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ABSTRACT

We examine how product market competition affects firm cash flows and stock returns in industry booms and busts. In competitive industries, we find that high industry-level stock-market valuation, investment and new financing are followed by sharply lower operating cash flows and abnormal stock returns. We also find that analyst estimates are positively biased and returns comove more when industry valuations are high in competitive industries. In concentrated industries these relations are weak and generally insignificant. Our results suggest that when industry stock-market valuations are high, firms and investors in competitive industries do not fully internalize the negative externality of industry competition on cash flows and stock returns.

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I Introduction

Industries commonly go through cycles in which firms have very high valuations. These high valuations are 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 similar patterns. 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, the 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]

Despite the attention that these industry booms and busts receive in the press, little is known about how industry competition affects both financial and real industry business cycles. Our paper examines the extent that real and financial outcomes following industry booms and busts are related to industry-level competition. These industry business cycles are significant and are often unaligned with market-wide cycles, suggesting that industry characteristics matter. We test theoretical predictions about whether competition, valuation uncertainty and high costs of information gathering are important to understanding ex post outcomes. We find strong support for the conclusion that market participants in competitive industries rely on common industry information and do not internalize the effects of high competition.

We find that changes in operating performance and future abnormal stock re-

[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."

turns are negatively related to ex ante industry-level valuation (our measure of industry booms) and new financing in competitive growth industries but much less so in concentrated industries. High stock-market valuations in competitive industries are likely to be followed by subsequent downturns in cash flows and stock returns, especially when there is substantial new financing and investment by firms in the industry. These relations are significantly more negative than similar relations in concentrated industries, and cannot be explained by standard controls including size and value/growth proxies. Our results also persist after controlling for recent changes in capital expenditures in the industry and after controlling for potential mean reversion in operating cash flows.

We examine whether the predictable busts we observe were predicted by analysts and investors, and we consider analyst forecasts of earnings per share (EPS). We perform predictive tests of future EPS using ex-ante analyst forecasts, and find that analyst estimates were positively biased in competitive growth industries, especially those with the high relative valuations. We do not find analogous biases in concentrated industries nor in industries with high market risk. Our findings are also robust to excluding the internet boom of 1998 to 2000 form our sample.

Our results for abnormal stock returns also show large differences in industries with high valuations. These patterns differ based on industry competitiveness. In competitive industries with the highest relative valuation, and also in competitive growth industries, we find that firm abnormal stock returns are negatively related to industry relative valuation, high investment and industry new finance. We also find that predictable busts are associated with high comovement of firm returns within competitive industries.

These 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 5.5 percent decline in operating cash flows.

In competitive growth industries, annual abnormal stock returns for an industry level portfolio in the highest quintile of relative industry valuation are over three percentage points lower than a portfolio in the lowest quintile. If we weight by firm rather than by industry, this abnormal return difference exceeds ten percentage points. In concentrated industries, quintile returns are non-monotonic, and magnitudes are less than half as large.

Our results are 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. The predictable busts we observe in competitive industries are consistent with a failure of investors and industry participants to internalize the effect of competition on longer term outcomes. These effects are not correctly forecasted by analysts and are not anticipated in stock returns using the latest style and factor adjustment models. In contrast, we do not find evidence of predictable busts in concentrated industries. 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) (PV) show that increases in systematic risk can cause industry busts after booms as industry participants adopt a standard technology. Aguerrevere (2006) and Carlson, Fisher, and Giammarino (2004) also predict that systematic risk might increase after booms associated with the exercise of real options. DeMarzo, Kaniel, and Kremer (2006a,b) predict that participants with relative wealth concerns rationally overinvest (both in physical and financial assets) in industries with high systematic risk.

We find that market betas increase and idiosyncratic risk decreases after industry booms consistent with PV (2005). We also find that adjusting stock returns by ex post measured changes in risk reduces the magnitude of the return predictability we document. However, in industries with the highest valuations, nearly all of the return predictability persists after adjusting for these changes. Hence, change-in-risk-based explanations cannot explain the extent of our findings in the most highly-valued competitive industries. Consistent with the concern for relative wealth, our results are stronger in competitive industries with higher ex ante market risk. However, while this effect may explain part of our results regarding high industry investment, relative investment is less significant than our other industry variables in predicting future cash flows and stock returns.

We conclude that although the effect of competition on changes in cash flows may be natural in competitive industries, current stock market theories cannot explain the extent of the predictability of stock returns that we document. Also, these theories

[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.

cannot explain the biased analyst estimates we find in some competitive industries. Overall, our findings in more extreme industries are consistent with stock market participants not anticipating the magnitude of the effects of competition.

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, misvaluation occurs at the sector and firm level in a rational setting, and this affects merger and acquisition activity. Managers are not able to distinguish between misvaluation and possible synergies, and merger waves can arise. This signal extraction problem is also related to papers on rational herding and investment cascades (early models are Scharfstein and Stein (1990) and Welch (1992)).[4]

What is shared by these models and our interpretation of our findings is that firms may make inefficient decisions when they rely on information common to all firms. Our study focuses on the impact of industrial organization given that firms face a coordination problem in competitive industries, and may not internalize, or have the incentives to internalize, the effect of their actions on industry prices and returns. These issues are likely to be most extreme when information about rival firms is costly or difficult to gather, as is likely the case in competitive industries where larger numbers of rival firms exist.

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, but not concentrated industries, experience significant downturns following high industry valuation and new industry financing. These downturns effect both stock returns and cash flows.[5] Second, 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. Third, we show that changes in firm risk only partially explain predictable boom and bust patterns. These results support key predictions of industrial organization theories, and theories of

[4]The idea that noisy signals can create cycles dates back to the original Lucas island economy and the real business cycle models of Kydland and Prescott.

[5]Although not considering the role of industry competition, related empirical work also documents results related to ours. Beneish and Nichols (2008) also use accounting based measures of investment, valuation, and financing activity and relate them to stock returns at the firm level. More specialized 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.

decision making under high uncertainty, and shed new light on how industry business cycles might form.

The remainder of this paper is organized as follows. Section II provides a discussion of industrial organization based theories of booms and busts and presents testable implications. Section III discusses the data and our empirical measures of firm valuation and relative valuation. Sections IV and V present and discuss the results on how industry valuation and financing booms impact subsequent operating cash flows and stock returns, respectively. Section VI concludes.

II Industrial Organization and Booms and Busts

In this section we review the existing theoretical models and empirical findings that are related to our paper. 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 Concentrated and Competitive Industries

There is a large body of work that has focused on the effects of competition in both concentrated and competitive 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."

Other articles suggest that competitive industries bear the greatest risk from new competition. Schumpeter's early work in 1912 focused on creative destruction in competitive industries. In Schumpeter's creative destruction story, there is an innovation and the market forms high expectations (rationally or irrationally) about the future prospects of this industry. 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 try to invest before competitors who receive the same investment opportunity as in Grenadier (2002). 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 of rival firms. In contrast to business stealing models, however, industries can be explicitly ex ante competitive with free entry.

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.

