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Real and Financial Industry Booms and Busts

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ABSTRACT

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ABSTRACT

We examine how industry valuation and product market competition affect firm cash flows and stock returns. In competitive industries we find that operating cash flows and stock returns decrease with industry-level stock-market valuation, investment and new financing. We find weak and generally insignificant results in concentrated industries. In competitive industries, firms in the most highly valued industry quintile have abnormal stock returns that are four percentage points lower than those in the least valuable industry quintile. Overall our results are consistent with a small probability of a new era of very high subsequent growth, or high competition among firms that affects both industry cash flows and stock prices in competitive industries.

I Introduction

The fact that industries go through cycles of very high valuations is well known. These high valuations are commonly written about as the start of a "new era" in which productivity increases and new products justify very high stock-prices.[1] These high valuations frequently are accompanied by very high investment when firms perceive the returns to investment to be high relative to their cost of capital. However, there also exists the perception that industries commonly go through periods of over investment followed by subsequent low returns to investment. These periods of very high investment followed by low returns have been seen most recently in the telecommunications industry. From 1997 to 2002 investors added $880 billion to this industry. Subsequently over one-half of this investment has been lost according to Thomson Financial in New York, with at least 63 telecommunications firms going bankrupt.

This phenomenon of very high investment followed by low subsequent investment is not just present in the recent internet boom. Other industries such as the Winchester disk drive industry and the early railroad industry have also experienced this pattern. Sahlmon and Stevenson (1987) note that in mid-1983 the Winchester disk drive industry had a market capitalization of 5.4 Billion but by years end, industry value fell to 1.4 Billion as net income fell by 98 percent. Extensive miles of track were laid (including spurs to future towns not yet built) by firms in the railroad industry only to be followed by extensive bankruptcies in the late 1870s.[2]

Our paper examines real and financial outcomes following industry booms, and the extent that these outcomes are related to industry-level competition. We document the existence of frequent and significant booms and busts in the economy and examine how these booms and busts, along with industry investment and financing, impact subsequent industry cash flows and stock returns in competitive and concentrated industries. We ask whether the factors that predict changes in operating performance and stock returns differ for competitive or concentrated industries and for industries that decrease in concentration.

In competitive industries, we find future operating performance and stock returns are negatively related to ex ante industry-level valuation (our measure of industry

[1] See WSJ March 23, 2000 "Is there rational for lofty prices?" and January 19, 1999 "IPOs are different in current era of net-stock mania".

[2] See: http://www.eslarp.uiuc.edu/ibex/archive/vignettes/rrboom.htm. The Chicago Sun Times wrote in 1872: that wealth from the railroads "will so overflow our coffers with gold that our paupers will be millionaires, and our rich men the possessors of pocket money which will put to shame the fortunes of Croesus."

booms) and new financing. High stock-market valuations in competitive industries are very likely to be followed by subsequent downturns in cash flows and stock returns, especially when there is substantial new financing by firms in the industry. We find that high ex ante systematic risk in industries magnifies the effect of industry-level valuation, investment and new financing on subsequent stock-market returns, particularly in competitive industries. These relations are significantly more negative than similar relations in concentrated industries.

Our findings are economically significant - both for operating cash flows and stock returns. In competitive industries, a one standard deviation increase in relative industry valuation is associated with a three percent decline in operating cash flows. A one standard deviation increase in industry financing is associated with a 6.5 percent decline in operating cash flows.

The results for abnormal stock returns show similar patterns. In competitive industries, annual abnormal stock returns for an industry level portfolio in the highest quintile of relative industry valuation are almost four percentage points lower than a portfolio in the lowest quintile. At the firm level, this difference is even larger. In concentrated industries, quintile returns are non-monotonic, and magnitudes are less than half as large.

Our results are most consistent with a new explanation not previously documented: the effect of high competition among firms on both cash flows and stock prices in competitive industries arising from lack of coordination and the externality of high industry investment and financing. In contrast, firms in concentrated industries, given their enhanced pricing power, are more likely to internalize the effect of their actions on industry-wide prices, cash flows, and stock returns.[3]

While the effect of competition on cash flows may be natural and expected, the predictability of stock returns following booms and busts, after adjusting for style characteristics and Fama-French factors, is more puzzling. We thus investigate whether our evidence is consistent with the predictions of recent rational models of booms and busts. Pastor and Veronesi (2005) show that increases in systematic risk can cause industry busts after booms as industry participants adopt a standard technology. Consistent with these predictions, we find that market betas increase and idiosyncratic risk declines after industry booms. Systematic risk also changes consistent with the recent real options models of Aguerrevere (2006) and Carlson,

[3]There is related research in economics that has examined theoretically whether there can be excessive competition and entry within industries. Weizsacker (1980), Martin (1984), Mankiw and Whinston (1986) and Scharfstein (1988) present models addressing this question. We discuss this literature more extensively in the next section.

Fisher, and Giammarino (2004). We find that adjusting stock returns by ex post measured changes in risk can explain part of the return predictability we document. However, in terciles of industries with the highest valuations and the highest market risk, this adjustment explains less than 30% of our findings. Hence, change-in-risk-based explanations cannot explain our findings in the most extreme industries.

In DeMarzo, Kaniel, and Kremer (2006a,b), participants with relative wealth concerns rationally overinvest (both in physical and financial assets) in industries with high systematic risk. Consistent with this view, our results are stronger in competitive industries with higher ex ante market risk. However, relative wealth is central to this theory and is difficult to directly test. Although this theory can explain part of our results, industry investment, which is most crucial to this theory, is less significant than some of our other variables in predicting future cash flows and stock returns.

We thus conclude that while the effect of competition on cash flows may be natural in competitive industries, current stock market theories cannot explain our findings on the predictability of stock returns following booms and busts, consistent with stock market participants not anticipating the effects of competition in competitive industries.

Related to our paper is the recent theoretical and empirical work by Rhodes-Kropf and Viswanathan (2004) and Rhodes-Kropf, Robinson, and Viswanathan (2005), respectively. In these papers, sector and firm rational misvaluation affects merger and acquisition activity, as managers cannot distinguish between misvaluation and possible synergies. Only over time are synergies revealed and misvaluations corrected. Also related are papers on rational herding in investment and financial markets (early models are Scharfstein and Stein (1990) and Welch (1992)). In these models there is a signal extraction problem combined with the ability to observe earlier decisions by other, potentially better informed, industry participants. We discuss these models more extensively in the next section.[4]

What is common to these models and our interpretation of our findings is that firms make investment decisions based on multiple signals that are imperfect. Firms invest based on market signals as well as their own private information. In particular, they might use the market values and investment decisions of their industry peers as inputs into their own investment decisions. Our study focuses on the impact of industrial organization given that firms face a coordination problem in competitive

[4]The idea that agents are attempting to extract information about fundamentals and how noisy signals create cycles can be found in the original Lucas island economy model and also in the real business cycle models of Kydland and Prescott.

industries and may not internalize or have the incentives to internalize the effect of their actions on industry prices and returns.

Although not considering the role of industry competition, related work in behavioral finance also documents results that are related to ours. Recent articles find low stock returns following high investment (see Titman, Wei, and Xie (2004) and Polk and Sapienza (2006) for cross-sectional results and Lamont (2000) for time-series results). Related to our results on industry financing, Baker and Wurgler (2000) show that when the share of equity issuance is in the top quartile, market-wide returns are 15 percent below the average market-wide returns over time.

Our results add to existing results in several new ways. First, our paper's main focus is on industry structure, and we show that subsequent outcomes after industry booms and busts vary dramatically across levels of industry competitiveness. Our results show that competitive industries, and not concentrated industries, experience significant downturns following high industry valuation and new industry financing. Second, our paper is the first to show that both stock returns and cash flows are low in competitive industries following high industry valuation, high industry investment and, in particular, new industry financing. Third, we show that the effects of industry new financing and industry valuation on stock returns in competitive industries are especially negative in the top tercile of ex-ante industry valuation and the top tercile of ex-ante industry market risk. Fourth, we examine the role of changing risk characteristics in explaining our predictable boom and bust patterns.

The remainder of this paper is organized as follows. Section II provides a more extensive discussion of the industrial organization theories that focus on how excessive competition may develop in industries and presents testable implications from these theories. Section III discusses the data and our empirical measures of firm valuation and relative valuation. Section IV provides summary statistics on booms and busts in different decades. Sections V and VI present and discuss the results on how industry valuation and financing booms impact subsequent operating cash flows and stock returns, respectively. Section VII concludes.

II Industrial Organization and Booms and Busts

Our central thesis is that industrial organization combined with industry valuation and financing are key to understanding industry booms and busts and subsequent industry outcomes. In this section we review the existing theoretical models that are related to our paper, and the empirical implications we examine from these theories.

Many existing theories of stock market booms and busts are silent on industrial organization. Given that our focus is on industrial organization, we focus first on the potential impact of industrial organization on booms and busts. At the end of this section we also consider the implications of risk-based theories of booms and busts.

A Competition in Concentrated Industries

There is a large body of work that has focused on the effects of competition in concentrated industries. The most famous work dates back to Schumpeter (1942) in which he coined the term "creative destruction." Schumpeter's work focused on the process of creative destruction in which entrants challenge the status quo through innovation. The view Schumpeter espoused in his posthumous book published in 1942 is that entrants with new technologies challenge firms in concentrated industries in order to displace established market leaders. Expansion and entry occurs in these industries as these industries are "where the money is."

Related to the extent of entry into industries are formal models of how excessive entry may occur. Work by Von Weizsacker (1980), Perry (1984), Mankiw and Whinston (1986) formalize how there can be a tendency for excessive entry relative to the social optimum as entrants rationally do not take into account previous fixed costs by rival firms. The general implication of these models is that the industries have to have large fixed costs and prices above marginal cost. Entrants enter and invest if they can price below current industry prices. Firms enter despite large fixed costs as they can subsequently steal market share away from existing firms. We formulate the following hypothesis to test these implications:

Hypothesis 1: In concentrated industries with high valuations, high investment and high financing decrease industry and firm profitability.

B Coordination Problems and Real Options in Competitive Industries

Unlike the previous work, it is possible that it is in competitive industries that the greatest risk from new competition exists. The following mechanism can explain this competitive risk. Opportunities arise that require additional financing and investment. These opportunities increase industry and firm valuations above their long-run historical levels. Firms observing these positive industry valuations, and positive own valuations, raise capital and invest. Firms may suffer from a signal extraction problem, as they may not know what fraction of the positive signal they receive is attributable to opportunities they have, or opportunities available to all firms in the industry. Individually, firms invest not taking full account of the investment decisions made by rivals who receive the same industry signal. Thus each firm's investment causes a negative externality on other firms. More broadly, firms in competitive industries suffer from an inability to coordinate their investment.

Related to this idea is the extensive research on R&D and patent races (summarized by Reinganum (1989)) showing there can be excessive entry. This literature predicts that industries facing new opportunities that are also characterized by either significant economies of scale or patent protection can suffer excessive ex ante competition with the total investment exceeding the amount that would be socially optimal. This key feature is similar to business stealing models, where firms rationally do not consider the effect on rival firms. In contrast to business stealing models, however, industries can be explicitly ex ante competitive with free entry. In our empirical work we test the following hypothesis:

Hypothesis 2A: In competitive industries with high valuations, high investment and high financing will be associated with decreased industry and firm profitability.

We also examine the effect of industry competition on abnormal stock returns. Recent work by Hou and Robinson (2005) empirically supports the contention that there is competitive risk priced in stock market returns. For theoretical consistency, if competitive risk is priced, assets exposed to this competitive risk factor should be more procyclical. In our context, competitive risk can be procyclical as follows. In boom times, opportunities arise that require additional financing and investment. These opportunities increase industry and firm valuations above their long-run historical levels. During times of high GDP growth, these valuations are likely to be even higher as access to capital is likely to be highest. However, in competitive industries, many firms can exploit these opportunities and thus these opportunities are less likely to persist. Capital will flow quickly into these industries, causing competitive industries to have a tendency to be more pro-cyclical.

In our empirical work we test the following risk-based hypothesis:

Hypothesis 2B: Decreased stock returns following industry booms in competitive industries result from a priced risk factor that varies with product market competition.

Aguerrevere (2006) introduces product market competition into a real options based model of the firm, and shows that competition can affect asset returns and firm risk via industry demand. A key prediction is that market risk will decrease as demand increases in competitive industries (industry booms), but will then increase as demand declines (industry busts). Decreases in market risk during booms arise because firms in competitive industries face a high likelihood of preemption by competitors. These firms find it optimal to exercise growth options earlier than firms in concentrated industries. When demand decreases, market risk increases more in competitive industries because firms in these industries optimally delay shut down decisions because the benefits of shutting down capacity accrue most to industry rivals. This increase in market risk in competitive industries is especially strong as these firms have higher operating leverage when demand declines.[5]

Hypothesis 2C: During industry booms, systematic risk decreases more for firms in competitive industries than in concentrated industries. Following decreases in demand (industry busts), systematic risk increases more for firms in competitive industries than in concentrated industries.

The alternative to Hypotheses 2B and 2C is that risk changes do not explain subsequent stock market returns given market participants fail to take into account the effect of product market competition on stock prices.

C Non-Industrial Organization Theories of Valuation Booms and Herding

Rhodes-Kropf and Viswanathan (2004) (RKV) model how asymmetric information about the size of synergies and misvaluations cause merger waves to develop. In RKV, both the bidder and target have private information about the extent they are misvalued. However, they do not know if this misvaluation is firm- or industry-specific and target firms do not know the size of potential synergies. Targets end up putting higher weight on potential synergies in periods of high industry misvaluation or industry booms. In our context, potential investors in a new technology may end up putting higher weight on the potential value of new technology in periods of industry booms.

In addition, there are many different models of industry herding that can produce booms. In Scharfstein and Stein (1990) firms again face a signal extraction problem. Uncertainty about the return on investment combined with uncertainty about own ability, causes managers to make decisions that are similar to those of prior participants. Welch (1992) models informational cascades and shows that herding can emerge in IPO markets as individuals find it rational to ignore their own private information and base their purchase decision on others' decisions. Likewise, in our

[5] The operating leverage effect on stock market risk and returns in a real option context was introduced by Carlson, Fisher, and Giammarino (2004).

context, uncertainty or asymmetric information about the value of new technologies may cause market participants to invest similarly to other firms causing a boom in both valuation and investment along with the financing of this investment.

Three recent articles offer explanations regarding how boom and bust patterns can develop rationally. Pastor and Veronesi (2005) and DeMarzo, Kaniel, and Kremer (2006a,b) model how new technological opportunities can play a role in the formation of rational boom and subsequent bust patterns. While many of these theories are hard to separate from models of excessive competition or herding, we do test two hypotheses about the role of risk in booms and busts.

In Pastor and Veronesi (2005), there is a rational boom and bust linked to a switch of uncertainty (risk) from idiosyncratic to systematic. This change in the composition of risk occurs after firms standardize on the winning technology. This increase in systematic risk will thus cause a subsequent drop in stock prices. We thus test the following prediction of their model:

Hypothesis 3A: Systematic risk will increase and idiosyncratic risk will decrease following industry valuation booms.

