed results.[10] Our results suggest an explanation for these mixed results: Firms with the same level of book-to-market are fundamentally different from one another depending on the market structure of the industry in which they operate. A low book-to-market firm in a concentrated industry is not well described as a "growth firm." This firm operates in an industry with a large asset base, high

[9] Using within-industry breakpoints addresses the fact that the cross-industry variation in the book-to-market ratio is not important for average stock returns; instead, most of the effect is the result of within-industry variation (Asness and Stevens (1996), Cohen, Polk, and Vuolteenaho (2003)).

[10] For evidence on the link between book-to-market and distress, see Fama and French (1995), Chen and Zhang (1998), Liew and Vassalou (2000), Shumway (1996), or Griffin and Lemmon (2002). For recent papers linking book-to-market to investment and costly reversibility, see Zhang (2005) and Cooper (2006).

Table VIII

Interaction between Industry Concentration and Book-to-Market Effects

Panel A presents results from monthly Fama–MacBeth cross-sectional regressions of individual stock returns on ln(Size), ln(B/M), Momentum, Beta, Leverage, H(Sales), and an interaction term between H(Sales) and ln(B/M). Time-series averages of the monthly regression coefficients, in percent, are reported with time-series t-statistics below. Panels B and C report value-weighted (Panel B) and equal-weighted (Panel C) average returns of B/M quintile portfolios, their t-statistics, and the difference in returns between Quintile 5 and Quintile 1 within each concentration quintile. Two-digit SIC Industries are first sorted into concentration quintiles based on their H(Sales) value. Firms within each industry are then sorted into quintiles based on their B/M. Finally, firms with the same B/M ranking from industries within the same concentration quintile are grouped into one portfolio to create the 5 × 5 double-sorted portfolios on H(Sales) and B/M. The row entitled "All" reports average returns of B/M quintiles formed across concentration quintiles.

Panel A: Fama–MacBeth Cross-Sectional Regressions

ln(Size)	ln(B/M)	Momentum	Beta	Leverage	H(Sales)	H(Sales) × ln(B/M)
−0.19	0.29	0.59	−0.41	−0.32	−0.37	0.25
−3.82	3.76	3.78	−1.99	−1.65	−3.14	2.38

H(Sales)	B/M Quintiles					
Quintiles	1 (Low)	2	3	4	5 (High)	5 − 1 Spread
Panel B: Value-Weighted Average Returns of H(Sales) and B/M Sorted Portfolios						
1 (Low)	1.11	1.26	1.24	1.42	1.58	0.47
	4.01	5.13	4.45	5.22	4.49	2.11
2	0.84	1.08	1.26	1.51	1.45	0.61
	3.23	4.33	4.93	5.95	5.23	2.80
3	0.98	1.04	1.13	1.32	1.64	0.65
	3.52	3.78	4.31	4.77	5.87	2.59
4	0.74	0.99	1.21	1.21	1.45	0.71
	2.85	3.93	5.27	4.74	5.07	3.35
5 (High)	0.62	1.03	1.05	1.33	1.38	0.76
	1.93	3.02	3.22	5.28	3.75	2.11
All	0.85	1.03	1.13	1.32	1.50	0.66
	3.31	4.65	5.11	5.73	5.78	3.19
Panel C: Equally Weighted Average Returns of H(Sales) and B/M Sorted Portfolios						
1 (Low)	0.81	1.34	1.31	1.61	1.83	1.02
	2.58	4.18	4.61	5.62	5.98	6.84
2	0.78	1.07	1.40	1.54	1.81	1.03
	2.47	3.80	5.07	5.64	6.28	6.99
3	0.70	0.99	1.34	1.56	1.82	1.13
	2.09	3.24	4.53	5.43	5.92	6.49
4	0.68	1.02	1.30	1.33	1.85	1.17
	1.89	3.40	4.41	4.50	5.91	4.70
5 (High)	0.15	0.97	1.10	1.17	1.59	1.43
	0.32	2.41	3.18	3.28	4.11	3.36
All	0.76	1.15	1.36	1.56	1.81	1.05
	2.47	3.97	4.92	5.68	6.22	8.12

unit profitability, and low R&D, and subsequently has high capitalized future profitability. Its book-to-market is low not because its growth prospects are high, but because its current and expected future profitability is high. High profitability, low-risk firms are thus being labeled growth firms, pulling down the average returns of low book-to-market stocks.