B High Information Costs and High Uncertainty

Understanding how information is produced around times of industry innovation is central to understanding how investment decisions might vary across industries. In this section, we discuss the theoretical motivation for how poor outcomes can arise in competitive industries, especially if firms are unable to efficiently gather information about rivals, and if valuation uncertainty is high. We begin by discussing non-Industrial Organization theories of valuation booms and busts, and the link to common industry comovements in cash flows and stock returns.

Veldkamp (2006) develops a rational model in which high fixed costs of producing information on individual firms causes investors to focus on signals that are common to many firms. How decisions are made when information is common to many firms is also central to Scharfstein and Stein (1990), Welch (1992), and Rhodes-Kropf and Viswanathan (2004) (RKV) regarding herding, cascades, and merger decisions. A unifying theme is that high uncertainty can lead managers to make decisions similar to those of prior participants.

Empirically we follow Chen, Goldstein, and Jiang (2007) and consider an economy in which cash flows for firm i are driven by common market wide and industry shocks that cause firms in the same industry to have stock returns that comove as follows:

$$r_{i,j,t} = B_{i,0} + B_{i,m} * r_{m,t} + B_{i,j} * r_{j,t} + \epsilon_{i,j,t} \tag{1}$$

where $r_{i,j,t}$ is the return of firm i in industry j at time t, $r_{m,t}$ is the market return, $r_{j,t}$ is the return of industry j and $\epsilon_{i,j,t}$ is a firm specific shock.

As Chen, Goldstein, and Jiang (2007) note, this expression for comovement is based on a large literature including Roll (1988) and recently Durnev, Morck, and Yeung (2004). The authors focus on the relationship between stock comovements and investment efficiency. It is important to note that, although stock price comovements can be related to demand shocks as well as numerous other theoretical causes,[6] virtually all theories predict that comovement mechanisms result in less information on firm-specific fundamentals being impounded into stock prices. When comovement is high, managers thus have little information outside of common signals, and are likely to make similar investment decisions, especially when information is difficult to gather from other sources.

We postulate that information about rivals and optimal investment policy is difficult and costly to gather when large numbers of firms exist as in a competitive industry. Thus, market participants are more likely to rely on common industry price movements. We abstract from the overall market in equation (1) and operationalize the link to industry concentration in the following specification ($H_{j,t}$ denotes the industry Herfindahl):

$$r_{i,j,t} = B_{i,j} * (1 - H_{j,t}) * r_{j,t} + \epsilon_{i,j,t} \tag{2}$$

The idea expressed here is that when the industry is very competitive, $H_{j,t}$ will be close to zero and industry-level shocks will drive more of each firm's stock return, consistent with the postulated high costs of gathering firm-specific information in competitive industries. In this setting, optimal investment policy will be a function of known quantities including industry returns, industry competitiveness, and information gathered from firm-specific sources including stock prices ($\eta_{i,j,t}$):

$$I^*_{i,j,t} = \delta(r_{j,t},\ H_{jt},\ \eta_{i,j,t}) \tag{3}$$

The following linear functional form operationalizes the assumption that managers face higher information gathering costs in competitive industries:

$$I^*_{i,j,t} = \delta_1 * (1 - H_{j,t}) * r_{j,t} + \delta_2 * H_{j,t} * \eta_{i,j,t} \tag{4}$$

[6] Comovement can also be linked to industry herding as discussed earlier, lack of transparency as modeled by Li and Myers (2005), contagion as in Pritsker and Kodres (2002) and Kyle and Xiong (2001), style investing as in Barberis and Shleifer (2003), and investor sentiment as in Barberis, Shleifer, and Wurgler (2005).

We note that investment is a function of a firm's marginal q, as well as the firm specific shock $\epsilon_{i,j,t}$, and that this information is contained in $\eta_{i,j,t}$. Substituting $q_{i,j,t}$ and $\epsilon_{i,j,t}$ for $\eta_{i,j,t}$ yields:

$$I^*_{i,j,t} = \delta_1 * (1 - H_{j,t}) * r_{j,t} + \delta_2 * H_{j,t} * q_{i,j,t} + \delta_3 * H_{j,t} * \epsilon_{i,j,t} \tag{5}$$

When the cost of gathering information on large numbers of rivals is high, firms in competitive industries will thus invest more following high industry stock returns ($r_{j,t}$). Firms in concentrated industries will rely more on firm specific information and research ($q_{i,j,t}$ and $\epsilon_{i,j,t}$). This relationship can be amplified by the fact that firms in highly competitive industries face a non-cooperative investment choice, wherein an optimal response to a new investment opportunity is to invest before competitors. Therefore more immediate investment is more likely to occur in competitive industries than in concentrated industries. This implies that the elasticity of investment to industry price shocks in competitive industries is high.

Durnev, Morck, and Yeung (2004) and Chen, Goldstein, and Jiang (2007) show that such a positive association between investment and returns creates tension because investment policy is less efficient. The authors attribute this to private information being less informative when returns are more synchronous, and investors convey less useful firm-specific information to managers through prices.

Initial positive returns following a shock might cause high investment. This in turn might generate additional positive returns and investment until the new capacity starts producing. The degree of resulting overinvestment can be amplified further by managerial motives to try to capture more of the market, and also because managers might be shielded from blame because rival managers make similar decisions.

Overinvestment following positive industry shocks can then lead to subsequent industry busts affecting subsequent returns and cash flows at the firm and industry level as follows:

$$r_{i,j,t+1} = B_{i,0} + B_{i,j} * (1 - H_{j,t}) * r_{j,t+1} + \epsilon_{i,t+1} + \alpha_i(I^*_{i,j,t} - I_{i,j,t}) + \alpha_j(I^*_{j,t} - I_{j,t}) \tag{6}$$

$$\Delta CF_{i,j,t,t+1} = \theta_{i,0} + \theta_{i,j}(1 - H_{j,t})\epsilon_{j,t+1} + \epsilon_{i,t+1} + \gamma_i(I^*_{i,j,t} - I_{i,j,t}) + \gamma_j(I^*_{j,t} - I_{j,t}) \tag{7}$$

These two equations motivate our examination of how ex post returns and cash flows may depend on ex ante industry returns and investment, and why we consider industry concentration.

Hypothesis 1: In competitive industries, especially those with high price uncertainty; high valuation, high investment and high financing will be associated with lower ex post industry and firm profitability and lower ex post stock returns. These predictable booms and busts should be associated with high return comovement and optimistic analyst forecasts.

C Alternative Risk Based Theories

Following our examination of cash flows, we 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. Industry valuations then increase above their historical values. These valuations can be leveraged when GDP growth is high, as access to capital is likely to be highest. However, in competitive industries, firms will aggressively exploit these opportunities and thus capital will flow more quickly into these industries, causing competitive industries to be more pro-cyclical. Return differences in competitive versus concentrated industries might thus load on a systematic priced risk factor related to changes in GDP, and we test the following hypothesis:

Hypothesis 2A: Decreased stock returns following booms in competitive industries result from a systematic priced risk factor related to 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.[7]

Hypothesis 2B: During industry booms, systematic risk decreases more for firms in competitive industries than in concentrated industries. Following decreases in

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

demand (industry busts), systematic risk increases more for firms in competitive industries than in concentrated industries.