We test a related hypothesis from DeMarzo, Kaniel, and Kremer (2006a) and DeMarzo, Kaniel, and Kremer (2006b). They predict that high risk technologies that are correlated with aggregate consumption can lead to excessive and often unprofitable investment. They model how profitable and fast growing firms have low expected returns because they provide consumption insurance to investors, especially when future resources are in limited supply. These relative wealth concerns can explain why overinvestment and herding can develop in industries that are viewed as providing large fractions of future consumption. As noted by the authors, these concerns should be most relevant when the distribution of industry returns is highly correlated with the market. The main idea is that high systematic risk implies comovement, and hence a more likely outcome that other agents in the economy will become rich if the new technology is successful. We thus test the following prediction:

Hypothesis 3B: In industries with high systematic risk, subsequent stock market returns will be negatively related to high industry valuation, investment, and financing.

III Data and Measures of Valuation

We merge data obtained from Compustat and CRSP to obtain information on firm financials and stock prices. Following standard practice in the literature, we exclude from our sample financial firms (SICs 6000-6999) and regulated utilities (SICs 4900-4999). We also restrict our sample to the years 1972 to 2004, as net equity and debt issuing activity are not available prior to this period. In order for a firm year to remain in our sample, at a minimum, the firm must have valid CRSP and COMPUSTAT data both in the given year and in the previous year. We define each firm's industry on the basis of three-digit SIC codes, and we discard all firms residing in industries that are identified as "miscellaneous" by the Census Bureau, as it is likely that firms in these groups cannot be classified (and hence they do not compete in similar product markets).[6] Merging the CRSP and Compustat databases, and applying these filters, yields a total of 108,522 firm year observations.

We classify industries into competitive and concentrated industries using both public and private firms. The main classification problem we face is that the Compustat database only covers public firms.[7] We calculate a measure of industry concentration that accounts for privately held firms by combining COMPUSTAT data with Herfindahl data from the Commerce Department and employee data from the Bureau of Labor Statistics (BLS).[8] The inclusion of BLS data is necessary to examine all industries with greater depth, as the Department of Commerce Herfindahl data only covers manufacturing industries.

To classify industries by their competitiveness, we calculate a Herfindahl–Hirschman Index (HHI) for each industry in each year using a two-step procedure. First, for the subsample of manufacturing industries (where we have actual HHIs including both public and private firms for every fifth year), we regress actual industry HHI from the Commerce Department on three variables: the Compustat public-firm-only Herfindahl,[9] the average number of employees per firm using the BLS data (based on public and private firms), and the number of employees per firm for public firms using Compustat data. We also include interaction variables of each of these firm size variables with the HHI calculated from Compustat data.

In our second stage, we use the coefficient estimates from this regression to compute fitted HHI for all industries. This fitted method has the advantage of capturing

[6]Because they operate in nearly identical product markets, we also combine the following industries in each set of parentheses: (20, 70), (210, 211), (220-225), (254, 259), (278, 279), (322, 323), (333, 334), (520, 521), (533, 539), (540, 541), (570, 571), and (700, 701).

[7]Our initial tables just used public firms to classify industries. These tables are available from the authors and showed similar, slightly stronger findings.

[8]We thank David Robinson for sharing this data with us.

[9]We compute Compustat HHI using the firm segment tapes in years the segment data is available (1984 onwards) to break a multi-segment firm's sales into the industries in which it operates. We then include two Compustat HHI variables in our regression. The first variable equals the HHI in years prior to 1984, and zero in years when the segment tapes are available. The second one equals the HHI in subsequent years using the segment tapes, and zero in previous years.

the influence of both public and private firms, and can also be computed for all industries. To mitigate measurement error, we do not use these fitted HHIs in any regression, but rather we classify industries into concentrated versus competitive terciles based on this variable. We classify industries in the highest tercile of fitted HHI as concentrated and those industries in lowest tercile as competitive.

The correlation between actual HHIs, as specified by the Department of Commerce for manufacturing industries, and our fitted HHIs, is 54.2%. The correlation between Compustat HHIs using segment data and the actual manufacturing HHIs is only 34.1%.[10] We conclude that our fitted HHIs offer significant improvements as a measure of true product-market competitiveness relative to the basic COMPUSTAT HHI used in past studies.

A Industry Valuation, Investment and Financing

In order to identify the conditions that likely surround industry booms and busts, we construct three proxies of new industry-level opportunities and relative industry valuation: (1) industry-wide valuation relative to historical values using a procedure described below, (2) industry-wide investment relative to predicted investment, and (3) industry financing. These proxies either reflect beliefs about an industry having good future prospects (industry valuation), or they measure current actions that are consistent with acting on new opportunities (investment and finance).

We define an industry and firm's "relative" time-series valuation (we refer to this measure as relative valuation subsequently) using a three step procedure that is based on the third valuation model in Rhodes-Kropf, Robinson, and Viswanathan (2005) (RRV). The difference between our valuation model and the one in RRV is that we only use lagged data in constructing our measure of relative valuation given we are examining ex post returns and operating performance and do not want to have a look ahead bias in our predictions. As RRV note, this valuation model is based on a long tradition in the accounting literature that examines the value relevance of accounting information.[11] We group each firm "i" into its industry "j" based on its three digit SIC code in year "t". (1) We estimate the parameters of the RRV valuation model using data from year t-10 to t-1. (2) These ten year fitted industry-specific regression coefficients are used to compute predicted values in year t. (3) Relative valuation is

[10] In an earlier version of this paper we conducted all of our tests results using the Herfindahls computed from Compustat and the Compustat segment tapes. The results were similar and slightly stronger than the ones we report in the tables.

[11] see Holthausen and Watts (2001), Kothari and Zimmerman (1995), Kothari (2001), and Barth, Beaver, and Landsman (2001) for surveys and discussion of the debates within this literature.

the actual value (log market capitalization) in year t minus the predicted value in year t. The fitted valuation model used in the first step assumes that each firm's value is a function of its characteristics and industry specific prices of characteristics as follows:

$$LnMVE_{i,j,t} = \beta_{j,0} + \beta_{j,1}LnBVE_{i,j,t} + \beta_{j,2}Ln(abs(NI_{i,j,t})) \qquad (1)$$
$$+\beta_{j,3}NEGNIDUM_{i,j,t} + \beta_{j,4}LEV_{i,j,t} + \epsilon_{i,j,t}$$

The left hand side variable is the natural logarithm of the firm's market value of equity.[12] The characteristics in equation 1 are the log book value of equity, log net income, a dummy for negative net income, and the firm's leverage ratio. Relative firm-level valuation is then equal to a firm's actual valuation less its predicted valuation using the coefficients from 10 years of lagged data and the actual firm accounting data in year t:

$$RelativeValuation_{i,j,t} = LOGMVE_{i,j,t} - Predicted\ LOGMVE_{i,j,t} \qquad (2)$$

Relative industry-level valuation is the average of all relative firm-level valuations over all firms in each three-digit SIC industry.

To show that these results are robust and do not depend on whether the first-stage regression is estimated in levels we also estimate the following model:

$$Ln(MVE_{i,j,t}/BVE_{i,j,t}) = \beta_{j,0} + \beta_{j,1}LnASSETS_{i,j,t} + \beta_{j,2}Ln(abs(NI_{i,j,t})) \qquad (3)$$
$$+\beta_{j,3}NEGNIDUM_{i,j,t} + \beta_{j,4}LEV_{i,j,t} + \epsilon_{i,j,t}$$

From this model we obtain relative (unpredicted) market to book equity in an analogous manner as above.

For robustness, we also estimate a simpler model that is analogous to a Price to Earnings (PE) model where we regress the log of the market value on log net income and a dummy for negative net income as follows:

$$LnMVE_{i,j,t} = \beta_{j,0} + \beta_{j,1}Ln(abs(NI_{i,j,t})) + \beta_{j,2}NEGNIDUM_{i,j,t} + \epsilon_{i,j,t} \qquad (4)$$

Again this equation is estimated on 10 years of lagged data by industry and then the coefficients are used to predict current period market value using current

[12] While these variables are in levels, estimation of this equation does not produce biased coefficients if the variables are cointegrated. Tests using residuals indicated that cointegration is supported. We also estimate an alternative model (equation 3) using the ratio of Market to Book Equity.

net income. Our measure of relative valuation is then calculated as the difference between the log of current market value and the predicted log market value.

Although we do not present results from these regressions to conserve space, we do note that the explanatory power from these regressions is high, similar to the results presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). The adjusted R-squareds from each of these industry-level regressions range from 63 percent at the 5th percentile (the lowest R-squared is 4.7 percent) to 96 percent at the 95th percentile, with a median R-squared of 85 percent.

Relative firm- and industry-level investment is computed using a similar method. We regress log capital expenditures on lagged Tobin's q, lagged assets (COMPUSTAT annual data item 6) and also the log of operating income before depreciation (COMPUSTAT annual data item 13). Tobin's q is calculated as the market value of equity plus the book value of debt divided by the book value of assets. We calculate relative unpredicted investment (which we call relative investment) as equal to actual investment less predicted investment from this industry panel regression. Relative industry investment is given as the average of relative firm-level investment in each industry.

We define a firm's "new financing" in a given year as the sum of its net equity issuing (COMPUSTAT annual data item 108 minus item 115) and net debt issuing activity (annual data item 111 minus item 114) in the given year, normalized by its assets. Unlike valuation and investment, we do not adjust financing patterns based on their long-term averages because year-to-year financing patterns are less stable.

These proxies are constructed using each industry's own characteristics as a benchmark for determining relative firm valuations. We use out-of-sample regression coefficients based on past data to predict our industry and firm valuations, so that our proxies can be used in an unbiased fashion to predict future stock returns and future accounting performance. For all three variables (relative valuation, relative investment, and new finance), we compute industry deviations as the raw industry average minus the predicted industry average. Firm-level deviations are equal to each variable's raw value minus its industry average.

B Operating Cash Flows and Stock Returns

This section describes how we calculate operating cash flows and abnormal stock returns. We examine whether firm and industry relative valuation, investment, and financing predict future operating cash flows and abnormal stock returns.

Our first set of tests regresses the change in firm-level operating cash flow divided by firm assets (year t+1 - year t) on relative industry- and firm-level valuation, investment and new finance. Our definition of operating cash flow is operating income (COMPUSTAT annual item 13), and we scale each year's operating cash flow by assets (COMPUSTAT annual item 6) in each year. For robustness, we also estimate our results using the change in operating cash flow by divided by beginning period assets (year t).

We compute abnormal returns using two methods advocated by recent studies. The first method is based on Daniel, Grinblatt, Titman, and Wermers (1997). A firm's "monthly abnormal return" is its raw return less the return of one of 125 benchmark portfolios formed on the basis of size, book to market, and past 12 month return.[13] Portfolios are formed at the end of each June,[14] and (1) firm size is the CRSP market capitalization on the formation date, (2) the book to market ratio uses accounting data from the most recent fiscal year ending in the last calendar year, and (3) past return is based on the 12 month period ending in May of the formation year. Portfolio breakpoints are based only on NYSE/AMEX firms, and we first form quintiles in each year based on firm size. Then, firms in each size quintile are further sorted into quintiles based on their industry-adjusted book to market ratio (firm-specific book to market ratio less the average book to market ratio of the corresponding Fama-French 48 industry).[15] Each of the 25 size and book to market portfolios is then further sorted into quintiles based on each firm's preceding 12 month return.

The second method uses the Fama-French factors with an adjustment proposed by Mitchell and Stafford (2000). We begin by identifying a firm year as one firm's returns from July to June. This designation permits us to use the same accounting based variables to predict annual returns as above. We regress each firm year's twelve monthly stock returns on four factors: the three Fama-French factors plus momentum.[16] From these time series regressions, we extract a database of yearly firm-specific intercepts describing each firm's abnormal return in the given year. We define a firm's "Mitchell/Stafford alpha" as its yearly intercept minus the average yearly intercept of firms residing in the given firm's benchmark portfolio based on size, book to market, and past 12 month returns (as described above). This two-

[13] Results are robust to forming benchmarks just based on 25 size and book to market portfolios (not displayed).

[14] Portfolios are formed at the end of June so all previous fiscal year accounting data is public at that time.

[15] Our results are not materially different if we do not adjust book to market within each industry. We use the industry-adjusted method to maintain consistency with past studies.

[16] We thank Ken French for providing these factors on his website.

stage method ensures that returns have sufficient control for known risk factors even when the relationship between factor loadings and returns is non-linear. Although we do not present results based on "buy and hold abnormal returns" due to the criticisms noted in Mitchell and Stafford (2000), we can report that our results are robust to using this method. To further ensure robustness, we present results using three regression methods: (1) OLS with year fixed effects and industry clustering adjustments, (2) OLS with year fixed effects and both industry and year clustering adjustments, and (3) the Fama-MacBeth method.

C Systematic and Idiosyncratic Risk

In order to explore whether changing risk attributes can explain industry busts following industry booms we examine both systematic and idiosyncratic risk. We first define a firm year as beginning on July first of year t, and ending on June 30th of year t+1. Where d denotes one trading day in year t, we then regress the daily stock returns associated with firm i in year t on the three Fama-French factors plus momentum as follows (one regression per firm-year)

$$r_{i,y,d} = \alpha_{i,y} + \beta_{i,y,1} MKT_d + \beta_{i,y,2} HML_d + \beta_{i,y,3} SMB_d + \beta_{i,y,4} UMD_d + \epsilon_{i,y,d} \quad (5)$$

We define a firm year's idiosyncratic risk as the standard deviation of the residuals from this regression. We examine various types of systematic risk as measured by each firm year's beta (factor loading) with respect to the four risk factors $(\beta_{i,y,1}, \beta_{i,y,2}, \beta_{i,y,3}, \beta_{i,y,4})$. To identify whether risk changes are associated with our industry and firm valuation measures, and thus might be related to the return predictability we document, we regress annual changes in these risk exposures (betas) on our industry and firm measures of relative valuation, investment and financing.

We also estimate nonpredictive regressions where we regress abnormal stock returns on all measures of risk for the year following the abnormal returns, and use the residual from this regression as a measure of "risk-adjusted stock returns".[17] The idea we are examining is whether market participants anticipate future risk changes. We examine if these risk-adjusted stock returns remain related to our industry and firm measures of relative valuation, investment and financing.

[17] We thank Lubos Pastor for this suggestion.

IV Descriptive Statistics

Table I lists the top 5 booms in competitive industries (those in the lowest tercile based on sales HHI using three-digit SIC codes from Compustat), in each of the following four decades: 1970s, 1980s, 1990s, and in the new millennium.