On the other hand, a low book-to-market stock in a competitive industry is indeed better characterized as a growth firm. These firms engage in more R&D on average and are less profitable, and thus the low market-to-book is not a reflection of high capitalized profitability, but rather of expected growth. Growth is risky, and this shows up in higher expected returns.

If we interpret book-to-market as a proxy for distress, then these findings help us to distinguish between the creative destruction and barriers-to-entry hypotheses offered in Section I. These findings favor the innovation risk interpretation, since the spreads in industry concentration are largest in the portion of the book-to-market spectrum where growth is most salient. Among high book-to-market firms, for which it is often argued that distress is more salient, we see a smaller spread in returns across concentration quintiles.

VII. Conclusion

What are the economic determinants of the cross section of stock returns? This is one of the fundamental questions in empirical asset pricing, and is especially important given the large body of recent research documenting return predictability based on a host of empirically motivated financial characteristics. We address this question from a new perspective, offering evidence that industry concentration—a feature of the product markets in which firms operate—is important for understanding stock returns.

Our main thesis is simple. We argue that the structure of product markets helps to determine a firm's risk by affecting the equilibrium operating decisions it makes. In particular, drawing on classic work in industrial organization from Schumpeter (1912) and Bain (1954), we link industry concentration to stock returns through innovation and distress risk. Industries in which innovation risk and distress risk are higher should command higher expected returns. Our analysis indicates that these are competitive industries.

We show that firms in competitive industries earn higher stock returns, even after controlling for the usual suspects that affect the cross section of average returns, such as size, book-to-market, and momentum. This holds both at the industry level and the firm level and is robust to alternative empirical specifications. Moreover, this result is not explained by differences in unexpected returns, and it has been a persistent feature of stock returns since the Great Depression.

These results suggest a number of fruitful areas for future research. First and foremost, our empirical evidence suggests a need for asset pricing models that explicitly incorporate features of product markets as determinants of asset returns. A more rigorous theory of why asset prices are affected by market structure will allow for a more careful exploration of the link that we demonstrate to be important in this paper.

Second, we argue in this paper that either innovation or distress risk is a likely culprit for the concentration premium. Our preliminary findings support an innovation risk interpretation, but clearly more work is needed to disentangle these potentially overlapping hypotheses. We find that the concentration spread in returns is larger for low book-to-market stocks than high book-to-market stocks. One interpretation is that low book-to-market stocks in concentrated industries have low returns because they have high capitalized future profitability and engage in less innovation, while low book-to-market stocks in less concentrated industries have higher returns because they engage in more innovative activity and thus have higher expected growth rates. This suggests that the links among value, growth, and product market structure are important questions for future work.

Finally, this paper primarily focuses on the unconditional roles played by industry characteristics for understanding the equilibrium trade-off between risk and return. However, much of the recent literature in empirical asset pricing uses industry membership as conditioning information, and explores whether certain asset pricing phenomena are attributable to industry effects. A better understanding of how industry characteristics affect expected returns can potentially yield insights into why many stylized facts about stock returns seem to contain important industry components.

We focus on risk-based explanations for the concentration premium. Of course, the alternative is that some behavioral bias causes investors to undervalue firms in less concentrated industries, producing high returns ex post. However, any behavioral explanation must stand up to a series of facts. The concentration premium exhibits sensible business cycle variation, growing in magnitude as expected future growth opportunities deteriorate. Moreover, there is substantial common variation in stock returns that is related to industry concentration.

The findings in this paper ultimately raise more questions than they answer. Are there other mechanisms through which market structure affects stock returns? Does the link between market structure and stock returns impact firms' investment and financing decisions? How does it impact the diffusion of information in the market? Is the geographic scope of the industry (national vs. local product markets) important? The story we propose in this paper is a reduced-form version of a more complicated analysis in which product markets affect investment opportunities and decisions about investment and capital structure. Ultimately, a better understanding of the precise mechanisms that link these phenomena is required. We leave these issues for future work.

REFERENCES

Almazan, Andres, and Carlos Molino, 2001, Intra-industry capital structure dispersion, Working paper, University of Texas.

Asness, Clifford, and Ross Stevens, 1996, Intra-industry and inter-industry factors in the cross-section of expected stock returns, Working paper, Goldman Sachs Asset Management.