Three recent articles offer explanations regarding how boom and bust patterns can develop rationally given effects of risk. 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 2C: Systematic risk will increase and idiosyncratic risk will decrease following industry valuation booms.

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 cash flows.

We test a related hypothesis from Demarzo, Kaniel, and Kremer (2006b) and Demarzo, Kaniel, and Kremer (2006a) (henceforth DKK). DKK 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 and when the technology is correlated with aggregate consumption.[8] 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 2D: In industries with high systematic risk, subsequent stock market returns will be especially negatively related to high industry valuation, investment, and financing.

[8]While they focus on the dissipation of rents in competitive industries with decreasing returns to scale, they do not model the differences between competitive and concentrated industries.

III Data and Methodology

A Industry Competitiveness

We classify industries by their competitiveness on the basis of three-digit SIC codes using measures that capture both public and private firms. 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).[9] We also classify industries into growth and value industries based on industry-average book to market ratios. We first winsorize firm book-to-market ratios at the 1/99 percentile level prior to taking industry averages and classify growth (value) industries as industries in the lowest (highest) tercile of industry book-to-market ratios.

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. 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.[10] 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).[11] 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

[9]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).

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

[11]We thank David Robinson for sharing these data with us.

from the Commerce Department on three variables: the Compustat public-firm-only Herfindahl,[12] 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 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%.[13] The less than perfect 54.2% correlation between our fitted measure and the actual HHIs suggests that the acquisition of additional data by future researchers might be useful. However, we conclude that our fitted HHIs offer significant improvements relative to the basic COMPUSTAT HHI, and also have the advantage over manufacturing HHIs in that they cover all industries.

B 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

[12]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.

[13]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 predictable cashflows and stock returns (significant coefficients) we found were similar to the ones we report in the tables.

measure as relative valuation subsequently) using a three step procedure that is based on the valuation model in Pastor and Veronesi (2003). From Pastor and Veronesi (2003), we use the empirical model they specifiy in equation (28) and the specification they report in model (0) of Table II. We do not use the more extended specifications of their Table II as we do not include as variables the forward looking measures for return on equity and stock returns. We only use lagged data in constructing our measure of relative valuation given that we are examining ex post returns and operating performance and do not want to have a look ahead bias in our predictions. To construct our measure of relative valuation for each firm and industry, we use the following three steps:

(1.) We estimate the Pastor and Veronesi (2003) valuation model using using data from year $t-10$ to $t-1$ for all firms in inudstry j. Using the same variable definitions they use, we regress the log of the market-to-book ratio, $log(\frac{M}{B})$, on minus the reciprocal of one plus firm age (AGE), a dividend dummy (DD), firm leverage (LEV), the log of total assets (SIZE), the volatility of profitability (VOLP), and current firm return on equity (ROE) for each firm i in industry j (we suppress the j industry subscript, as the equation is estimated separately for each industry). Given VOLP is constant for each firm, we estimate this equation using an unbalanced panel with random firm fixed effects.

$$log(\frac{M}{B})_{i,\tau} = a + bAGE_{i,\tau} + cDD_{i,\tau} + dLEV_{i,\tau} + elog(SIZE_{i,\tau}) + fVOLP_{i,\tau} + gROE_{i,\tau}, \tag{8}$$

$$\tau = t-10, ..., t-1$$

(2.) From this estimation we use the estimated industry-specific regression coefficients to compute predicted values for firm market-to-book in year t. We estimate the valuation regression above using rolling 10 year windows of lagged data in each industry to get a set of coefficients that we apply to each year t to get a measure of predicted valuation. The fitted valuation model used in the first step assumes that firm i's market-to-book at time t is a function of its current characteristics and the industry specific prices of characteristics estimated from past years. Thus we use time t characteristics and coefficient estimates estimated from $t-10$ to $t-1$ to compute predicted firm market-to-book ratios for time t.

(3) The last step is to compute relative (undpredicted) valuations , which we henceforth call relative valuations, for each firm i at time t. A firm's total relative valuation is its actual $log(\frac{M}{B})$ less its predicted $log(\frac{M}{B})$ for year t as follows:

$$RelativeValuation_{i,t} = log(\frac{M}{B})_{i,t} - Predicted(\ log(\frac{M}{B})_{i,t}) \tag{9}$$

Relative industry-level valuation is the average of all valuations over all firms in each three-digit SIC industry. Firm-level relative valuation is the total relative valuation minus this industry-level component.

The results we obtain later are robust to other valuation models including model (3) from Rhodes-Kropf, Robinson, and Viswanathan (2005), where the dependent variable is is the log of firm market value. In addition, 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.

These models were also estimated on 10 years of lagged data by industry and then the coefficients are used to predict current period market value using current characteristics including 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.

Relative firm- and industry-level investment is computed using a similar method. We regress log capital expenditures divided by lagged property plant and equipment on standard variables from investment models, including lagged Tobin's q, variables capturing the cash firms of firms (cash flow divided by book value of equity (ROE) and a dividend paying dummy (DD)).[14] We also include additional variables given the existing literature. Leverage (LEV) captures the debt-overhang effect on investment that Hennessy (2004) models. Age of the firm captures potential firm differences in replacement rates of capital and recovery rates if disinvestment occurs. Volatility of cash flow (VOLP) captures the real option effect of volatility of cash flows on investment. Tobin's q is calculated as the market value of equity plus the book value of debt and preferred stock divided by the book value of assets.

$$log(\frac{Invest_{i,t}}{PPE_{i,t-1}}) = a + bTOBINQ_{i,t-1} + cROE_{i,t} + dDD_{i,t} + eAGE_{i,t} + \tag{10}$$

$$fLEV_{i,t} + gVOLP_{i,t} + hlog(SIZE_{i,t})$$

From this model, we calculate relative (unpredicted) investment (which we call relative investment) as the actual investment less the predicted investment using each fitted industry regression. Relative industry investment is the average total relative investment in each industry. Relative firm investment is the total relative investment minus this industry component.

We define total "new financing" in a given year as the sum of a firm's net equity issuing (COMPUSTAT annual data item 108 minus item 115) and net debt issuing

[14] Cash flow has been shown by many papers to be related to investment. We do not take a view on the cause of this relation.

activity (annual data item 111 minus item 114) in a given year divided by assets. Industry new financing is the sum the total amount of new financing over firms in the industry divided by the total industry assets. Firm-specific new financing is then the total new financing less the industry component.

These proxies are constructed using each industry's known ex-ante characteristics. These proxies can be used in an unbiased fashion to predict future stock returns and future accounting performance.