[Insert Table I here]

Table I shows that in all cases, Herfindahl indices are below .25. Some of the most extreme booms have over one hundred publicly traded firms competing in the same SIC code. The business services industry had 843 public firms. Although this last example is part of the well-known late 1990s technology boom, the other examples suggest that high levels of valuation at the industry level are not unique. Many of the most extreme competitive industries in the 1980s (over 100% above predicted industry valuation) deviated even further from their long-term valuations than those in the 1990s (70% to 90% above predicted industry valuation). The table also shows that the most extreme booms were not necessarily in technology industries, as was the case in the late 1990s. For example, at least two of the most extreme 1980s boom industries were based in retail operations. In the 1970s, more traditional industries including petroleum and electrical work were among the most extreme booms. Finally, because the column of weighted high industry valuations is generally the same as the unweighted column, we conclude that both large and small firms alike are prone to industry booms and busts.

[Insert Table II here]

Table II lists the top 5 booms in concentrated industries (those in the highest tercile based on predicted HHI), in the 1970s, 1980s, 1990s, and 2000s. The selected industries generally have concentration levels exceeding 0.4. Tables I and II show that the differences between the herfindahls constructed using public Compustat data alone and the fitted herfindahls using both public and private firms are generally small, with most industries remaining in the high or low competition terciles on both measures. Given our tests do not use the concentration measures explicitly but rather examine industries by high and low competition categories, we thus expect and find similar results using either herfindahl measure.

The most striking difference between concentrated and competitive industries is that booms appear to be more extreme in concentrated industries. For example, Beer and Ale Distributors were 234% above their predicted industry valuation in 2005, and yarn and thread mills were 175% above their predicted industry valuation in 1996. Statistical noise might be one reason for the larger magnitude of booms in the most extreme concentrated industries, as their smaller number of firms makes the practice of computing industry-specific valuation models more difficult. Although these booms appear to be larger, our later tables presented in this paper show that we do not find evidence that concentrated industries experiencing booms actually underperform. Hence high industry valuations in concentrated industries likely last more than several years.

Table III reports summary statistics for the boom and bust proxies, and for the key variables that our study explains.

[**Insert Table III here**]

The sample wide statistics in Panel A show that the standard deviation of industry "relative" (valuation above predicted valuation) is significant, indicating that many industries have valuations above and below predicted levels. Financing tends to be slightly positive, as more firms raise new capital relative to those who are paying down debt and repurchasing shares. The table also shows that all three firm level variables have higher standard deviations than their industry counterparts. These results suggest that actual industry valuations can vary dramatically, as one standard deviation is a full 45% of the value of an industry.

Panels B and C display descriptive statistics for competitive and concentrated industries, respectively. For virtually all variables, mean levels are close to zero. The table also shows that concentrated industries generally have higher standard deviations. This difference is most stark for investment relative to predicted levels (concentrated industries have 38% more standard deviation), but rather moderate for relative industry valuation (18% difference). Interestingly, at the firm level, the reverse is true and competitive industry firms appear to have more volatile characteristics than concentrated industry firms (although differences are a bit more modest). The average returns in Panels B and C also confirm the results of Hou and Robinson (2005). The annual equivalent of the difference in monthly returns across the two panels suggests that concentrated industries underperform competitive ones by about 2% per year. In contrast, we find no material difference in accounting performance across these two groups, a result that also supports Hou and Robinson (2005)'s findings.

V Operating Cash Flows

We now examine the effect of industry booms on subsequent firm-level operating performance. We regress the change in operating cash flow on both firm- and industry-level valuation relative to predicted valuation, investment relative to predicted values and also new finance. We use the term "relative" valuation and "relative" investment to refer to actual valuation and investment less their predicted values.

A Firm Level Results

Table IV displays the results of firm-level regressions of the change in operating cash flow on relative valuation, relative investment, and new financing. For each independent variable, we separately examine the difference between the actual industry average and the predicted industry average and its firm specific deviation from its industry average.[18] We separately include industry averages to directly study the main topic of this paper: industry booms and busts, and their link to an industry's organization. The firm-level components provide a natural test of our relative valuation proxy, and permit us to ask whether a firm that deviates from its explained valuation (as explained by the industry-specific price of its own characteristics), experiences operating cash flow decreases or increases as might be predicted by a high industry valuation.

We estimate the regressions using OLS and random firm effects using an unbalanced panel. We also correct for correlated standard errors within years and within industries and heteroskedasticity in the regression errors. We do not present results for the fixed effects specification at the firm level as Moulton (1986) has shown that fixed effects estimation at the firm level is inappropriate when you have additional variables at the industry level. We also do not estimate Fama-MacBeth regressions when examining operating cash flow, as our tests document the existence of firm-level effects. Petersen (2005) has recently shown that Fama-MacBeth regressions are biased when there is a significant firm-level effect (which we find in this case, as is common when examining accounting data).

[Insert Table IV here]

Panel A of IV shows that industry-level variables matter. High industry valuation

[18] All three firm-level variables are less than ten percent correlated with their corresponding industry components, so including both variable classes does not induce multicollinearity. This low correlation is expected by construction.

and investment relative to predicted industry values, and an industry's average new financing are negatively related to future operating performance. These results are also robust across specifications, and are also robust when we exclude the technology boom of 1998-2000. This result suggests that the technology boom was indeed an important example of a recent boom and bust, but also that the sequence of events surrounding the technology boom are not new, as other industries have befell similar fates throughout our sample period. It is natural to ask if industrial organization can explain these striking industry patterns.

Panels B and C display results for the most competitive tercile of industries and the most concentrated tercile of industries, respectively. Terciles are formed based on the fitted Herfindahl, which is predicted using data on both public and private firms in each industry. We find that high industry-level investment and new finance are indeed more important in Panel B for competitive industries than they are in Panel C. The industry valuation coefficient is especially noteworthy, and is statistically stronger in competitive versus concentrated industries. In addition to the higher significance levels, which might be partially due to the larger number of observations in Panel B (competitive industries have more firms), the table also shows that the coefficient magnitudes are significantly different across levels of industry competitiveness. In competitive industries, a one standard deviation increase in industry valuation is associated with an 6.5 percent decline in operating cash flows - compared to a slight increase for concentrated industries. We conclude that industry valuation plays a larger role in predicting industry booms and busts in competitive industries than in concentrated ones. These results support Hypothesis 2A, which predicts a decline in competitive industries following high industry valuation.

Panel D shows that relative industry valuation and new industry financing are highly important in industries with declining concentration. The magnitudes of the coefficients for high industry valuation and industry financing are both larger than they are for other subsets of data.

Panel D supports the proposition that high competition might be a primary driver of extreme industry busts, as theories of industrial organization suggest that declining concentration is one way to measure increasing competitiveness. As new technologies or opportunities emerge in a changing industry, multiple firms invest and exploit the new opportunity when it might only be optimal for a small number to do so. This coordination failure that stems from high valuations cause large amounts of investment, and industry booms soon become industry busts. The significance of both firm and industry new finance suggests that not only do industries suffer from very high competition, but also that the most aggressive rivals likely suffer most.

We also conduct the following robustness checks. We examine results using our alternative M/B model and the simpler "PE" model. The results are similar to the results discussed above.

B High Market Risk Industries

We examine whether the boom and bust patterns are more prevalent in industries with high systematic risk, as predicted by Hypothesis 3B. DeMarzo, Kaniel, and Kremer (2006a) (DKK) note that relative wealth concerns should be most relevant when the distribution of industry returns is highly correlated with the market. The main idea is that high systematic risk implies co-movement, and hence a more likely outcome that other agents in the economy will become rich if the new technology is successful. DKK link their predictions to very high investment and high valuation, and hence their model makes the specific prediction that industry valuation and industry investment should be most relevant when the industry has a high loading on systematic risk. DKK also predict that these relationships will be most extreme in competitive industries.

Table V tests this hypothesis for operating cash flows, displaying the results of regressions that only include firms in industries in the highest market risk tercile. Panels B and C then further limit the sample to industries that are also in the most competitive and most concentrated terciles respectively. Panel A contains roughly one third of all industries, and Panels B and C contain roughly one ninth of all industries.

[Insert Table V here]

The table supports predictions of DKK. The industry valuation variable is negative and significant in competitive industries, and significantly larger (almost ten times larger) than in concentrated industries. The size of the coefficient on industry valuation for competitive industries in Panel B is -.02 to -.03 across specifications compared to -.002 to -.006 for concentrated industries. These coefficients are also significantly larger than those presented in Table IV.

Lastly, tests of significance of the difference in the coefficients in Panel B and C reveal that the coefficients on industry valuation are significantly different at the 1% level in all specifications when the technology boom of 1998 to 2000 is included. When these years are omitted, this difference is only significant in two of the three specifications at the 5% level. Importantly, with or without the exclusion of these years, the economic size of the coefficient on the industry variables in Panel B (competitive industries) are larger than those in Panel C (concentrated industries). These results support the conclusion that high industry investment and valuation is associated with subsequent declines in high systematic risk industries, and illustrate that the technology boom and bust of 1998 to 2000 likely contains a component that might be explained by DKK's theory. We present additional evidence in later sections. These results can also be viewed as consistent with investment herding in industries with high market risk. These findings point to the need for future theoretical models to explore how industrial organization may affect herding.

VI Stock Returns and Industry Factors

A Firm Level Results

Table VI displays the results of firm-level regressions of monthly abnormal returns on relative valuation (actual valuation above predicted levels), relative investment, and new financing. For each independent variable, we separately examine its industry average and its firm-specific deviation from its industry average.

[Insert Table VI here]

Panel A of Table VI shows that both relative valuation and new financing are significantly related to future stock returns and these relations are robust across regression specifications, and robust to excluding the technology boom (1999-2000). In contrast, relative investment is not reliably related to future stock returns. The highly significant and negative coefficient on relative firm valuation affirms the role of our relative valuation proxy as a measure of fundamental value, as firms have a strong tendency to revert back to the valuation suggested by their industry characteristics.

Panel A shows that new financing matters at the firm level. We conclude that firms obtaining new financing above their industry average underperform. At the industry level, high valuation and high new financing are negatively related to future stock returns. These results are robust across specifications, and also robust to excluding the technology boom. We conclude that an industry's relative valuation and financing patterns provide insights into understanding the industry's future outlook.

Inspection of Panel A reveals that both industry coefficients lose up to 25% of their magnitudes when the recent technology boom is excluded from the sample. This result suggests that while the technology boom was indeed an important example of a recent boom and bust, the sequence of events surrounding industry booms are not new, as other industries befell similar fates throughout our sample period. Our results suggest that industry declines following recent booms are predictable, and that firms and investors should consider industry valuation and financing levels when making investment decisions.

Given our strong industry results, it is natural to ask about the role of industrial organization. Panels B and C display results for the most competitive tercile industries and the most concentrated tercile industries, respectively. As in earlier sections, we use the "fitted concentration measure," which predicts an industry's concentration from a combination of public and private industry data.

We posit that high competition and coordination failure by industry rivals might explain why some industries might suffer underperformance while others might not. We find that industry new finance is more important in Panel B for competitive industries than in the concentrated industries in Panel C, consistent with Hypothesis 2A. The industry new financing coefficient is significant at the 1% level for all but one specification in Panel B, and is not significant for any specification in Panel C. The difference in coefficients is significant in two of the four specifications. In addition to the higher significance levels, which might be partially due to the larger number of observations in Panel B (competitive industries have more firms), the table also shows that the coefficient magnitudes are also different. For example, the industry new finance coefficients are roughly two times larger for some specifications in Panel B than in Panel C. The results are mixed for the relative valuation coefficients. We conclude that industry new finance appears to play a broader role in predicting industry booms and busts in competitive industries than in concentrated industries.

Panel D shows that industry new financing is nearly as important for industries with declining concentration as it is for industries with low concentration. Combined with the operating cash flow results, these results further support the possibility that high competition is important to understanding industry booms and busts, as theories of industrial organization suggest that declining concentration is one way to measure increasing competitiveness. The significance of both firm-level and industry-level new finance suggest that not only do industries suffer from high competition, but also, as in the case of operating cash flows, that the most highly valued firms have more negative outcomes than the less highly valued firms. Inferences from our PE model (not reported to conserve space) are essentially identical to or stronger than those presented.

B High Valuation Industries

Table VII displays the results of monthly firm level regressions for firms in industries in the highest relative valuation tercile. Panels B and C then further limit the sample to industries that are also in the most competitive and most concentrated terciles respectively. Hence, Panel A contains roughly one third of all industries, and Panels B and C contain roughly one ninth of all industries.

[**Insert Table VII here**]

Examination of the results of Panel A in Table VII reveals that they are generally consistent with those in Table VI. We find continued support for the importance of new industry financing, and stronger support for high industry valuation, in predicting future returns.

Panel B shows that return predictability for competitive industries becomes especially striking in the high valuation group. Despite the reduced sample size, the industry valuation coefficient is significant in every specification. The industry new finance coefficient is significant in every specification except for one (new finance is not significant in the Fama-MacBeth specification that excludes the technology boom). These coefficients are also much larger than those reported in Table VII

The strong results for relative industry valuation in Panel B, competitive industries, and the absence of a similar result in Panel C, concentrated industries, supports the hypothesis that high competition is important in explaining the timing and severity of industry booms and busts. This difference is also economically large, as the industry valuation coefficient is positive in Panel C for concentrated industries.

C Risk-Based Explanations for Industry Booms and Busts

The boom and bust patterns we document are striking, and two recent theories attempting to explain boom and bust patterns make specific predictions regarding the link between these patterns and systematic risk.

C.1 The Level of Systematic Risk

DeMarzo, Kaniel, and Kremer (2006a) (DKK) present a full theory of investment and relative wealth concerns, and predict that predictable bust patterns should be largest in high systematic risk industries and in competitive industries.

Table VIII tests the prediction of DKK regarding the importance of systematic risk to industry booms and busts. The table displays the results of monthly firm level regressions that limit the sample to firms residing in industries in the highest market risk tercile. Panels B and C then further limit the sample to industries that are also in the most competitive and most concentrated terciles respectively. As before, Panel A contains roughly one third of all industries, and Panels B and C contain roughly one ninth of all industries.

[**Insert Table VIII here**]

Inspection of Table VIII shows that the industry relative investment variable in these high market risk industries is negative and significant in competitive industries, and not in concentrated industries. Tests of significance of the difference in the coefficients in Panel B and C reveal that the coefficients are significantly different at the 5% level in all specifications when the technology boom of 1998 to 2000 is included. When these years are omitted, this difference is only significant in the Fama-MacBeth specification at the 10% level. Importantly, with or without the inclusion of these years, the economic size of the industry relative investment coefficient in Panel B (competitive industries) dwarfs that in Panel C (concentrated industries). Although not presented to save space, we do not find similar patters when we examine high idiosyncratic risk rather than high market risk.

C.2 Changes in Systematic and Idiosyncratic Risk

Pastor and Veronesi (2005), posit that high valuations are, in part, due to lower levels of ex-ante systematic risk. As technologies are adopted, systematic risk rises, resulting in a negative return event (a bust) that is associated with stocks being penalized for their rise in systematic risk (Hypothesis 3A). We now test the hypothesis from Pastor and Veronesi (2005) that subsequent industry busts following industry booms are characterized by increased systematic risk and decreased idiosyncratic risk.