Bain, Joe, 1954, Economies of scale, concentration and the condition of entry in twenty manufacturing industries, *American Economic Review* 44, 15–39.

Barclay, Michael J., and Clifford W. Smith, 1995, The maturity structure of corporate debt, *Journal of Finance* 50, 609–631.

Campbell, John Y., and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Good beta, bad beta, *American Economic Review* 94, 1249–1279.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chen, Nai-Fu, and Feng Zhang, 1998, Risk and returns of value stocks, *Journal of Business* 71, 501–535.

Cohen, Randolph, Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Cooper, Ilan, 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility, *Journal of Finance* 61, 139–170.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristics-based benchmarks, *Journal of Finance* 52, 1035–1058.

Davis, Jim, Eugene F. Fama, and Kenneth French, 2000, Characteristics, covariances, and average returns: 1929–1997, *Journal of Finance* 55, 389–406.

Fama, Eugene F., 1990, Stock returns, expected returns, and real activity, *Journal of Finance* 45, 1089–1108.

Fama, Eugene F., 1998, Determining the number of priced state vectors in the ICAPM, *Journal of Financial and Quantitative Analysis* 33, 217–231.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Fama, Eugene F., and Kenneth R. French, 1992. The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns of bonds and stocks, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–155.

Fama, Eugene F., and Kenneth R. French, 2000, Forecasting profitability and earnings, *Journal of Business* 73, 161–175.

Fama, Eugene F., and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Geroski, P. A., 1990, Innovation, technological opportunity, and market structure, *Oxford Economic Papers* 42, 586–602.

Gibbons, Michael R., Steven A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Griffin, John, and Michael Lemmon, 2002, Book-to-market equity, distress risk, and stock returns, *Journal of Finance* 57, 2317–2336.

He, Kathy, Randall Mørck, and Bernard Yeung, 2003, Corporate stability and economic growth, Working paper, University of Alberta.

Hou, Kewei, 2003, Industry information diffusion and the lead-lag effect in stock returns, Working paper, Ohio State University.

Kahle, Kathleen M., and Ralph A. Walkling, 1996, The impact of industry classifications on financial research, *Journal of Financial and Quantitative Analysis* 31, 309–335.

Knott, Anne Marie, and Hart Posen, 2003, Does competition increase innovation? New evidence from old industries, Working paper, Mack Center for Technological Innovation.

Kothari, S.P., and Jay Shanken, 1992, Stock return variation and expected dividends: A time-series and cross-sectional analysis, *Journal of Financial Economics* 31, 177–210.

Lewellen, Jonathan, 1999, The time-series relations among expected return, risk, and book-to-market, *Journal of Financial Economics* 54, 5–43.

Liew, Jimmy, and Maria Vassalou, 2000, Can book-to-market, size and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57, 221–245.

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

Merton, Robert C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 127–147.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum? *Journal of Finance* 54, 1249–1290.

Reinganum, Jennifer, 1985, Innovation and industry evolution, *Quarterly Journal of Economics* 100, 81–99.

Ross, Steven A., 1976, The arbitrage theory of asset pricing, *Journal of Economic Theory* 13, 341–360.

Salop, Steven C., 1979, Strategic entry deterrence, *American Economic Review* 69, 335–338.

Schmalensee, Richard, 1978, Entry deterrence in the ready-to-eat breakfast cereal industry, *The Bell Journal of Economics* 9, 305–327.

Schmalensee, Richard, 1981, Economies of scale and barriers to entry, *Journal of Political Economy* 89, 1228–1238.

Schumpeter, Joseph, 1912, *The Theory of Economic Development* (Harvard University Press, Cambridge, Mass).

Schumpeter, Joseph, 1942, *Capitalism, Socialism, and Democracy* (Harper & Row, New York and London).

Shumway, Tyler, 1996, Size, overreaction, and book-to-market effect as default premia, working paper, University of Michigan.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Sutton, John, 1991, *Sunk Cost and Market Structure: Price Competition, Advertising, and the Evolution of Concentration* (MIT Press, Cambridge).

Sutton, John, 1998, *Technology and Market Structure: Theory and History* (MIT Press, Cambridge).

Titman, Sheridan, 1984, The effects of capital structure and a firm's liquidation decision, *Journal of Financial Economics* 13, 137–151.

Vuolteenaho, Tuomo, 2002, What drives firm level stock returns? *Journal of Finance* 57, 233–264.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.