C Descriptive Industry 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 competitive industries, 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. Extreme competitive industries in the 1980s (valuations are over 100% above predicted industry valuations) deviated just as far from their long-term valuations as those in the 1990s. More broadly, most extreme booms were not in technology industries, as was the case in the late 1990s. For example, at least two of the extreme 1980s boom industries were related to groceries and apparel. In the 1970s, more traditional industries including petroleum extraction and electrical work were among the most extreme booms. Finally, because weighted relative valuations are similar to unweighted valuations, 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 same four decades. The selected industries generally have concentration levels near or exceeding 0.4. Tables I and II also show that basic Compustat Herfindahls are generally similar to our fitted Herfindahls. Because our tests do not use the concentration measures explicitly, but rather examine industries based on high and low competition categories, we thus expect and find similar results using either Herfindahl measure.

Perhaps one difference between concentrated and competitive industries is that booms appear to be somewhat more extreme in concentrated industries. For example, Guided Missiles and Space Vehicles were 298% above their predicted industry valuations in 1995, and Musical Instruments were 220% above their predicted industry valuations in 1987. The existence of large booms in concentrated industries indicates that ample power exists to examine whether subsequent busts occur. However, our later tables show that we do not find evidence that concentrated industries experiencing booms actually underperform. Hence, unlike those in competitive industries, high industry valuations in concentrated industries likely last several years.

D Firm-Level Data and Summary Statistics

We compute changes in firm-level operating cash flow (COMPUSTAT annual item 13) scaled by assets (COMPUSTAT annual item 6) in each year. We later examine if they are related to ex ante industry and firm level relative valuation, investment and new finance. For robustness, we also estimate our results using the change in operating cash flow scaled by beginning period assets (year t) and find similar results.

We compute abnormal returns using two methods advocated by recent studies. Our main results are 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. Portfolios are formed at the end of each June, 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.[15] Portfolio breakpoints are based only on NYSE/AMEX firms, and we first form quintiles in each year based on firm size. Firms in each size quintile are then further sorted into quintiles based on industry-adjusted book to market ratios. Each portfolio is then further sorted into quintiles based on each firm's past 12 month return. We also consider a separate method based on adjustments proposed by Mitchell and Stafford (2000) (see robustness in Section V).

Table III reports summary statistics for these cashflow and return variables, and for our key boom and bust proxies. Panel A shows that industry relative valuation has a sample-wide mean that is near zero and a standard deviation that is large at

[15]This timing ensures that previous fiscal year accounting data is public information.

nearly 24%. This indicates that many industries have valuations both above and below predicted levels. Our New Financing variables are 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. Hence, firms can deviate far from industry valuations, as one standard deviation is a full 47% of the value of an industry.

[Insert Table III here]

Panels B and C display descriptive statistics for competitive and concentrated industries, respectively. For virtually all variables, mean levels remain close to zero. Comparing the two panels also reveals that most variables have similar distributions in competitive and concentrated industries. For example, both groups have industry relative valuation standard deviations of 19.9%. We conclude that industry booms appear to be quite similar in both groups from an ex ante perspective, and so it is unlikely that our comparative tests are biased toward any finding. Hence, our broad findings regarding ex post busts only being predictable in competitive industries (documented later) are perhaps especially surprising.

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 2.4% per year. We find a weak but opposite difference in accounting performance across these two groups, a result that is also consistent with Hou and Robinson (2005)'s findings.

IV Operating Cash Flows and Analyst Forecasts

We now examine the effect of industry booms on subsequent firm-level operating performance and the accuracy of analyst forecasts.

A Ex Post Cash Flows

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 industry and firm specific components as discussed earlier.[16] We focus on the industry variables to directly study the

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

main topic of our paper: industry booms and busts, and their link to industrial organization. The firm-specific components provide a natural test of our relative valuation and investment variables, and permit us to both control for results found in existing studies and to examine whether firms that deviate from explained valuations experience even worse outcomes holding industry relative valuations fixed.

Throughout our analysis, we also control for investment spikes (lagged one period investment change) and mean reversion (lagged change in firm cash flows). These controls account for the possibility that margins in an industry may decrease as customers wait for a new innovation to hit the market. Investment would be high in such a case as the industry might be in the process of replacing itself before introducing the new product or innovation.[17] Although not reported, our main results do not change if we remove these controls.

We estimate the regressions using an unbalanced panel, and we correct standard errors for correlation within years and within industries (three digit SIC), and for heteroskedasticity. We do not present results for the fixed effects specification at the firm level as Moulton (1986) has shown that this method is inappropriate and produces negatively biased standard errors 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 Table IV includes the entire sample and shows that industry-level variables matter. Industry investment and industry new finance are most negative for the one year horizon. Relative industry valuation, in contrast, is most negative for the two year horizon.

Panels B and C display results for the most competitive and concentrated tercile industries, respectively. Terciles are formed based on the fitted Herfindahl discussed earlier. A key result is that industry relative valuation is far more important in competitive industries, both statistically and economically, than in concentrated industries. Although industry relative valuation does not significantly predict one year cash flow changes, it predicts two year changes at better than the 1% level in

is expected by construction.

[17]We thank Matt Rhodes-Kropf for these suggestions.

competitive industries, and the coefficient in concentrated industries is nearly zero. The table also shows that a formal test of differences in means indicates that the competitive industries coefficient is also significantly different from the concentrated industries coefficient at the 1% level.

Panels B and C also show that the negative one year industry investment coefficient in Panel A is also driven by competitive industries. This coefficient is roughly five times as large as the analogous coefficient for concentrated industries. Overall, the results support Hypothesis 1, and suggest that cash flows are negatively related to proxies for industry booms in competitive industries, but not in concentrated industries. The analysis of both one and two year cash flow changes also suggests that industry booms in competitive industries generally experience increases in valuation prior to increases in investment activity. This more refined result is consistent with Hypothesis 1. In particular, the theory outlined in Section II.B suggests that aggressive investment decisions might follow positive price signals such as high ex ante industry returns.

Panel D shows that relative industry valuation, relative industry investment, and new industry financing are also highly important in industries with declining concentration. These results support 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. These results are consistent with multiple firms in the same industry making investment decisions based on common public signals.

[**Insert Table V here**]

Table V repeats the tests of Table IV for the subsample of firms residing in the high growth tercile (those in the lowest tercile based on yearly sorts of industry book to market ratios). The motivation for this test is that growth industries likely have higher price uncertainty, and hence the predictions of Hypothesis 1 are likely to be stronger in this subsample. As before, Panel A shows that high industry valuation is negatively related to ex post cash flows, especially for the two year horizon. Relative investment and finance are most negatively related to ex post cash flows for the one year horizon.

As before, Panels B to D show that these results are driven by firms in competitive industries and by firms in industries with declining concentration. However, the coefficient magnitudes are larger for high growth industries (Table V) than for the set of all industries (Table IV). For example, both the one and two year relative industry valuation coefficients are negative and significant in Panel B, and this coefficient is at least twice as large as the coefficient in Table IV. These results confirm the prediction that predictable busts are both limited to competitive industries, and are larger in growth industries where price uncertainty is expected to be high.