To test this prediction, and to test for changes in risk predicted by other theories such as real option based theories, we regress ex-post changes in risk (ex-ante risk level minus ex-post risk level) on our measures of relative valuation, investment and financing at the industry and firm level. For independent variables collected using data from calendar year t, the ex-ante risk level is measured from July of year t+1 to June of year t+2, and the ex-post risk level is measured from July of year t+2 to June of year t+3. This measure is forward looking as we ultimately seek to understand the impact changes in risk have on stock returns. However, we can also report that similar, perhaps stronger, results obtain if we use risk measured using one year earlier risk data. We also include a lagged risk exposure term in each regression to control for the mean reverting nature of risk exposures. We also include year fixed effects to maintain our focus on cross sectional relationships across competitive and concentrated industries. The inclusion of year fixed effects also controls for the well-known time trend associated with economy-wide risk (see Campbell, Lettau, Malkiel, and Xu (2001)).

[**Insert Table IX: Changes in Risk in Competitive Industries**]

Table IX displays the results for total risk, market risk, and idiosyncratic risk in competitive industries. Although we do not present results for concentrated industries, d,e,f superscripts in Table IX indicate whether coefficients are significantly different from their concentrated counterparts. The results for industries with high valuation provide modest support for Pastor and Veronesi (2005), and suggest that market risk (Panel B) increases when relative valuations are high in competitive industries. The impact of market risk is considerably larger for competitive industries than for concentrated industries, especially when 1998 to 2000 are included in the sample. These findings are also consistent with the recent real options paper of Aguerrevere (2006). We also find results supporting Pastor and Veronesi (2005) for idiosyncratic risk in Panel C. Regardless of specification, idiosyncratic risk drops considerably in competitive industries following high industry valuations but not in concentrated industries (not reported), where idiosyncratic risk actually increases. These results are consistent with Hypothesis 3A.

Because a key focus of our study is industrial organization, we also examine whether an additional risk factor based on industry competition, as suggested by Hou and Robinson (2005) (Hypothesis 2B), can explain our results. We construct such a factor by first sorting industries into terciles based on their ex-ante concentration levels (based on sales Herfindahl indices as discussed earlier). This new factor is then defined as the equal weighted return of firms in the highest concentration tercile industries minus the equal weighted return of firms in the lowest concentration tercile industries. After including a control for this competitive risk factor, we find that our results are materially unchanged. We also test whether including concentration as an additional independent variable in our return predictability regressions (i.e. concentration might be more accurately measured as a characteristic) can explain our results. Once again, our results are materially unchanged, and we conclude that this form of competitive risk cannot explain our findings. Because our paper conditions on concentration along with valuation and financing activity, and Hou and Robinson (2005) condition on industry concentration alone, these findings are not inconsistent. Rather, we conclude that our findings are distinct.

The evidence presented in this section suggests that risk based explanations, especially theory presented by DeMarzo, Kaniel, Kremer(2006a,b), Pastor and Veronesi (2005), and Aguerrevere (2006), can explain part of the link between high industry valuations, high industry investment, and subsequent return reversals in competitive industries.

However, many results remain unexplained. For example, because high new financing is associated with a rise in both systematic and idiosyncratic risk, it appears less likely that current risk based explanations can explain all of the patterns observed. Explanations that might be consistent with the importance of industry financing, and some of our broader findings, include herding based explanations, and some behavioral explanations. Herding explanations can also give rise to increases in systematic risk if investors act together in sufficient numbers based on actual or anticipated actions of others. However, because theoretical work has not yet examined the role that industrial organization might play in these alternate theoretical settings, the role of these theories is difficult to test.

D Can Ex Post Changes in Risk Explain Our Results?

In this section we examine if future risk changes, after the period for which we compute our abnormal returns, might explain or reduce the ability of relative industry valuation, investment, and high financing to predict stock returns. Future risk changes might be important if market participants are reacting to anticipated risk changes rather than just contemporaneous risk changes.

We test this hypothesis using a two-stage approach. First, for a return observation in year t+1 (given that our right-hand-side variables are indexed as year t), we regress our monthly firm-level style matched abnormal returns on changes in the four risk factors (MKT, HML, SMB, UMD) and idiosyncratic risk from year t to year t+2. We also include controls for the year t risk levels given that our previous section's results show that risk exposures are mean reverting. These regressions are non-predictive, as we examine changes in risk across the same period in which returns are measured. Second, we take the residuals of this first stage regression and regress them on our usual set of relative valuation, relative investment, and relative financing variables.

We present the results in Table X. To conserve space, we only present results for competitive industries, high relative valuation competitive industries, and high market risk competitive industries. The coefficients and significance levels in the three panels can be compared to Panel B in Tables VI, VII, and VIII, respectively. Pastor and Veronesi (2005) predict that changes in risk will explain part of the return predictability, while DeMarzo, Kaniel, and Kremer (2006a) predict that changes in risk will explain little of this return predictability (underperformance is driven by relative wealth concerns, not changes in risk attributes).

[**Insert Table X here**]

Comparing the coefficients and significance levels in Table X with those in our earlier tables yields some support for the Pastor and Veronesi (2005) prediction that risk increases following periods of high industry relative valuation. We find that changes in risk reduce the explanatory power of industry high valuation in competitive industries in the broad sample (Panel A), in the high valuation tercile (Panel B), and in the high market risk tercile (Panel C). Support for Pastor and Veronesi (2005) and hypothesis 3A is strongest in the broad sample (Panel A), and modest in the high industry valuation tercile and the high market risk tercile (Panels B and C). In Panels B and C, for example, changes in risk explain roughly 30% of the high industry valuation coefficient. Hence, Pastor and Veronesi (2005) can explain a portion of the high valuation term's return predictability (roughly 30%), but accounting for changes in risk cannot explain all of this variable's return dynamics.

Comparing the significance of industry relative investment in Table X to earlier results shows that we find almost no change in the economic size of the industry investment coefficient when controls for changes in risk are accounted for in all three Panels. Because DeMarzo, Kaniel, and Kremer (2006a) attribute lower returns in competitive industries with high investment to relative wealth concerns, we expect that changes in risk will not be able to explain the observed return patterns if their predictions hold. Our findings regarding the relative industry investment variable support this finding.

Regarding the industry new finance term, we see modest reductions in coefficients when we include controls for changes in risk. However all coefficients remain highly significant. Because this evidence, and earlier evidence, regarding this term is not uniformly linked to any specific theory, we leave explanation of its dynamics to future research. Herding in competitive industries, driven by market participants raising money and investing in physical capital, is consistent with the continued significance of these variables after adjusting for risk.

Overall, we conclude that our results provide some support for Pastor and Veronesi (2005), DeMarzo, Kaniel, and Kremer (2006a,b), and for theories linked to high competition in competitive industries. The significance of industry finance and also industry relative valuation in the highest valuation industries, which remains even after adjusting for risk, are consistent with market participants failing to incorporate the effects of industry competition in competitive industries. However, as stated earlier, our results can thus be seen as a call to theorists to develop a richer set of implications regarding herding and risk in an industrial organizational setting.

E Economic Magnitude of Stock Market Returns

We examine the economic magnitude of both firm and industry-level stock returns in the year after our measures of relative industry valuation, investment, and financing.

[**Insert Table XI here**]

In Tables XI and XII we calculate both firm- and industry-level abnormal returns for quintile portfolios based on ex-ante relative industry valuation, industry investment, and industry new financing. At the industry level, abnormal returns are equal weighted averages of firm abnormal returns in the given month over all firms residing in the given three digit SIC code. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). As in earlier tests, to ensure all accounting data is public before return predictability is measured, we assign monthly abnormal returns occurring between July of year t+1 and June of year t+2 to portfolios on the basis of accounting data with fiscal years ending in year t.

[**Insert Table XII here**]

The tables show that the magnitude of stock underperformance by industries with high relative industry valuation in competitive industries is significant. For example, Table XII shows that, at the industry level, the highest quintile of relative industry valuation underperforms the lowest quintile by 3.4% percentage points annually. Table XI shows that, at the firm level, the highest quintile of relative industry valuation has abnormal performance that underperforms the lowest quintile by over ten percentage points annually. This extraordinary level of underperformance is unique to the highest valuation quintile in competitive industries, indicating that this group of industries is where the effects of high competition are most prevalent. Similar magnitudes obtain for new industry financing and investment.

F Additional Robustness Tests

We examine the robustness of our stock-market results using additional tests of return predictability. These robustness tests are in addition to using the Market-to-Book and PE based model of relative valuation discussed earlier. Mitchell and Stafford (2000) (MS) show that some abnormal return predictability tests, such as those based on buy and hold returns, or those based on matching portfolios, might produce overly-aggressive inferences. We follow MS and conduct tests using the two-step method they recommend as follows: (1) compute regression intercepts using the three Fama-French factors (we also include momentum), and (2) subtract the average regression intercept of randomly chosen firms residing in the same style grouping. These industry-level and firm-level tests reveal that our main results are robust to the MS method.

VII Conclusions

Our paper examines real and financial outcomes of industry booms and busts and whether these outcomes are related to industry-level characteristics. We document significant booms and subsequent busts in the economy. We find that increases in industry valuations above predicted levels are followed by significantly lower operating cash flows and stock returns in competitive industries. Firms in these industries have especially negative cash flows and negative abnormal stock returns following episodes high industry financing and high relative industry valuation.

Our findings are economically significant both for operating cash flows and stock returns. In competitive industries, a one standard deviation increase in industry financing is associated with a 6.5 percent ex-post decline in operating cash flows. In the stock market, style and risk-adjusted abnormal stock returns for a competitive industry portfolio in the highest quintile of ex-ante relative industry valuation are four percentage points lower than a similar portfolio in the lowest quintile. At the firm level, these results are even larger in magnitude.

Additional adjustments for contemporaneous changes in risk do explain some of our findings, which is consistent with the model of Pastor and Veronesi (2005) and the real option model of Aguerrevere (2006). However, after these adjustments, risk- and characteristic-adjusted stock returns remain predictable and are negatively related to industry new financing and relative industry valuation in competitive industries with the most extreme valuation booms.

Our results are most consistent with high competition among firms impacting both cash flows and stock returns in competitive industries arising from lack of coordination and the externality of high industry investment and financing. The impact on industry outcomes is likely to be greatest if industry participants fail to consider, or do not have incentives or information to be able to consider, the actions of other firms when making investment decisions. In contrast, firms in concentrated industries are more likely to internalize the effects of their actions on industry-wide prices, cash flows, and stock returns. While the effect of competition on cash flows may be natural in competitive industries, current stock market valuation theories cannot explain our findings on the predictability of stock returns following booms and busts, consistent with stock market participants not anticipating the effects of competition in competitive industries.

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Table I: Examples of Industry Booms in Competitive Industries

Three Digit SIC Code	Industry Name	Decade/ Year	Weighted Market to Book	Average Firm Mkt Value	Wgt % Above Predicted Valuation	% Above Predicted Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
	Competitive Industries							
		1970s						
799	Amusement Parks and Recreation	1979	5.18	191.70	68.4%	44.6%	0.12	0.18
385	Ophthalmic Goods	1978	3.08	20.00	89.6%	51.3%	0.25	0.20
173	Electrical Work	1979	2.01	86.70	43.2%	52.5%	0.15	0.19
131	Oil and gas extraction	1979	2.73	349.94	68.2%	66.6%	0.13	0.18
287	Fertilizers and Agriculture Chemicals	1979	2.97	244.12	80.9%	77.1%	0.29	0.19
		1980s						
232	Men's Apparel	1986	2.53	362.23	86.0%	97.5%	0.09	0.20
422	Farm Product Warehousing+Storage	1989	1.43	130.23	98.8%	98.8%	0.25	0.23
233	Women's Apparel	1985	4.90	153.42	106.7%	106.2%	0.13	0.20
329	Abrasive Products	1988	3.65	319.11	127.7%	109.0%	0.14	0.24
783	Motion Picture Theaters	1985	3.19	230.19	118.1%	109.1%	0.28	0.23
385	Ophthalmic Goods	1984	4.85	125.72	146.6%	125.3%	0.42	0.24
		1990s						
737	Business Services	1999	20.27	2,790.01	94.3%	70.7%	0.04	0.13
367	Semiconductors + Elect. Components	1999	11.37	4,500.18	99.1%	76.6%	0.04	0.18
122	Coal mining	1999	7.65	5,461.49	96.0%	76.9%	0.09	0.22
272	Publishing and Printing	1995	8.68	643.04	82.9%	82.6%	0.14	0.21
324	Cement Manufacturing	1994	2.13	1,106.86	91.9%	90.5%	0.19	0.22
422	Farm Product Warehousing+Storage	1996	4.40	229.42	137.4%	128.0%	0.20	0.20
		2000s						
122	Coal mining	2001	2.46	1,594.03	102.3%	100.2%	0.11	0.23
245	Prefabricated Buildings	2003	9.77	233.23	102.5%	100.4%	0.14	0.20
783	Motion Picture Theaters	2005	32.77	1,423.60	137.5%	111.6%	0.35	0.21
391	Jewelry, Precious Metal	2004	31.56	200.76	124.5%	112.8%	0.67	0.23
442	Farm Product Warehousing+Storage	2004	1.47	1,446.76	116.6%	132.7%	0.26	0.24

Explanation: This table lists the top five industries with the highest relative valuation in each decade for competitive industries. Competitive industries are those in the lowest tercile of the fitted sales based HHI (Herfindahl index) in each year. We present each three digit SIC industry's identifying information and the year in which it's relative valuation peaked. Weighted market to book equity is the industry's value weighted average of firm market-to-book ratios. Average firm market values are reported in millions. Percent relative valuation is the log difference in actual market value and predicted market value, where predicted values are based on valuation models presented in Rhodes-Kropf, Robinson, and Viswanathan (2005), using 10 years of lagged data. In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). CSTAT concentration is the sales weighted Herfindahl index for each industry (based on segment data when available) using COMPUSTAT data only. The fitted concentration index is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. We make one deviation from selecting the top five industries in each decade: we add two industries (one in the 1980s and one in the 1990s) from the top ten that have a very large number of firms (we list them due to their importance).