The relative industry investment coefficient also increases in size in the high growth subsample, and the industry new finance coefficient also increases in Panel D (this variable is not significant in Panel B in either table). It is especially noteworthy that these coefficients increase in magnitude and in significance despite the smaller sample size in Table V, and that none of these variables are significant for concentrated industries in Panel C. These results strongly support Hypothesis 1 and more broadly confirm that price uncertainty plays an important role.

These results are also robust across specifications (not reported) including models with random firm effects, and to excluding the technology boom of 1998-2000 (reported in an earlier version).[18] In a previous version of the paper, we also present results using the alternative models in Rhodes-Kropf, Robinson, and Viswanathan (2005) and a simpler "PE" model. The results are similar to the results discussed above.

Although we do find that the mean reversion variable (change in EBITDA) suggests that cash flows do mean revert over longer horizons, and that recent investment spikes (change in CAPX) induce some shorter-term reversion, our key findings regarding relative valuation, investment, and new finance obtain regardless of whether these controls are included.

B Analyst Forecasts

In this section, we examine whether analysts accurately predict cash flow realizations conditioning on our measures of industry valuation, financing, and investment. This test helps us to address whether analysts forecast the cash flow declines we observe, and in particular, whether they forecast the effect of increased competition on ex-post outcomes. Under Hypothesis 1, we would expect that industry relative valuations would be associated with positively biased analyst forecasts given H1, but only in competitive industries when valuation uncertainty is high.

We use the methods outlined in Hong and Kubik (2003) to examine analyst forecast optimism. We use I/B/E/S analyst forecast data from 1983 to 2005, and we

[18] 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.

use the I/B/E/S summary database as we are only interested in examining whether analysts are biased in aggregate. To generate our measure of forecast optimism, we first define $F_{i,t}$ as the consensus mean forecast of earnings per share one year before firm i's fiscal year end in year t, and $A_{i,t}$ as the actual earnings per share ultimately realized at year t's fiscal year end. $P_{i,t}$ denotes the share price at the time the forecast is made. Analyst forecast optimism is then defined as follows:

$$\text{Optimism}_{i,t} = \frac{F_{i,t} - A_{i,t}}{P_{i,t}} \tag{11}$$

In Table VI, we explore whether ex-post analyst forecast optimism is related to our ex-ante measures of industry booms. We present results for competitive and concentrated industries, as well as subsamples limited to firms that also reside in industries in the high growth tercile. All terciles are formed by sorting industries in each year on the basis of the given characteristic.

[Insert Table VI here]

Table VI shows that forecasts are biased upward in the competitive high growth tercile, but not in the concentrated high growth tercile. We find no evidence of an analyst bias in the broader sample of competitive or concentrated industries.

We conclude that analysts likely anticipate the effects of industry valuation on future earnings accurately on average in broader samples, but do not anticipate the more extreme cash flow declines observed in high growth industries. These results suggest that, like managers, analysts face similarly high information gathering costs in competitive industries, and are more likely to make predictions based on aggregate price signals, especially valuation uncertainty is high. The findings in the high growth competitive subsample are consistent with Hypothesis 1.

These findings suggest that some of the predictable busts we observe in broader industry subsamples might be consistent with alternative theories including rational risk-based theories. We explore this conjecture more in later sections and find support. However, the results in more extreme subsamples (eg those in high growth industries) are more consistent with Hypothesis 1.

V Stock Returns and Industry Factors

A Industry Competition and Stock Returns

We now consider the effect of competition on outcomes in the stock market. Table VII displays the results of firm-level regressions of monthly abnormal returns on relative valuation, relative investment, and new financing. As before, for each independent variable, we separately examine its industry average and its firm-specific deviation from its industry average.

[**Insert Table VII here**]

Panel A of Table VII shows that industry relative valuation, relative investment and new financing are negatively related to future stock returns. The relative industry valuation coefficient is especially negative in the more extreme subsamples including high growth industries, high valuation industries, and high market risk industries. This suggests that booms and predictable busts are larger for these more extreme industries, consistent with valuation uncertainty being higher in these industries. The relative industry investment and industry finance variables are more uniformly negative across subsamples.

The highly significant and negative coefficients on the firm-level variables affirms the findings of existing studies, and the role of our proxies as valid measures of firm value, and suggest that firms have a strong tendency to revert back to the valuation suggested by their industry characteristics. Unique to our study is the inclusion of the industry-level variables, and our finding that they are especially relevant in competitive industries.

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 and 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.

Hypothesis 1 predicts that that abnormal stock returns will be negative in competitive industries following periods of high valuation and investment. In the broad sample (first column), we find that industry new finance is more important in Panel B for competitive industries than in concentrated industries in Panel C, consistent with Hypothesis 1. This coefficient is negative and significant at the 1% level in Panel B, and is not significant in Panel C. The difference in coefficients is also significant in two of three specifications. These results are also economically meaningful. For example, the industry new finance coefficients are roughly two to three times larger for some specifications in Panel B than in Panel C. The relative industry valuation and relative industry investment variables are not significantly different in this broad sample (first column).

Because Hypothesis 1 predicts that these variables should matter more when price uncertainty is high, we next examine the extreme subsamples in the last three columns. In all three extreme subsamples, we continue to find that industry new finance matters, but we also now find that relative industry valuation is significantly different across competitive (Panel B) and concentrated industries (Panel C). The sign of this variable even reverses in some concentrated industry subsamples, and it remains consistently negative and significant in competitive industries. We conclude that our proxies for industry booms play a considerably stronger role in predicting industry busts in competitive industries as is predicted by Hypothesis 1, and that this result is most noteworthy in extreme industries where it is likely that valuation uncertainty is high .

Panel D shows that industry new financing and relative investment are also important for industries with declining concentration and in particular, in the extreme industry groupings with declining concentration. These findings further support Hypothesis 1, 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 variables suggests that, as in the case of operating cash flows, the most extreme firms also have more negative outcomes. Inferences from the RRV models (not reported to conserve space) are essentially identical to those presented.

Demarzo, Kaniel, and Kremer (2006b) (DKK) (Hypothesis 2D) present a theory of investment and relative wealth concerns, and suggest that predictable bust patterns should be largest in high systematic risk industries. The high market risk tercile in the last column of Table VII tests this prediction . In Panel B, we find that the industry relative investment variable in the high market risk tercile is indeed more negative and significant than in other subsamples, providing some support for Hypothesis 2D. However, this result is rather weak, as a test of significance of the difference in the coefficients between Panel B and C reveals that this coefficient is not significantly different. Moreover, we do not find a significant result in the high market risk tercile for declining concentration industries in Panel D.

B Return Comovement

In this section we test the key prediction of Hypothesis 1 that return comovement will be higher in competitive industries, especially when price uncertainty and valuations are high (Chen, Goldstein, and Jiang (2007), Roll (1988), and Durnev, Morck, and Yeung (2004)). In particular, the same variables associated with predictable busts in competitive industries should also be associated with greater return comovement with aggregate prices such as industry and market wide returns.

In Table VIII, the dependent variable is the R-squared of a regression of each firm's daily stock returns in the given year on the value weighted market index and the firm's value weighted three-digit SIC industry excluding the firm itself. We report regression coefficients and t-statistics (in parentheses) for panel data regression models where t-statistics are adjusted for clustering over time and industry, and corrected for heteroskedasticity. One observation is one firm in one year. We examine this regression for competitive and concentrated subsamples, and for subsamples that further limit firms to those in the highest growth or highest valuation tercile.

[**Insert Table VIII: Return Comovement in Competitive Industries**]

The first column in Table VIII strongly supports the conclusion that firm returns comove more with aggregate prices in competitive industries when industry valuations are higher. In particular, the coefficient on relative industry valuation is significantly positive in competitive industries, and also significantly different from the coefficient in concentrated industries, both at the one percent level. The fourth column shows that this relationship is entirely absent in concentrated industries. A comparison of column one to columns two and three also illustrate that this result is larger in high relative valuation industries, as the high relative valuation coefficient increases from .08 in column one to nearly 0.20 for the high value competitive industry subsample in column three. These findings strongly support Hypothesis 1. The absence of this finding in concentrated industries is consistent with firms in concentrated industries facing lower information gathering costs due to the smaller number of rival firms, and hence returns rely less on aggregate price changes.

Although the results for high industry valuation are strong, we find little if any link between return comovement and relative industry investment and new financing in either competitive or concentrated industries. These results are consistent with high valuations being key to the predictable busts predicted by Hypothesis 1.

C Changes in Systematic and Idiosyncratic Risk

Pastor and Veronesi (2005) posit that high valuations and subsequent busts are, in part, due to levels of systematic risk that can increase over time. Our findings regarding stock returns in the high market risk tercile in Table VII are consistent with this prediction, but this evidence is indirect. The theory further suggests that as technologies are adopted, systematic risk can rise, resulting in a negative return event (a bust) that is associated with stocks being penalized for their rise in systematic risk (Hypotheses 2B, 2C). We now test the more specific prediction that observed industry busts are characterized by increased systematic risk and decreased idiosyncratic risk.

We first define a firm year as beginning on July first of year y, and ending on June 30th of year t+1. Where d denotes one trading day in year y, we then regress the daily stock returns associated with firm i in year y on the three Fama-French factors plus momentum as follows (one regression per firm-year):

$$r_{i,y,d} = \alpha_{i,y} + \beta_{i,y,1} MKT_d + \beta_{i,y,2} HML_d + \beta_{i,y,3} SMB_d + \beta_{i,y,4} UMD_d + \epsilon_{i,y,d} \quad (12)$$

We define a firm year's idiosyncratic risk as the standard deviation of the residuals from this regression. We then focus on the specific theoretical predictions regarding the market beta ($\beta_{i,y,1}$) and idiosyncratic risk noted above by regressing annual changes in risk on our industry and firm measures of relative valuation, investment and financing.

To conserve space, and because our goal is to explain the predictable industry returns on Table VII, we only present results for competitive industries (we only find predictable industry returns for this subsample). For independent variables collected using data from calendar year t, the ex-ante risk level is measured from July of year t to June of year t+1, and the ex-post risk level is measured from July of year t+1 to June of year t+2.

This method permits us to understand the impact that future changes in risk have on simultaneously measured stock returns, as the theories we examine predict that risk will change ex-post while busts are in progress. 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 risk changes. The inclusion of year fixed effects also controls for the well-known increasing 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 market risk (Panel A) and idiosyncratic risk (Panel B) in competitive industries. The results in Panel A suggest that market risk increases when relative valuations are high in competitive industries. This finding is true both in the broad competitive sample (column 1) and in the extreme competitive subsamples (columns 2 to 4). However, these results support not only Hypothesis 2C, but also Hypothesis 1 which predicts that firms in competitive industries will experience higher comovement with aggregate price signals (ie, they will have higher market and industry betas). These findings in Panel A are also consistent with Hypothesis 2B and the real options model of Aguerrevere (2006).

Panel B helps to clarify the ambiguity associated with the results in Panel A. The results in Panel B support the Pastor and Veronesi (2005) predictions in the broad sample, and in the high systematic risk subsample, as idiosyncratic risk falls while market risk increases. However, high industry valuation is not related to ex post changes in idiosyncratic risk in the high valuation subsample. We thus conclude that our results support Hypothesis 2C for broad industry groupings and for high systematic risk industries, but not for high valuation industries where valuation uncertainty is likely to be high. Results in these latter industries are most consistent with Hypothesis 1, and hence consistent with our paper's broader findings for these extreme industries.

We do not find support for Hypothesis 2C for either the high industry investment or the new industry finance coefficients. In particular, neither variable exhibits positive association with ex post market risk along with negative association with ex post idiosyncratic risk.

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 2A), 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 Pastor and Veronesi (2005) and Aguerrevere (2006), can explain part of the link between high industry valuations and subsequent return reversals in competitive industries. However , these theories are not able to explain our findings in extreme industry groups where price uncertainty and relative valuations are high.

Also, we conclude that some results remain unexplained. For example, because industry new financing is associated with a modest rise in systematic risk and a sharper rise in idiosyncratic risk, it appears less likely that current risk based explanations can explain the patterns observed. Possible explanations for our industry financing results include some broader theories including herding based explanations and behavioral explanations including market timing. Theoretical work has not yet examined the role that industrial organization might play in these alternative settings. What is clear throughout our findings is that large differences in changes in cash flow, risk, and returns exist based on product market competition.

D Can Ex Post Changes in Risk Explain Our Results?

In this section, we examine if ex post risk changes might explain or reduce the ability of relative industry valuation, investment, and high financing to predict ex post stock returns in competitive industries.[19] The idea we are examining is whether market participants anticipate future risk changes. Ex post risk changes might be important if market participants are reacting to anticipated risk changes rather than unexpected contemporaneous risk changes consistent with Hypothesis 2C.

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.

Table X displays the results for the entire sample (Panel A) and for competitive industries (Panel B), and for subsamples based on high growth, high relative valuation, and high market risk, within each panel. The coefficients in each specification can be compared to analogous models based on standard abnormal returns in Panel A and Panel B in Table VII. We omit concentrated industries to conserve space, and because there is no return predictability to explain in Table VII for this subsample. Pastor and Veronesi (2005) (Hypothesis 2C) predict that changes in risk will explain

[19]We thank Lubos Pastor for this suggestion.

all or part of the return predictability we reported in these earlier tables, while Hypothesis 1 and other alternatives including Demarzo, Kaniel, and Kremer (2006b) (Hypothesis 2D) predict that changes in risk will explain little of this return predictability. Hypothesis 2D predicts that underperformance will be 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 Table VII yields some support for the Pastor and Veronesi (2005) prediction that changes in risk can explain some of the return predictability we find. In Panel A (the entire sample), for example, we find that changes in risk greatly reduce the explanatory power of the industry relative valuation variable. However, in Panel B (competitive industries), changes in risk are far less influential. For example, the high relative industry valuation coefficient barely declines from 0.029 to just 0.027 in the high valuation subsample in Panel B. In the broad sample (Panel A), this coefficient's reduction is much more substantial from 0.015 to 0.006.