Table II: Examples of Industry Booms in Concentrated Industries

Three Digit SIC Code	Industry Name	Decade/ Year	Weighted Market to Book	Average Firm Mkt Value	Wgt % Above Predicted Valuation	% Above Predicted Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
	Concentrated Industries							
		1970s						
516	Plastics Materials and Basic Forms	1979	1.24	309.89	16.9%	24.9%	0.74	0.36
517	Petroleum Stations + Terminals	1979	1.14	1,252.48	33.7%	34.9%	0.51	0.49
348	Ordnance and Accessories	1979	1.42	34.43	35.3%	35.3%	0.41	0.34
387	Watches, Clocks, and Clockwork	1975	0.54	5.58	59.6%	50.4%	0.40	0.29
321	Flat Glass	1978	1.16	145.93	56.6%	57.8%	0.57	0.38
		1980s						
322	Glass Containers	1983	1.31	231.46	119.1%	97.3%	0.40	0.32
211	Tobacco manufactures	1988	2.52	10,304.94	63.7%	98.7%	0.27	0.60
253	Public Building and Related Furniture	1986	1.22	42.38	69.1%	99.1%	0.38	0.44
277	Greeting Cards	1985	2.27	571.78	71.1%	100.3%	0.63	0.58
396	Fasteners, Buttons, Needles, and Pins	1985	3.14	92.95	100.4%	100.4%	0.31	0.35
		1990s						
387	Watches, Clocks, and Clockwork	1993	5.95	100.28	103.0%	121.4%	0.54	0.50
301	Tires and Inner Tubes	1992	3.93	3,794.58	126.2%	124.4%	0.68	0.90
376	Guided Missiles and Space Vehicles	1995	2.87	7,040.29	116.9%	138.1%	0.23	0.56
792	Theatrical Producers	1998	3.98	1,240.59	199.7%	167.6%	0.46	0.55
228	Yarn and Thread Mills	1996	1.45	207.02	175.3%	175.3%	0.34	0.38
		2000s						
375	Motorcycles, Bicycles, and Parts	2003	4.59	7,893.29	63.1%	90.5%	0.51	0.48
207	Vegatable Oil Mills	2004	2.92	200.07	83.3%	92.4%	0.16	0.65
179	Structural Steel Erection	2005	1.97	133.38	118.3%	118.3%	0.23	0.50
332	Iron and Steel Foundaries	2004	2.86	2,075.31	134.0%	156.7%	0.33	0.36
518	Beer+Ale Distributors and Wholesale	2005	2.19	1,351.28	233.8%	233.8%	0.49	0.49

Explanation: This table lists the top five industries with the highest relative valuation in each decade for concentrated industries. Concentrated industries are those in the highest tercile of the fitted sales based HHI (Herfindahl index) in each year. We present each three digit SIC industry's identifying information and the year in which it's relative valuation peaked. Weighted market to book equity is the industry's value weighted average of firm market-to-book ratios. Average firm market values are reported in millions. Percent relative valuation is the log difference in actual market value and predicted market value, where predicted values are based on valuation model presented in Rhodes-Kropf, Robinson, and Viswanathan (2005), using 10 years of lagged data. In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). CSTAT concentration is the sales weighted Herfindahl index for each industry (based on segment data when available) using COMPUSTAT data only. The fitted concentration index is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data.

Table III: Summary statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
		Panel A: Entire Sample			
Relative Industry Valuation	-.007	.452	-2.133	2.195	116,322
Industry New Financing	.024	.064	-.408	.766	116,322
Relative Industry Investment	-.039	.422	-3.322	2.687	116,322
Relative Firm Valuation	-.028	.698	-3.368	3.308	116,322
Firm New Financing	.022	.157	-.849	1.790	116,322
Relative Firm Investment	.001	.833	-3.953	3.328	116,322
Operating Cash Flow Change	-.009	.139	-1.447	1.780	109,077
Abnormal Return	.000	.182	–1.192	23.504	1,431,128
		Panel B: Competitive Industries			
Relative Industry Valuation	.058	.374	-1.695	1.469	64,079
Industry New Financing	.028	.058	-.281	.586	64,079
Relative Industry Investment	-.057	.334	-2.412	2.553	64,079
Relative Firm Valuation	-.032	.745	-3.368	3.308	64,079
Firm New Financing	.033	.183	-.849	1.790	64,079
Relative Firm Investment	-.000	.888	-3.715	3.328	64,079
Operating Cash Flow Change	-.010	.165	-1.447	1.780	59,644
Abnormal Return	.001	.201	-1.192	13.867	803,992
		Panel C: Concentrated Industries			
Relative Industry Valuation	.014	.440	-2.133	1.676	14,303
Industry New Financing	.019	.073	-.408	.766	14,303
Relative Industry Investment	-.038	.462	-3.322	2.426	14,303
Relative Firm Valuation	-.025	.612	-3.325	2.821	14,303
Firm New Financing	.009	.119	-.727	1.375	14,303
Relative Firm Investment	.001	.713	-3.953	2.848	14,303
Operating Cash Flow Change	-.009	.099	-1.235	1.175	13,493
Abnormal Return	-.001	.145	-.954	5.196	173,245

Explanation: The table displays summary statistics for the entire sample (Panel A), and for subgroupings based on the level of ex-ante fitted concentration (Panels B and C). The fitted concentration index is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005), using 10 years of lagged data. In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). relative investment is computed using the same method, replacing log investment with log market cap. Relative industry valuation, relative industry investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average. Operating cash flow is defined as operating income (COMPUSTAT annual item 13) divided by assets (COMPUSTAT annual item 6). A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997).

Table IV: Regressions predicting Firm-level Operating Cash Flow Changes

Variable	*Whole Sample* OLS w/ Year Clusters	*Whole Sample* OLS w/ Year + Ind. Clusters	*Whole Sample* Random Firm Effects	*Excluding 1998-2000* OLS w/ Year Clusters	*Excluding 1998-2000* OLS w/ Year + Ind. Clusters	*Excluding 1998-2000* Random Firm Effects
Panel A: Sample-wide results						
Industry Relative Valuation	–0.0070 (–2.150)^{b}	–0.0070 (–1.790)^{c}	–0.0071 (–2.280)^{b}	–0.0096 (–2.580)^{a}	–0.0096 (–3.040)^{a}	–0.0105 (–2.840)^{a}
Firm Relative Valuation	–0.0007 (–0.420)	–0.0007 (–0.620)	–0.0034 (–1.470)	–0.0013 (–0.840)	–0.0013 (–1.130)	–0.0039 (–1.840)^{c}
Industry Relative Investment	–0.0149 (–4.730)^{a}	–0.0149 (–4.030)^{a}	–0.0183 (–5.520)^{a}	–0.0174 (–4.600)^{a}	–0.0174 (–4.810)^{a}	–0.0191 (–5.970)^{a}
Firm Relative Investment	–0.0047 (–4.100)^{a}	–0.0047 (–4.610)^{a}	–0.0077 (–5.440)^{a}	–0.0051 (–4.230)^{a}	–0.0051 (–4.680)^{a}	–0.0077 (–5.790)^{a}
Industry New Finance	–0.0786 (–2.830)^{a}	–0.0786 (–3.450)^{a}	–0.0484 (–1.750)^{c}	–0.0487 (–3.180)^{a}	–0.0487 (–3.030)^{a}	–0.0139 (–0.930)
Firm New Finance	–0.0158 (–2.150)^{b}	–0.0158 (–1.420)	0.0078 (1.040)	–0.0099 (–1.460)	–0.0099 (–0.790)	0.0132 (2.100)^{b}
Observations	102,815	102,815	102,815	90,390	90,390	90,390
Panel B: Competitive Industries						
Industry Relative Valuation	–0.0096 (–2.000)^{b,f}	–0.0096 (–1.260)	–0.0089 (–1.980)^{b,f}	–0.0121 (–1.770)^{c}	–0.0121 (–1.960)^{b,f}	–0.0131 (–1.910)^{c,f}
Firm Relative Valuation	0.0007 (0.320)	0.0007 (0.450)	–0.0016 (–0.530)	0.0006 (0.270)	0.0006 (0.320)	–0.0014 (–0.510)
Industry Relative Investment	–0.0211 (–3.840)^{a}	–0.0211 (–3.020)^{a}	–0.0253 (–4.140)^{a,f}	–0.0254 (–4.100)^{a,f}	–0.0254 (–4.010)^{a,f}	–0.0264 (–4.610)^{a,f}
Firm Relative Investment	–0.0051 (–2.760)^{a}	–0.0051 (–3.450)^{a}	–0.0080 (–3.610)^{a}	–0.0055 (–2.840)^{a}	–0.0055 (–3.430)^{a}	–0.0082 (–3.820)^{a}
Industry New Finance	–0.0895 (–1.780)^{c}	–0.0895 (–2.230)^{b}	–0.0740 (–1.410)	–0.0429 (–1.770)^{c}	–0.0429 (–1.610)	–0.0172 (–0.730)
Firm New Finance	–0.0212 (–2.700)^{a}	–0.0212 (–1.470)	–0.0033 (–0.410)	–0.0153 (–2.080)^{b}	–0.0153 (–0.890)	0.0039 (0.570)
Observations	53,977	53,977	53,977	45,507	45,507	45,507
Panel C: Concentrated Industries						
Industry Relative Valuation	0.0007 (0.180)^{f}	0.0007 (0.220)	0.0006 (0.150)^{f}	–0.0003 (–0.070)	–0.0003 (–0.080)^{f}	–0.0007 (–0.160)^{f}
Firm Relative Valuation	–0.0017 (–1.070)	–0.0017 (–1.010)	–0.0035 (–1.700)^{c}	–0.0020 (–1.100)	–0.0020 (–1.160)	–0.0040 (–1.690)^{c}
Industry Relative Investment	–0.0113 (–3.180)^{a}	–0.0113 (–3.160)^{a}	–0.0134 (–3.450)^{a,f}	–0.0114 (–2.940)^{a,f}	–0.0114 (–2.950)^{a,f}	–0.0135 (–3.130)^{a,f}
Firm Relative Investment	–0.0041 (–2.480)^{b}	–0.0041 (–1.910)^{c}	–0.0065 (–4.080)^{a}	–0.0048 (–2.710)^{a}	–0.0048 (–2.090)^{b}	–0.0071 (–4.160)^{a}
Industry New Finance	–0.0583 (–1.840)^{c}	–0.0583 (–2.170)^{b}	–0.0173 (–0.690)	–0.0379 (–1.290)	–0.0379 (–1.490)	0.0016 (0.060)
Firm New Finance	0.0011 (0.070)	0.0011 (0.060)	0.0226 (1.680)^{c}	0.0031 (0.180)	0.0031 (0.170)	0.0252 (1.870)^{c}
Observations	18,914	18,914	18,914	17,137	17,137	17,137
Panel D: Industries with Declining Concentration						
Industry Relative Valuation	–0.0171 (–1.920)^{c,e}	–0.0171 (–2.650)^{a,d}	–0.0165 (–1.930)^{c,e}	–0.0155 (–2.630)^{a,e}	–0.0155 (–2.650)^{a,e}	–0.0152 (–2.540)^{b,e}
Firm Relative Valuation	–0.0021 (–1.360)	–0.0021 (–1.170)	–0.0048 (–2.460)^{b}	–0.0019 (–1.220)	–0.0019 (–1.010)	–0.0046 (–2.370)^{b}
Industry Relative Investment	–0.0194 (–3.720)^{a}	–0.0194 (–3.350)^{a}	–0.0186 (–3.320)^{a}	–0.0216 (–3.270)^{a,f}	–0.0216 (–3.750)^{a,e}	–0.0199 (–3.000)^{a}
Firm Relative Investment	–0.0061 (–3.170)^{a}	–0.0061 (–3.370)^{a}	–0.0082 (–3.430)^{a}	–0.0073 (–3.180)^{a}	–0.0073 (–3.890)^{a,f}	–0.0091 (–3.350)^{a}
Industry New Finance	–0.0938 (–3.270)^{a,f}	–0.0938 (–3.110)^{a}	–0.0762 (–2.670)^{a}	–0.0733 (–3.130)^{a,f}	–0.0733 (–2.990)^{a,f}	–0.0556 (–2.180)^{b}
Firm New Finance	–0.0054 (–0.820)	–0.0054 (–0.330)	0.0077 (1.080)	–0.0037 (–0.600)	–0.0037 (–0.200)	0.0093 (1.440)
Observations	43,771	43,771	43,771	40,057	40,057	40,057

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and also new finance on firm-level changes in operating cash flows. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) and random firm effects regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). One observation is one firm in one year, and the dependent variable is the firm's change in operating cash flow from year t to year t+1. Operating cash flow is defined as operating income (COMPUSTAT annual item 13) divided by assets (COMPUSTAT annual item 6). The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Relative industry valuation, industry relative investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries in Panels B, C, and decreasing versus increasing concentration in Panel D) at the 1%, 5%, and 10% levels, respectively.

Table V: Regressions predicting firm-level operating cash flows in high market risk terciles

	Whole Sample			***Excluding 1998-2000***		
Variable	OLS w/ Year Clusters	OLS w/ Year + Ind. Clusters	Random Firm Effects	OLS w/ Year Clusters	OLS w/ Year + Ind. Clusters	Random Firm Effects
			Panel A: High Market Risk Tercile (all firms)			
Industry Relative Valuation	–0.0152 (–3.150)^{a}	–0.0152 (–2.000)^{b}	–0.0149 (–3.170)^{a}	–0.0212 (–3.610)^{a}	–0.0212 (–3.740)^{a}	–0.0226 (–3.610)^{a}
Firm Relative Valuation	–0.0013 (–0.480)	–0.0013 (–0.720)	–0.0041 (–1.180)	–0.0020 (–0.770)	–0.0020 (–1.030)	–0.0048 (–1.450)
Industry Relative Investment	–0.0216 (–3.570)^{a}	–0.0216 (–3.630)^{a}	–0.0228 (–3.790)^{a}	–0.0235 (–3.580)^{a}	–0.0235 (–4.300)^{a}	–0.0225 (–4.230)^{a}
Firm Relative Investment	–0.0072 (–4.570)^{a}	–0.0072 (–4.050)^{a}	–0.0104 (–5.380)^{a}	–0.0076 (–4.330)^{a}	–0.0076 (–3.930)^{a}	–0.0102 (–4.920)^{a}
Industry New Finance	–0.1503 (–2.690)^{a}	–0.1503 (–3.640)^{a}	–0.1389 (–2.420)^{b}	–0.0597 (–2.220)^{b}	–0.0597 (–2.260)^{b}	–0.0356 (–1.320)
Firm New Finance	–0.0210 (–2.030)^{b}	–0.0210 (–1.320)	–0.0053 (–0.570)	–0.0130 (–1.140)	–0.0130 (–0.680)	0.0046 (0.520)
Observations	45,145	45,145	45,145	38,856	38,856	38,856
			Panel B: High Market Risk Tercile (Competitive Industries Only)			
Industry Relative Valuation	–0.0225 (–3.740)^{a,e}	–0.0225 (–1.820)^{c}	–0.0216 (–3.630)^{a,e}	–0.0316 (–4.320)^{a,d}	–0.0316 (–3.290)^{a,e}	–0.0335 (–4.130)^{a,d}
Firm Relative Valuation	–0.0002 (–0.070)	–0.0002 (–0.100)	–0.0019 (–0.460)	–0.0001 (–0.030)	–0.0001 (–0.030)	–0.0015 (–0.360)
Industry Relative Investment	–0.0267 (–3.190)^{a}	–0.0267 (–2.500)^{b}	–0.0269 (–3.070)^{a}	–0.0274 (–3.390)^{a}	–0.0274 (–2.910)^{a}	–0.0245 (–3.320)^{a}
Firm Relative Investment	–0.0092 (–3.880)^{a,f}	–0.0092 (–3.800)^{a}	–0.0117 (–4.520)^{a,e}	–0.0098 (–3.530)^{a,f}	–0.0098 (–3.660)^{a}	–0.0123 (–4.110)^{a,f}
Industry New Finance	–0.2048 (–2.100)^{b}	–0.2048 (–2.940)^{a}	–0.2057 (–2.090)^{b}	–0.0634 (–1.360)	–0.0634 (–1.430)	–0.0505 (–1.100)
Firm New Finance	–0.0280 (–3.010)^{a}	–0.0280 (–1.500)	–0.0187 (–2.120)^{b}	–0.0223 (–2.150)^{b}	–0.0223 (–0.950)	–0.0100 (–1.230)
Observations	26,478	26,478	26,478	21,308	21,308	21,308
			Panel C: High Market Risk Tercile (Concentrated Industries Only)			
Industry Relative Valuation	–0.0023 (–0.410)^{e}	–0.0023 (–0.450)	–0.0045 (–0.830)^{e}	–0.0049 (–0.830)^{d}	–0.0049 (–0.930)^{e}	–0.0067 (–1.210)^{d}
Firm Relative Valuation	–0.0023 (–0.680)	–0.0023 (–0.850)	–0.0043 (–1.150)	–0.0041 (–1.190)	–0.0041 (–1.430)	–0.0063 (–1.760)^{c}
Industry Relative Investment	–0.0161 (–2.370)^{b}	–0.0161 (–2.530)^{b}	–0.0179 (–2.620)^{a}	–0.0155 (–2.240)^{b}	–0.0155 (–2.340)^{b}	–0.0159 (–2.330)^{b}
Firm Relative Investment	–0.0027 (–0.860)^{f}	–0.0027 (–0.780)	–0.0044 (–1.320)^{e}	–0.0027 (–0.840)^{f}	–0.0027 (–0.760)	–0.0044 (–1.260)^{f}
Industry New Finance	–0.0651 (–1.210)	–0.0651 (–1.270)	–0.0487 (–1.040)	–0.0307 (–0.620)	–0.0307 (–0.690)	–0.0226 (–0.520)
Firm New Finance	0.0058 (0.200)	0.0058 (0.210)	0.0174 (0.830)	0.0080 (0.280)	0.0080 (0.290)	0.0200 (0.940)
Observations	8,145	8,145	8,145	7,679	7,679	7,679