It is also noteworthy that changes in risk do have some impact in the high systematic risk subsample in Panel B. Here, the high relative industry valuation coefficient reduces from 0.018 to 0.010. Hence, our findings support Hypothesis 1 in competitive industries where valuation uncertainty is high, and support Hypothesis 2C in broader industry groupings, especially in samples where systematic risk (ex ante market beta) is high.

Table X also shows that accounting for changes in risk does not explain the return predictability of other variables including industry relative investment. Because Demarzo, Kaniel, and Kremer (2006b) (DKK) attribute lower returns in industries with high investment to relative wealth concerns, we expect that changes in risk will not be able to explain returns if DKK's predictions hold. Our findings regarding the relative industry investment variable thus are consistent with both Hypothesis 2D and Hypothesis 1, which is also generally silent regarding whether or not changes in ex post risk will explain stock returns cross sectionally. Regarding the industry new finance term, we also continue to see unchanged strong negative coefficients when we adjust returns for changes in risk.

E Economic Magnitude of Stock Market Returns

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

[Insert Table XI here]

In Table XI, 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).

Table XI shows that the magnitude of stock price underperformance in competitive industries with high relative industry valuation is economically relevant, especially within the high growth subsample where price uncertainty is high. For example, at the industry level in Panel C, the highest quintile of relative industry valuation underperforms the lowest quintile by over 3.3% percentage points annually. We find similar findings for industry relative investment and industry relative finance. The highest quintile of high industry relative investment and financing shows significant underperformance in portfolio abnormal returns.

Table XI shows that these results are even stronger at the firm level - analogous to weighting one observation as one firm. The highest quintile of relative industry valuation has abnormal performance that is roughly 4.2 percentage points (per year) lower than the lowest quintile in Panel B, and 15 percentage points lower in Panel C. More modest, but still large, magnitudes obtain for new industry financing and investment. Although we do not report results for concentrated industries to conserve space, we do not find economically meaningful return differences across quintiles in concentrated industries, especially for industry level variables.

F Additional Robustness Tests

We examine robustness to using abnormal returns based on an adjustment proposed by Mitchell and Stafford (2000) (MS). We first define a firm year as July to June. We then regress each firm year's twelve monthly stock returns on four factors: the three Fama-French factors plus momentum.[20] From these time series regressions, we extract a database of yearly firm-specific intercepts describing each firm's abnormal

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

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 (based on 125 portfolios as described earlier). This two-stage method ensures that returns are sufficiently adjusted for known risk factors even when the relationship between factor loadings and returns is non-linear. These tests reveal that our main results are robust.

To further ensure robustness, we also repeat our tests 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. Our inferences do not depend on the chosen specification.

VI 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 industry booms and subsequent busts in the economy. Our results show how real and financial components impact industry business cycles. We find that in competitive industries, increases in industry valuations above predicted levels are followed by significantly lower operating cash flows and stock returns. Firms in competitive industries, and in particular in competitive growth industries, have especially negative cash flows and negative abnormal stock returns following episodes of high industry financing and high relative industry valuation. We also find that analyst forecasts of future earnings per share are biased upwards in these industries. In contrast, in concentrated industries these relations are weak and generally insignificant.

These 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 5.5 percent ex-post decline in operating cash flows. In the stock market, style and risk-adjusted abnormal stock returns for a competitive high growth industry portfolio in the highest quintile of ex-ante relative industry valuation are over three percentage points lower than a similar portfolio in the lowest quintile using industry weighted returns. Using firm weighted returns, abnormal stock returns in competitive industries are more than ten percentage points lower in the high industry valuation quintile than in a similar portfolio in the lowest quintile.

Additional adjustments for contemporaneous changes in risk do explain some of our findings, as predicted by recent theories of booms and busts. However, in industries with the highest valuations, nearly all of the return predictability persists after adjusting for these changes. Hence, change-in-risk-based explanations cannot explain the extent of our findings in the most highly-valued competitive industries.

Our results are most consistent with managers, analysts, and investors relying on common industry signals in competitive industries. The resulting lack of coordination and the externality of high investment and financing on all firms generates poor ex post outcomes in these competitive industries. This effect is likely to be greatest if industry participants fail to consider, or do not have incentives to consider, the effect of competition when making investment and financing decisions. In contrast, in concentrated industries these relations are weak and generally insignificant, consistent with market participants internalizing the effects of competition on industry-wide prices, cash flows, and stock returns.

References

Aguerrevere, Felipe, 2006, Real options, product market competition and asset returns, Working Paper, University of Calgary.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *The Journal of Finance* 55, 2219–2257.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

——— , and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Beneish, MD, and Craig Nichols, 2008, Identifying overvalued equity, Cornell University and Indiana University Working Paper.

Campbell, John, Martin Lettau, Burton Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk, *The Journal of Finance* 56.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *The Journal of Finance* 61, 171–194.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock prices, *Review of Financial Studies* 20, 619–650.

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

Demarzo, Peter, Ron Kaniel, and Ilan Kremer, 2006a, Relative wealth concerns and financial bubbles, Duke University Working Paper.

——— , 2006b, Technological innovation and real investment booms and busts, Duke University Working Paper.

Durnev, Art, Randall Morck, and Bernard Yeung, 2004, Value enhancing capital budgeting and firm-specific stock return variation, *The Journal of Finance* 59, 65–105.

Grenadier, S. R., 2002, Option exercise games: An application to the equilibrium investment strategies of firms, *Review of Financial Studies* 15, 691–721.

Hennessy, Christopher, 2004, Tobins q, debt overhang, and investment, *The Journal of Finance* 59, 1717–1742.

Hong, Harrison, and Jeffrey Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance* 58, 313–351.

Hou, Kewei, and David Robinson, 2005, Industry concentration and average stock returns, *The Journal of Finance* 61.

Kyle, Albert, and Wei Xiong, 2001, Contagion as a wealth effect, *The Journal of Finance* 56, 1401–40.

Lamont, Owen, 2000, Investment plans and stock returns, *The Journal of Finance* 55.

Mankiw, Gregory, and Michael Whinston, 1986, Free entry and social inefficiency, *Rand Journal of Economics* 17, 48–58.

Martin, Perry, 1984, Scale economies, imperfect competition, and public policy, *Journal of Industrial Economics* 32, 313–330.

Mitchell, Mark, and Erik Stafford, 2000, Managerial decisions and long-term stock-price performance, *Journal of Business* 73, 287–329.

Moulton, B, 1986, Random group effects and the precision of regression estimates, *Journal of Econometrics* 32, 385–97.

Pastor, Lubos, and Pietro Veronesi, 2003, Stock valuation and learning about profitability, *The Journal of Finance* 58, 1749–89.

———, 2005, Technological revolutions and stock prices, CRSP Working Paper No. 606.

Petersen, Mitchell, 2005, Estimating standard errors in finance panel data sets: Comparing approaches, 2005 Working Paper.