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and also new finance on firm-level changes in operating cash flows in industries with high market risk. Industries with high market risk are those in the upper tercile (yearly sorts) based on their past-year market beta. Market betas are estimated using daily firm-level returns, and industry market betas are the equal weighted average of firm-level betas based on three-digit SIC codes. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) and random firm effects regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). One observation is one firm in one year, and the dependent variable is the firm's change in operating cash flow from year t to year t+1. Operating cash flow is defined as operating income (COMPUSTAT annual item 13) divided by assets (COMPUSTAT annual item 6). The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Relative Industry valuation, industry relative investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average.
* a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries in Panels B, C) at the 1%, 5%, and 10% levels, respectively.

Table VI: Regressions predicting monthly firm-level stock returns

	Whole Sample			***Excluding 1998-2000***		
Variable	Industry Clusters	Ind+Year Clusters	Fama-MacBeth	Industry Clusters	Ind+Year Clusters	Fama-MacBeth
			Panel A: Sample-wide results			
Industry Relative Valuation	–0.0045 (–2.730)[a]	–0.0045 (–2.640)[a]	–0.0030 (–1.664)[c]	–0.0040 (–2.430)[b]	–0.0040 (–2.550)[b]	–0.0032 (–2.059)[b]
Firm Relative Valuation	–0.0025 (–6.700)[a]	–0.0025 (–8.140)[a]	–0.0023 (–7.159)[a]	–0.0025 (–7.650)[a]	–0.0025 (–8.390)[a]	–0.0023 (–6.943)[a]
Industry Relative Investment	–0.0030 (–1.680)[c]	–0.0030 (–2.140)[b]	–0.0032 (–2.088)[b]	–0.0002 (–0.140)	–0.0002 (–0.190)	–0.0010 (–0.915)
Firm Relative Investment	–0.0015 (–8.740)[a]	–0.0015 (–6.480)[a]	–0.0015 (–5.173)[a]	–0.0012 (–7.170)[a]	–0.0012 (–5.440)[a]	–0.0013 (–4.806)[a]
Industry New Finance	–0.0312 (–4.650)[a]	–0.0312 (–4.440)[a]	–0.0249 (–3.758)[a]	–0.0255 (–3.960)[a]	–0.0255 (–3.820)[a]	–0.0219 (–3.209)[a]
Firm New Finance	–0.0157 (–8.060)[a]	–0.0157 (–6.420)[a]	–0.0143 (–5.956)[a]	–0.0195 (–13.170)[a]	–0.0195 (–8.680)[a]	–0.0161 (–7.006)[a]
Observations	1,224,201	1,224,201	1,224,201	1,081,614	1,081,614	1,081,614
			Panel B: Competitive Industries			
Industry Relative Valuation	–0.0037 (–1.600)	–0.0037 (–1.450)	–0.0030 (–1.163)	–0.0042 (–1.840)[c]	–0.0042 (–1.700)[c]	–0.0044 (–1.980)[b]
Firm Relative Valuation	–0.0031 (–6.260)[a,e]	–0.0031 (–7.220)[a,e]	–0.0030 (–6.710)[a,e]	–0.0032 (–7.080)[a,e]	–0.0032 (–7.530)[a,e]	–0.0030 (–6.550)[a,e]
Industry Relative Investment	–0.0054 (–1.760)[c]	–0.0054 (–2.080)[b]	–0.0055 (–2.209)[b]	–0.0002 (–0.070)	–0.0002 (–0.090)	–0.0025 (–1.196)
Firm Relative Investment	–0.0014 (–4.930)[a]	–0.0014 (–4.390)[a]	–0.0014 (–3.573)[a]	–0.0009 (–3.880)[a]	–0.0009 (–3.130)[a]	–0.0011 (–3.041)[a]
Industry New Finance	–0.0458 (–3.970)[a,f]	–0.0458 (–4.070)[a,f]	–0.0280 (–2.598)[a]	–0.0296 (–3.270)[a]	–0.0296 (–3.000)[a]	–0.0202 (–1.808)[c]
Firm New Finance	–0.0152 (–6.880)[a,f]	–0.0152 (–5.250)[a,f]	–0.0120 (–4.142)[a,e]	–0.0193 (–10.430)[a]	–0.0193 (–6.980)[a]	–0.0136 (–4.743)[a]
Observations	674,367	674,367	674,367	570,673	570,673	570,673
			Panel C: Concentrated Industries			
Industry Relative Valuation	–0.0028 (–1.370)	–0.0028 (–1.280)	–0.0024 (–1.112)	–0.0029 (–1.360)	–0.0029 (–1.300)	–0.0028 (–1.269)
Firm Relative Valuation	–0.0010 (–1.200)[e]	–0.0010 (–1.310)[e]	–0.0010 (–1.246)[e]	–0.0011 (–1.540)[e]	–0.0011 (–1.540)[e]	–0.0012 (–1.458)[e]
Industry Relative Investment	–0.0026 (–1.470)	–0.0026 (–1.470)	–0.0029 (–1.709)[c]	–0.0022 (–1.240)	–0.0022 (–1.170)	–0.0021 (–1.196)
Firm Relative Investment	–0.0012 (–2.420)[b]	–0.0012 (–1.850)[c]	–0.0014 (–1.897)[c]	–0.0011 (–2.120)[b]	–0.0011 (–1.750)[c]	–0.0014 (–1.873)[c]
Industry New Finance	–0.0164 (–1.250)[f]	–0.0164 (–1.230)[f]	–0.0207 (–1.564)	–0.0128 (–0.860)	–0.0128 (–0.950)	–0.0188 (–1.367)
Firm New Finance	–0.0239 (–5.220)[a,f]	–0.0239 (–4.830)[a,f]	–0.0251 (–4.665)[a,e]	–0.0227 (–5.060)[a]	–0.0227 (–4.430)[a]	–0.0236 (–4.098)[a]
Observations	153,288	153,288	153,288	140,358	140,358	140,358
			Panel D: Industries with Declining Concentration			
Industry Relative Valuation	–0.0047 (–1.940)[c]	–0.0047 (–1.670)[c]	–0.0047 (–1.795)[c]	–0.0045 (–2.060)[b]	–0.0045 (–1.700)[c]	–0.0051 (–2.238)[b]
Firm Relative Valuation	–0.0034 (–5.810)[a,e]	–0.0034 (–5.900)[a,e]	–0.0031 (–5.779)[a,e]	–0.0030 (–5.400)[a,f]	–0.0030 (–5.580)[a,e]	–0.0029 (–5.378)[a,e]
Industry Relative Investment	–0.0064 (–2.210)[b,e]	–0.0064 (–2.530)[b,d]	–0.0045 (–1.882)[c,e]	–0.0003 (–0.130)	–0.0003 (–0.140)	–0.0006 (–0.381)
Firm Relative Investment	–0.0019 (–7.030)[a]	–0.0019 (–4.430)[a]	–0.0018 (–3.947)[a]	–0.0016 (–5.280)[a]	–0.0016 (–3.880)[a]	–0.0016 (–3.657)[a]
Industry New Finance	–0.0291 (–2.800)[a]	–0.0291 (–2.720)[a]	–0.0317 (–2.928)[a]	–0.0315 (–3.250)[a]	–0.0315 (–3.000)[a]	–0.0294 (–2.556)[b]
Firm New Finance	–0.0123 (–3.470)[a,f]	–0.0123 (–3.320)[a,f]	–0.0114 (–3.095)[a]	–0.0182 (–5.630)[a,f]	–0.0182 (–6.690)[a,f]	–0.0130 (–3.504)[a]
Observations	429,019	429,019	429,019	374,709	374,709	374,709

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and new financing on monthly risk-adjusted firm-level stock returns. We report regression coefficients and t-statistics (in parentheses) for various panel data regression models. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) with year fixed effects (industry clustering adjustments), OLS with year fixed effects (industry and year clustering adjustments), and Fama-MacBeth regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). One observation is one firm in one month, and the dependent variable is the firm's monthly abnormal return. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, independent variables are constructed using accounting data with fiscal years ending in year t. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Relative Industry valuation, industry relative investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries in Panels B, C, and decreasing versus increasing concentration in Panel D) at the 1%, 5%, and 10% levels, respectively.

Table VII: Regressions predicting firm-level stock returns in high relative valuation terciles

Variable	*Whole Sample* Industry Clusters	Ind+Year Clusters	Fama-MacBeth	*Excluding 1998-2000* Industry Clusters	Ind+Year Clusters	Fama-MacBeth
Panel A: High Relative Valuation Tercile (all firms)						
Industry Relative Valuation	–0.0140 (–3.510)^{a}	–0.0140 (–4.130)^{a}	–0.0091 (–2.802)^{a}	–0.0057 (–1.520)	–0.0057 (–1.930)^{c}	–0.0050 (–1.770)^{c}
Firm Relative Valuation	–0.0023 (–5.130)^{a}	–0.0023 (–4.600)^{a}	–0.0024 (–4.246)^{a}	–0.0023 (–5.590)^{a}	–0.0023 (–4.450)^{a}	–0.0024 (–4.038)^{a}
Industry Relative Investment	–0.0034 (–1.390)	–0.0034 (–1.490)	–0.0015 (–0.664)	0.0013 (0.730)	0.0013 (0.800)	0.0016 (1.049)
Firm Relative Investment	–0.0006 (–1.610)	–0.0006 (–1.460)	–0.0010 (–2.015)^{b}	–0.0001 (–0.180)	–0.0001 (–0.180)	–0.0008 (–1.525)
Industry New Finance	–0.0351 (–3.310)^{a}	–0.0351 (–3.540)^{a}	–0.0233 (–2.355)^{b}	–0.0267 (–2.740)^{a}	–0.0267 (–3.080)^{a}	–0.0173 (–1.701)^{c}
Firm New Finance	–0.0229 (–7.820)^{a}	–0.0229 (–5.360)^{a}	–0.0185 (–5.418)^{a}	–0.0273 (–6.800)^{a}	–0.0273 (–6.490)^{a}	–0.0197 (–5.526)^{a}
Observations	351,869	351,869	351,869	298,764	298,764	298,764
Panel B: High Relative Valuation Tercile (Competitive Industries Only)						
Industry Relative Valuation	–0.0227 (–3.660)^{a,d}	–0.0227 (–3.940)^{a,d}	–0.0148 (–2.368)^{b}	–0.0113 (–1.950)^{c,e}	–0.0113 (–2.280)^{b,e}	–0.0112 (–1.911)^{c}
Firm Relative Valuation	–0.0026 (–3.750)^{a}	–0.0026 (–3.740)^{a}	–0.0027 (–3.303)^{a}	–0.0026 (–4.120)^{a}	–0.0026 (–3.550)^{a}	–0.0028 (–3.101)^{a}
Industry Relative Investment	–0.0085 (–1.910)^{c,f}	–0.0085 (–1.940)^{c,f}	–0.0005 (–0.119)	0.0020 (0.510)	0.0020 (0.540)	0.0046 (1.330)
Firm Relative Investment	–0.0001 (–0.210)^{f}	–0.0001 (–0.190)^{f}	–0.0003 (–0.480)	0.0008 (1.360)^{e}	0.0008 (1.390)^{e}	0.0000 (0.000)
Industry New Finance	–0.0566 (–3.710)^{a,e}	–0.0566 (–3.770)^{a,e}	–0.0450 (–2.293)^{b}	–0.0339 (–2.570)^{b}	–0.0339 (–2.730)^{a,f}	–0.0278 (–1.388)
Firm New Finance	–0.0242 (–6.850)^{a}	–0.0242 (–4.780)^{a}	–0.0170 (–3.329)^{a}	–0.0307 (–6.350)^{a,f}	–0.0307 (–6.140)^{a}	–0.0182 (–3.279)^{a}
Observations	186,338	186,338	186,338	144,059	144,059	144,059
Panel C: High Relative Valuation Tercile (Concentrated Industries Only)						
Industry Relative Valuation	0.0048 (0.910)^{d}	0.0048 (0.830)^{d}	–0.0012 (–0.170)	0.0078 (1.540)^{e}	0.0078 (1.290)^{d}	–0.0017 (–0.235)
Firm Relative Valuation	–0.0022 (–2.120)^{b}	–0.0022 (–1.820)^{c}	–0.0027 (–1.786)^{c}	–0.0020 (–1.940)^{c}	–0.0020 (–1.650)^{c}	–0.0023 (–1.404)
Industry Relative Investment	0.0012 (0.430)^{f}	0.0012 (0.430)^{f}	–0.0018 (–0.462)	0.0004 (0.150)	0.0004 (0.140)	–0.0026 (–0.727)
Firm Relative Investment	–0.0021 (–2.100)^{b,f}	–0.0021 (–1.980)^{b}	–0.0022 (–1.672)^{c}	–0.0017 (–1.600)^{e}	–0.0017 (–1.680)^{c,e}	–0.0017 (–1.269)
Industry New Finance	0.0161 (0.610)^{e}	0.0161 (0.670)^{e}	0.0042 (0.180)	0.0142 (0.420)	0.0142 (0.550)	–0.0042 (–0.174)
Firm New Finance	–0.0208 (–3.570)^{a}	–0.0208 (–2.900)^{a}	–0.0270 (–3.169)^{a}	–0.0176 (–3.060)^{a,f}	–0.0176 (–2.470)^{b,f}	–0.0247 (–2.718)^{a}
Observations	51,435	51,435	51,435	46,971	46,971	46,971

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and new financing on monthly risk-adjusted firm-level stock returns in high valuation industries. Industries with high valuation are those in the upper tercile (yearly sorts) based on their past-year relative industry valuation. We report regression coefficients t-statistics (in parentheses) for various panel data regression models. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) with year fixed effects (industry clustering adjustments), OLS with year fixed effects (industry and year clustering adjustments), and Fama-MacBeth regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). One observation is one firm in one month, and the dependent variable is the firm's monthly abnormal return. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, independent variables are constructed using accounting data with fiscal years ending in year t. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Relative Industry valuation, industry relative investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries in Panels B, C) at the 1%, 5%, and 10% levels, respectively.

Table VIII: Regressions predicting firm-level stock returns in high market risk terciles

	Whole Sample			*Excluding 1998-2000*		
Variable	Industry Clusters	Ind+Year Clusters	Fama-MacBeth	Industry Clusters	Ind+Year Clusters	Fama-MacBeth
			Panel A: High Market Risk Tercile (all firms)			
Industry Relative Valuation	–0.0091 (–4.250)^{a}	–0.0091 (–3.850)^{a}	–0.0063 (–2.217)^{b}	–0.0058 (–3.750)^{a}	–0.0058 (–2.740)^{a}	–0.0039 (–1.593)
Firm Relative Valuation	–0.0029 (–5.210)^{a}	–0.0029 (–5.930)^{a}	–0.0029 (–5.670)^{a}	–0.0029 (–6.220)^{a}	–0.0029 (–6.110)^{a}	–0.0029 (–5.501)^{a}
Industry Relative Investment	–0.0087 (–4.250)^{a}	–0.0087 (–4.180)^{a}	–0.0072 (–2.904)^{a}	–0.0040 (–2.210)^{b}	–0.0040 (–1.980)^{b}	–0.0033 (–1.838)^{c}
Firm Relative Investment	–0.0013 (–3.590)^{a}	–0.0013 (–3.260)^{a}	–0.0011 (–2.639)^{a}	–0.0009 (–3.330)^{a}	–0.0009 (–2.390)^{b}	–0.0009 (–2.122)^{b}
Industry New Finance	–0.0453 (–3.590)^{a}	–0.0453 (–3.450)^{a}	–0.0275 (–2.582)^{a}	–0.0299 (–2.820)^{a}	–0.0299 (–2.640)^{a}	–0.0202 (–1.872)^{c}
Firm New Finance	–0.0155 (–7.780)^{a}	–0.0155 (–4.760)^{a}	–0.0123 (–4.378)^{a}	–0.0202 (–11.670)^{a}	–0.0202 (–6.640)^{a}	–0.0142 (–5.144)^{a}
Observations	501,298	501,298	501,298	427,119	427,119	427,119
			Panel B: High Market Risk Tercile (Competitive Industries Only)			
Industry Relative Valuation	–0.0115 (–4.150)^{a,e}	–0.0115 (–3.500)^{a,e}	–0.0086 (–2.079)^{b}	–0.0069 (–3.410)^{a}	–0.0069 (–2.360)^{b}	–0.0054 (–1.423)
Firm Relative Valuation	–0.0035 (–5.330)^{a,d}	–0.0035 (–5.900)^{a,d}	–0.0038 (–5.321)^{a,d}	–0.0036 (–6.080)^{a,d}	–0.0036 (–5.960)^{a,d}	–0.0038 (–5.073)^{a,d}
Industry Relative Investment	–0.0116 (–4.310)^{a,e}	–0.0116 (–3.350)^{a,e}	–0.0129 (–3.052)^{a,e}	–0.0052 (–1.880)^{c}	–0.0052 (–1.510)	–0.0101 (–2.360)^{b,f}
Firm Relative Investment	–0.0012 (–2.030)^{b}	–0.0012 (–2.290)^{b}	–0.0012 (–1.889)^{c}	–0.0007 (–1.690)^{c}	–0.0007 (–1.460)	–0.0010 (–1.474)
Industry New Finance	–0.0803 (–4.010)^{a,d}	–0.0803 (–4.220)^{a,d}	–0.0339 (–1.597)	–0.0393 (–2.500)^{b}	–0.0393 (–2.390)^{b}	–0.0140 (–0.646)
Firm New Finance	–0.0153 (–6.830)^{a}	–0.0153 (–4.230)^{a}	–0.0102 (–2.661)^{a,e}	–0.0202 (–10.640)^{a}	–0.0202 (–5.870)^{a}	–0.0117 (–2.900)^{a}
Observations	321,042	321,042	321,042	257,939	257,939	257,939
			Panel C: High Market Risk Tercile (Concentrated Industries Only)			
Industry Relative Valuation	–0.0017 (–0.590)^{e}	–0.0017 (–0.500)^{e}	–0.0021 (–0.515)	–0.0018 (–0.590)	–0.0018 (–0.490)	–0.0016 (–0.399)
Firm Relative Valuation	0.0005 (0.390)^{d}	0.0005 (0.490)^{d}	0.0020 (1.392)^{d}	–0.0004 (–0.360)^{d}	–0.0004 (–0.380)^{e}	0.0003 (0.254)^{d}
Industry Relative Investment	–0.0022 (–0.690)^{e}	–0.0022 (–0.720)^{e}	–0.0025 (–0.774)^{e}	–0.0021 (–0.630)	–0.0021 (–0.650)	–0.0010 (–0.334)^{f}
Firm Relative Investment	–0.0002 (–0.330)	–0.0002 (–0.250)	0.0001 (0.103)	0.0000 (0.020)	0.0000 (0.020)	0.0005 (0.355)
Industry New Finance	0.0014 (0.070)^{d}	0.0014 (0.080)^{d}	–0.0216 (–0.907)	–0.0007 (–0.030)	–0.0007 (–0.030)	–0.0276 (–1.084)
Firm New Finance	–0.0225 (–3.210)^{a}	–0.0225 (–3.230)^{a}	–0.0341 (–3.776)^{a,e}	–0.0196 (–2.790)^{a}	–0.0196 (–2.790)^{a}	–0.0262 (–2.955)^{a}
Observations	65,905	65,905	65,905	63,167	63,167	63,167

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and new financing on monthly risk-adjusted firm-level stock returns in high market risk industries. Industries with high market risk are those in the upper tercile (yearly sorts) based on their past-year market beta. Market betas are estimated using daily firm-level returns, and industry market betas are the equal weighted average of firm-level betas based on three digit SIC codes. We report regression coefficients t-statistics (in parentheses) for various panel data regression models. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) with year fixed effects (industry clustering adjustments), OLS with year fixed effects (industry and year clustering adjustments), and Fama-MacBeth regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). One observation is one firm in one month, and the dependent variable is the firm's monthly abnormal return. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, independent variables are constructed using accounting data with fiscal years ending in year t. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. The independent variables are constructed from observed levels of firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Relative Industry valuation, industry relative investment, and industry new financing are the equal weighted averages of each quantity over all firm observations in year t. Each firm-level variable is equal to its raw value minus its industry average. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries in Panels B, C) at the 1%, 5%, and 10% levels, respectively.

Table IX: Regressions predicting annual changes in risk (competitive industries only)

Variable	*Whole Sample* Industry Clusters	Ind+Year Clusters	Fama-MacBeth	*Excluding 1998-2000* Industry Clusters	Ind+Year Clusters	Fama-MacBeth
			Panel A: Changes in Total Risk			
Industry Relative Valuation	–0.0013 (–2.340)^{b}	–0.0013 (–1.860)^{c}	–0.0002 (–0.274)	–0.0023 (–3.180)^{a,e}	–0.0023 (–2.820)^{a,e}	–0.0011 (–1.485)
Firm Relative Valuation	–0.0015 (–4.650)^{a}	–0.0015 (–5.270)^{a}	–0.0008 (–2.700)^{a,e}	–0.0014 (–5.310)^{a}	–0.0014 (–4.280)^{a}	–0.0007 (–2.087)^{b,f}
Industry Relative Investment	–0.0017 (–1.680)^{c}	–0.0017 (–2.090)^{b}	–0.0012 (–1.391)	–0.0005 (–0.710)^{f}	–0.0005 (–0.630)^{f}	–0.0004 (–0.766)^{f}
Firm Relative Investment	–0.0007 (–3.300)^{a}	–0.0007 (–3.890)^{a}	–0.0006 (–3.607)^{a}	–0.0006 (–2.550)^{b}	–0.0006 (–3.010)^{a}	–0.0005 (–3.075)^{a}
Industry New Finance	0.0202 (4.320)^{a}	0.0202 (4.830)^{a}	0.0190 (3.964)^{a}	0.0215 (4.220)^{a}	0.0215 (4.760)^{a}	0.0196 (3.680)^{a}
Firm New Finance	0.0123 (5.380)^{a,f}	0.0123 (8.850)^{a}	0.0094 (7.825)^{a,d}	0.0118 (5.730)^{a}	0.0118 (7.680)^{a}	0.0087 (6.919)^{a,e}
Lagged Total Risk	–0.2858 (–6.000)^{a}	–0.2858 (–7.740)^{a}	–0.2307 (–7.353)^{a}	–0.2560 (–5.700)^{a}	–0.2560 (–5.640)^{a}	–0.2118 (–6.491)^{a}
Observations	50,137	50,137	50,137	42,176	42,176	42,176
			Panel B: Changes in Market Beta			
Industry Relative Valuation	0.1328 (1.910)^{c}	0.1328 (3.410)^{a,f}	0.0911 (1.603)	0.0654 (0.760)	0.0654 (1.490)	0.0507 (0.917)
Firm Relative Valuation	0.0892 (10.730)^{a}	0.0892 (12.130)^{a}	0.0905 (10.640)^{a}	0.0903 (13.090)^{a}	0.0903 (12.100)^{a}	0.0915 (10.548)^{a}
Industry Relative Investment	–0.1783 (–2.910)^{a,e}	–0.1783 (–4.310)^{a,d}	–0.1071 (–2.159)^{b}	–0.0984 (–2.020)^{b}	–0.0984 (–2.460)^{b,f}	–0.0715 (–1.986)^{b}
Firm Relative Investment	–0.0038 (–0.630)	–0.0038 (–0.760)	–0.0058 (–0.882)	0.0002 (0.030)	0.0002 (0.040)	–0.0047 (–0.638)
Industry New Finance	–0.0359 (–0.220)	–0.0359 (–0.230)	0.2453 (1.030)	0.1673 (1.020)	0.1673 (1.030)	0.3357 (1.293)
Firm New Finance	0.1583 (3.440)^{a}	0.1583 (4.590)^{a}	0.1550 (3.565)^{a}	0.1486 (3.010)^{a}	0.1486 (4.140)^{a}	0.1592 (3.446)^{a}
Lagged Market Beta	–0.6248 (–29.310)^{a}	–0.6248 (–49.910)^{a}	–0.6076 (–24.468)^{a}	–0.6609 (–33.020)^{a}	–0.6609 (–53.930)^{a}	–0.6258 (–26.169)^{a}
Observations	50,137	50,137	50,137	42,176	42,176	42,176
			Panel C: Changes in Idiosyncratic Risk			
Industry Relative Valuation	–0.0014 (–2.350)^{b}	–0.0014 (–1.950)^{c}	–0.0004 (–0.484)	–0.0023 (–2.920)^{a,e}	–0.0023 (–2.770)^{a,e}	–0.0010 (–1.514)
Firm Relative Valuation	–0.0015 (–4.320)^{a}	–0.0015 (–5.150)^{a}	–0.0008 (–2.932)^{a,e}	–0.0014 (–4.910)^{a}	–0.0014 (–4.130)^{a}	–0.0007 (–2.237)^{b,f}
Industry Relative Investment	–0.0014 (–1.470)	–0.0014 (–1.780)^{c}	–0.0009 (–1.261)	–0.0003 (–0.550)^{f}	–0.0003 (–0.490)^{f}	–0.0003 (–0.572)^{f}
Firm Relative Investment	–0.0006 (–3.110)^{a}	–0.0006 (–3.680)^{a}	–0.0005 (–3.428)^{a}	–0.0005 (–2.440)^{b}	–0.0005 (–2.860)^{a}	–0.0005 (–2.898)^{a}
Industry New Finance	0.0203 (4.380)^{a}	0.0203 (5.080)^{a}	0.0184 (4.042)^{a}	0.0207 (4.250)^{a}	0.0207 (4.790)^{a}	0.0186 (3.672)^{a}
Firm New Finance	0.0119 (5.320)^{a,e}	0.0119 (8.820)^{a,f}	0.0088 (7.578)^{a,d}	0.0114 (5.750)^{a}	0.0114 (7.590)^{a}	0.0082 (6.659)^{a,e}
Lagged Idio. Risk	–0.2852 (–5.920)^{a}	–0.2852 (–7.640)^{a}	–0.2278 (–7.240)^{a}	–0.2542 (–5.640)^{a}	–0.2542 (–5.600)^{a}	–0.2087 (–6.438)^{a}
Observations	50,137	50,137	50,137	42,176	42,176	42,176

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and new financing on yearly changes in risk. We report regression coefficients t-statistics (in parentheses) for various panel data regression models. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) with year fixed effects (industry clustering adjustments), OLS with year fixed effects (industry and year clustering adjustments), and Fama-MacBeth regression methods. Results in all three panels of this table are restricted to competitive industries, which are those in the lowest fitted HHI tercile. One observation is one firm in one year. For independent variables collected using data from calendar year t, the dependent variable is the change in risk (ex-post risk minus ex-ante risk). Ex-ante risk is measured from July of year t+1 to June of year t+2, and ex-post risk is measured from July of year t+2 to June of year t+3 (similar results obtain if we use risk measured using one year earlier data). The dependent variable in Panel A is based on total risk, which is equal to the standard deviation of daily stock returns measured over one year. The market betas in Panel B are estimated using daily firm-level daily stock returns using one year of data. Idiosyncratic risk in Panel C is the standard deviation of the residuals of a regression of daily stock returns on the three Fama-French factors (HML, MKT, SMB) using one year of data. The explanatory variables are discussed in Table III. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries at the 1%, 5%, and 10% levels, respectively.

Table X: Regressions predicting change-in-risk adjusted monthly firm-level stock returns

Variable	*Whole Sample* Industry Clusters	*Whole Sample* Ind+Year Clusters	*Whole Sample* Fama-MacBeth	*Excluding 1998-2000* Industry Clusters	*Excluding 1998-2000* Ind+Year Clusters	*Excluding 1998-2000* Fama-MacBeth
Panel A: Competitive Industries Only						
Industry Relative Valuation	0.0003 (0.160)	0.0003 (0.140)	0.0000 (0.012)	–0.0013 (–0.690)	–0.0013 (–0.610)	–0.0019 (–0.821)
Firm Relative Valuation	–0.0032 (–6.200)^{a,e}	–0.0032 (–7.260)^{a,d}	–0.0031 (–6.598)^{a,d}	–0.0034 (–7.100)^{a,d}	–0.0034 (–7.550)^{a,d}	–0.0031 (–6.445)^{a,d}
Industry Relative Investment	–0.0061 (–2.140)^{b}	–0.0061 (–2.400)^{b}	–0.0057 (–2.283)^{b}	–0.0005 (–0.190)	–0.0005 (–0.230)	–0.0028 (–1.361)
Firm Relative Investment	–0.0014 (–4.510)^{a}	–0.0014 (–4.410)^{a}	–0.0014 (–3.465)^{a}	–0.0010 (–3.660)^{a}	–0.0010 (–3.160)^{a}	–0.0012 (–2.950)^{a}
Industry New Finance	–0.0408 (–3.740)^{a,e}	–0.0408 (–3.890)^{a,e}	–0.0244 (–2.184)^{b}	–0.0255 (–3.070)^{a}	–0.0255 (–2.770)^{a}	–0.0166 (–1.431)
Firm New Finance	–0.0141 (–5.870)^{a,f}	–0.0141 (–4.640)^{a}	–0.0113 (–3.769)^{a,e}	–0.0184 (–8.790)^{a}	–0.0184 (–6.140)^{a}	–0.0129 (–4.320)^{a}
Observations	629,696	629,696	629,696	526,113	526,113	526,113
Panel B: High Relative Valuation Tercile (Competitive Industries Only)						
Industry Relative Valuation	–0.0161 (–3.100)^{a,f}	–0.0161 (–3.140)^{a,f}	–0.0108 (–1.671)^{c}	–0.0079 (–1.550)	–0.0079 (–1.540)	–0.0072 (–1.168)
Firm Relative Valuation	–0.0026 (–3.660)^{a}	–0.0026 (–3.500)^{a}	–0.0026 (–2.978)^{a}	–0.0026 (–3.980)^{a}	–0.0026 (–3.240)^{a}	–0.0026 (–2.771)^{a}
Industry Relative Investment	–0.0091 (–1.850)^{c}	–0.0091 (–2.070)^{b}	–0.0013 (–0.322)	0.0014 (0.340)	0.0014 (0.400)	0.0036 (1.048)
Firm Relative Investment	–0.0001 (–0.090)^{e}	–0.0001 (–0.080)^{f}	–0.0002 (–0.264)	0.0009 (1.550)^{d}	0.0009 (1.560)^{e}	0.0002 (0.244)
Industry New Finance	–0.0496 (–3.480)^{a,e}	–0.0496 (–3.410)^{a,e}	–0.0338 (–1.654)^{c}	–0.0275 (–2.160)^{b,f}	–0.0275 (–2.210)^{b,f}	–0.0158 (–0.754)
Firm New Finance	–0.0234 (–6.370)^{a}	–0.0234 (–4.570)^{a}	–0.0169 (–3.150)^{a}	–0.0301 (–6.410)^{a,e}	–0.0301 (–5.850)^{a,f}	–0.0181 (–3.116)^{a}
Observations	177,838	177,838	177,838	135,607	135,607	135,607
Panel C: High Market Risk Tercile (Competitive Industries Only)						
Industry Relative Valuation	–0.0084 (–2.910)^{a}	–0.0084 (–2.560)^{b}	–0.0074 (–1.758)^{c}	–0.0053 (–2.400)^{b}	–0.0053 (–1.640)	–0.0049 (–1.245)
Firm Relative Valuation	–0.0037 (–5.740)^{a,d}	–0.0037 (–6.000)^{a,d}	–0.0039 (–5.370)^{a,d}	–0.0037 (–6.500)^{a,d}	–0.0037 (–5.940)^{a,d}	–0.0040 (–5.109)^{a,d}
Industry Relative Investment	–0.0143 (–4.840)^{a,d}	–0.0143 (–3.670)^{a,d}	–0.0136 (–3.157)^{a,e}	–0.0080 (–2.900)^{a,f}	–0.0080 (–1.960)^{b,f}	–0.0111 (–2.572)^{b,e}
Firm Relative Investment	–0.0013 (–2.220)^{b}	–0.0013 (–2.500)^{b}	–0.0013 (–1.946)^{c}	–0.0009 (–1.960)^{b}	–0.0009 (–1.720)^{c}	–0.0010 (–1.540)
Industry New Finance	–0.0681 (–4.030)^{a,d}	–0.0681 (–3.820)^{a,d}	–0.0307 (–1.425)	–0.0314 (–1.990)^{b}	–0.0314 (–1.900)^{c}	–0.0130 (–0.587)
Firm New Finance	–0.0153 (–6.430)^{a}	–0.0153 (–3.880)^{a}	–0.0099 (–2.527)^{b,e}	–0.0203 (–9.210)^{a}	–0.0203 (–5.180)^{a}	–0.0114 (–2.751)^{a}
Observations	301,794	301,794	301,794	238,753	238,753	238,753

Explanation: Regressions examine the effect of relative firm- and industry-level valuation (industry booms), investment and new financing on monthly risk-adjusted firm-level stock returns. We report regression coefficients and t-statistics (in parentheses) for various panel data regression models. t-statistics (in parentheses) are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. We report results for ordinary least squares (OLS) with year fixed effects (industry clustering adjustments), OLS with year fixed effects (industry and year clustering adjustments), and Fama-MacBeth regression methods. The first three columns are based on the entire sample (1972 to 2004), and the latter three columns exclude the technology boom (1998 to 2000). We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data. Panel A displays results for the most competitive tercile, Panel B for industries in the highest relative valuation tercile and the most competitive tercile, and Panel C for industries in the highest market risk tercile and the most competitive tercile. One observation is one firm in one month, and the dependent variable is the firm's monthly abnormal return adjusted for changes in risk. To adjust for risk, we regress each year t+1 return on the change in risk (market, HML, SMB, momentum, and idiosyncratic risk) from year t to year t+2 (we also include the year t risk levels to control for the autocorrelation of risk exposures). A firm's (unadjusted) abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, independent variables are constructed using accounting data with fiscal years ending in year t. The independent variables are constructed from industry averages of observed firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Industries with high market risk are those in the upper tercile (yearly sorts) based on their past-year market beta. Market betas are estimated using daily firm-level returns, and industry market betas are the equal weighted average based on three digit SIC codes. * a, b, and c denote significant differences from zero at the 1%, 5%, and 10% levels, respectively. d, e, and f denote significant differences from opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

Table XI: Average firm level quintile portfolio abnormal returns

	Whole Sample					***Excluding 1998-2000***				
Variable	1	2	3	4	5	1	2	3	4	5
Panel A: Sample-wide results										
Industry Relative Valuation	1.894	1.572	0.310	1.440	−5.863	2.157	0.427	0.181	−0.904	−3.108
Firm Relative Valuation	3.395	0.560	1.509	0.492	−1.155	2.916	0.778	1.244	−0.182	−1.785
Industry Relative Investment	1.867	2.249	−0.142	−0.752	−3.823	−0.356	0.858	0.150	0.272	−2.709
Firm Relative Investment	2.166	0.838	1.042	1.093	0.396	1.500	0.676	0.799	0.877	−0.177
Industry New Finance	1.748	0.472	2.834	0.051	−5.220	3.127	−0.273	0.001	0.795	−3.503
Firm New Finance	2.150	2.303	1.597	0.321	−2.248	2.469	1.655	0.934	0.583	−3.417
Panel B: Competitive Industries										
Industry Relative Valuation	1.991	2.377	0.951	4.399	−9.613	2.309	−0.289	−0.231	−0.739	−5.888
Firm Relative Valuation	4.883	1.506	2.351	0.956	−1.058	3.355	0.816	1.276	−0.817	−2.684
Industry Relative Investment	2.542	4.381	0.068	−1.577	−6.499	−1.908	1.452	0.254	−0.843	−5.284
Firm Relative Investment	3.084	1.276	1.955	1.935	1.437	1.083	0.434	0.609	0.986	−0.173
Industry New Finance	2.245	1.083	4.915	0.863	−7.058	3.862	−1.177	−0.656	1.766	−5.350
Firm New Finance	2.619	3.499	3.436	1.129	−2.469	2.405	1.674	1.540	0.801	−5.019
Panel C: Concentrated Industries										
Industry Relative Valuation	2.070	0.136	−0.788	−3.029	−2.380	2.778	0.773	0.753	−2.037	−0.698
Firm Relative Valuation	−0.486	−1.377	−0.262	−0.277	−2.376	0.201	0.502	0.387	0.704	−1.341
Industry Relative Investment	−1.371	1.272	0.055	−3.205	−2.544	−0.749	2.333	0.308	−0.976	−1.327
Firm Relative Investment	−0.314	−0.499	−0.931	0.050	−0.475	0.822	0.046	0.262	0.468	1.080
Industry New Finance	1.786	−1.449	−0.995	−1.702	−2.410	3.486	−0.061	0.630	−1.632	−1.304
Firm New Finance	1.184	0.426	−1.835	−0.342	−3.792	2.463	1.779	−1.018	0.480	−2.793
Panel D: Industries with Declining Concentration										
Industry Relative Valuation	1.246	4.967	0.400	2.993	−5.449	1.820	1.796	0.851	−1.509	−3.388
Firm Relative Valuation	4.706	1.533	2.232	1.424	−1.354	2.946	1.448	1.746	−0.399	−2.378
Industry Relative Investment	5.996	3.459	−0.047	−0.212	−5.242	0.019	0.276	0.557	0.758	−3.353
Firm Relative Investment	3.231	1.626	2.053	1.436	1.535	1.711	1.166	0.814	1.118	0.426
Industry New Finance	2.205	−1.654	6.252	1.365	−4.872	4.151	−1.112	−0.361	2.776	−3.784
Firm New Finance	2.197	3.184	2.376	1.200	−0.501	2.845	1.713	1.199	0.808	−3.304

Explanation: The table presents average risk-adjusted monthly firm-level stock returns for various portfolios. Reported abnormal returns are annual-equivalent monthly returns (actual monthly abnormal returns times twelve), and they are reported as percentages. The averages are based on the entire sample (1972 to 2004), and for the sample that excludes the technology boom (1998 to 2000). Within each portfolio, one observation is one firm in one month. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, portfolio assignments are constructed using accounting data with fiscal years ending in year t. We form quintile portfolios based on industry averages of observed firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Panel A includes all industries, Panel B includes competitive industries only (lowest fitted HHI tercile), Panel C includes concentrated industries only (highest fitted HHI tercile), and Panel D includes industries in the most negative tercile of change in fitted HHI. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data.

Table XII: Average industry level quintile portfolio abnormal returns

Variable	*Whole Sample* 1	2	3	4	5	*Excluding 1998-2000* 1	2	3	4	5
Panel A: Sample-wide results										
Industry Relative Valuation	–0.024	–1.150	–0.905	–1.704	–2.140	0.934	0.329	–0.446	–1.094	–1.787
Industry Relative Investment	–0.781	–1.008	–0.278	–1.175	–2.702	–0.195	–0.003	0.203	–0.351	–1.734
Industry New Finance	–0.961	–1.287	0.157	–1.418	–2.424	0.072	–0.636	0.856	–1.172	–1.183
Panel B: Competitive Industries										
Industry Relative Valuation	–0.266	–0.486	–1.202	–1.812	–3.671	–0.600	0.978	–1.077	–1.992	–3.273
Industry Relative Investment	–0.596	–0.434	–0.855	–2.072	–3.687	–0.684	–0.617	–0.743	–1.523	–2.337
Industry New Finance	–1.882	–1.735	1.112	–1.967	–2.705	–0.672	–1.463	1.300	–2.869	–1.727
Panel C: Concentrated Industries										
Industry Relative Valuation	–0.180	–3.365	1.621	–3.934	–0.768	2.492	–2.241	2.756	–2.590	–0.271
Industry Relative Investment	–1.161	–0.962	–1.293	–0.720	–2.553	0.310	0.952	0.262	0.710	–1.857
Industry New Finance	–1.028	–2.708	0.387	–1.550	–1.740	–0.440	–1.596	2.198	0.219	0.210
Panel D: Industries with Declining Concentration										
Industry Relative Valuation	–1.034	–0.940	–1.510	–1.401	–3.602	0.033	0.281	–1.044	–0.233	–2.801
Industry Relative Investment	–1.723	–1.848	–1.498	–0.615	–2.832	–0.650	–0.346	–1.123	0.421	–2.117
Industry New Finance	–2.366	–0.798	–0.451	–1.936	–2.969	–0.294	–0.284	0.034	–1.651	–1.563

Explanation: The table presents average risk-adjusted industry-level stock returns for various portfolios. Reported abnormal returns are annual-equivalent monthly returns (actual monthly abnormal returns times twelve), and they are reported as percentages. The averages are based on the entire sample (1972 to 2004), and for the sample that excludes the technology boom (1998 to 2000). Within each portfolio, one observation is one industry in one month. Industry average abnormal returns are equal weighted averages of firm abnormal returns in the given month over all firms residing in the given three digit SIC code in the given month. A firm's abnormal return is its raw monthly return minus the monthly return of a portfolio matched on the basis of NYSE/AMEX breakpoints of size, industry-adjusted book to market, and past year returns as in Daniel, Grinblatt, Titman, and Wermers (1997). For monthly abnormal return observations between July of year t+1 and June of year t+2, portfolio assignments are constructed using accounting data with fiscal years ending in year t. We form quintile portfolios based on industry averages of observed firm-specific relative valuation, relative investment, and new financing. A firm's "new financing" is the sum of its net equity issuing and net debt issuing activity in year t (normalized by assets). A firm's relative valuation is based on the empirical measure of industry valuation presented in Rhodes-Kropf, Robinson, and Viswanathan (2005). In particular, we compute expected valuation by (1) regressing year t-10 to t-1 firm observations of log market cap on four variables (market to book ratio, log net income, a dummy for negative net income, and the firm's leverage ratio). These long-term regression coefficients are used to compute predicted valuations in year t, and relative valuation is the actual year t log market cap minus the predicted year t log market cap (predictions are based on each firm's year t characteristics). Relative investment is computed using the same method, replacing log investment with log market cap. Panel A includes all industries, Panel B includes competitive industries only (lowest fitted HHI tercile), Panel C includes concentrated industries only (highest fitted HHI tercile), and Panel D includes industries in the most negative tercile of change in fitted HHI. We define concentration as the fitted concentration index, which is based on three digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, Bureau of Labor Statistics employee data, and Compustat sales data.