Polk, Chris, and Paola Sapienza, 2006, The stock market and corporate investment, Northwestern University Working Paper.

Pritsker, Matthew, and Laura Kodres, 2002, A rational expectations model of financial contagion, *The Journal of Finance* 57, 769–99.

Rhodes-Kropf, Matthew, David Robinson, and S Viswanathan, 2005, Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561–603.

Rhodes-Kropf, Matthew, and S Viswanathan, 2004, Market valuation and merger waves, *The Journal of Finance* 59, 2685–2718.

Roll, Richard, 1988, R^2, *The Journal of Finance* 43, 541–566.

Scharfstein, David, 1988, Product-market competition and managerial slack, *RAND Journal of Economics* 19, 147–155.

———, and Jeremy Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465–79.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, University of Texas Working Paper.

Veldkamp, Laura, 2006, Information markets and the comovement of asset prices, *Review of Economic Studies* 73, 823–845.

Weizsacker, C. C., 1980, A welfare analysis of barriers to entry, *Bell Journal of Economics* 11, 399–420.

Welch, Ivo, 1992, Sequential sales, learning and cascades, *The Journal of Finance* 47, 695–732.

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	Weighted Relative Valuation	Relative Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
	Competitive Industries							
		1970s						
131	Oil and Gas Extraction	1979	2.72	362.0	71.0%	72.7%	0.13	0.18
233	Woman's Apparel	1976	1.18	51.4	58.5%	76.5%	0.05	0.18
173	Electrical Work	1978	1.61	110.1	53.4%	102.1%	0.15	0.19
287	Fertilizers and Agriculture Chemicals	1979	2.97	244.1	104.6%	114.5%	0.16	0.19
571	Home Furnishing Stores	1975	1.01	31.6	242.7%	126.0%	0.16	0.18
		1980s						
514	Groceries - Wholesale	1983	1.09	196.5	109.4%	128.3%	0.08	0.18
385	Ophthalmic Goods	1984	4.79	125.7	155.6%	131.3%	0.20	0.24
233	Woman's Apparel	1985	1.85	165.1	114.0%	132.0%	0.10	0.20
731	Advertising	1982	1.73	124.8	144.7%	135.5%	0.15	0.20
483	Radio and Television Broadcasting	1985	5.23	321.7	174.3%	185.0%	0.13	0.22
		1990s						
367	Semi-Conductors + Elec. Comp.	1999	11.00	5,079.7	88.8%	64.6%	0.04	0.18
737	Business Services	1999	18.77	2,502.3	100.2%	82.0%	0.04	0.13
872	Accounting + Bookkeeping Svs.	1998	10.63	325.8	138.2%	115.7%	0.17	0.22
571	Home Furnishing Stores	1993	6.68	636.5	141.2%	124.6%	0.09	0.16
233	Woman's Apparel	1990	2.26	1,862.9	136.8%	136.8%	0.07	0.16
422	Public Warehousing And Storage	1996	4.40	323.6	190.0%	176.4%	0.18	0.20
513	Apparel - Wholesale	1992	19.17	22.0	212.6%	193.3%	0.23	0.21
		2000s						
596	Catalog and Mail Order Houses	2004	5.40	344.5	97.6%	85.0%	0.08	0.16
122	Coal Mining	2003	4.68	1,442.0	76.5%	89.7%	0.09	0.23
835	Child Day Care Services	2004	6.36	765.6	101.5%	100.8%	0.18	0.18
153	Operative Builders	2003	1.70	1,491.4	96.8%	120.5%	0.08	0.14
783	Motion Picture Theaters	2005	26.45	1,423.6	188.4%	150.8%	0.49	0.21
245	Prefabricated Buildings	2004	1.49	296.5	140.4%	174.2%	0.18	0.20

Explanation: This table lists the top five industries with the highest relative valuation (valuation less predicted 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. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. 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 three industries (two in the 1990s and one in 2000s) 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	Weighted Relative Valuation	Relative Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
	Concentrated Industries							
		1970s						
517	Petroleum Stations and Terminals	1979	1.14	1,252.5	40.2%	45.2%	0.62	0.49
422	Public Warehousing And Storage	1979	1.20	201.4	115.1%	98.8%	0.94	0.32
321	Flat Glass	1978	1.16	145.9	99.7%	105.1%	0.60	0.38
516	Chemicals + Allied Products	1979	1.26	390.9	102.6%	147.7%	0.76	0.36
387	Watches, Clocks, and Clockwork	1975	0.27	3.2	185.2%	185.2%	0.52	0.29
		1980s						
458	Airport Terminals	1982	3.69	21.3	152.1%	138.2%	0.74	0.28
211	Tobacco Manufactures	1986	2.57	2,095.5	144.1%	144.1%	0.27	0.68
736	Personnel Supply Services	1986	6.88	107.4	170.5%	179.0%	0.17	0.39
732	Consumer Credit Reporting Agencies	1985	5.63	73.5	160.6%	191.4%	0.43	0.44
393	Musical Instruments	1987	1.28	76.3	220.8%	220.8%	1.00	0.65
		1990s						
301	Tires And Inner Tubes	1992	3.93	3,794.6	121.3%	119.6%	0.68	0.90
102	Copper Ores	1995	6.83	6,274.7	131.4%	124.4%	0.18	0.38
502	Furniture And Home Furnishings	1993	16.17	33.2	165.0%	140.4%	0.46	0.33
387	Watches, Clocks, and Clockwork	1993	6.88	12.2	237.1%	237.1%	0.49	0.50
376	Guided Missiles And Space Vehicles	1995	2.93	10,252.5	188.0%	298.3%	0.27	0.56
		2000s						
301	Tires And Inner Tubes	2004	16.12	2,932.7	109.7%	100.3%	0.48	0.88
422	Public Warehousing And Storage	2002	2.74	4,539.6	125.3%	125.3%	0.72	0.50
784	Video Tape Rental	2005	4.94	1,177.5	115.9%	132.4%	0.55	0.55
376	Guided Missiles And Space Vehicles	2001	3.17	9,479.3	153.1%	165.5%	0.61	0.79
332	Iron and Steel Fasteners	2004	2.86	2,971.1	150.0%	175.4%	0.31	0.36

Explanation: This table lists the top five industries with the highest relative valuation (valuation less predicted 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. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. 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			
Industry Relative Valuation	-0.022	0.239	-1.27	1.53	104,024
Industry New Financing	0.021	0.041	-.408	.638	104,024
Industry Relative Investment	-0.018	0.069	-.598	1.54	104,024
Firm Relative Valuation	-0.000	0.466	-3.21	3.31	104,024
Firm New Financing	0.012	0.137	-.849	1.46	104,024
Firm Relative Investment	-0.000	0.301	-2.25	5.24	104,024
Operating Cash Flow Change	-.008	.116	-1.45	1.59	97,780
Abnormal Return	0.001	0.157	-1.192	9.24	1,077,793
		Panel B: Competitive Industries			
Industry Relative Valuation	0.016	0.199	-1.03	1.03	48,558
Industry New Financing	0.024	0.040	-0.188	0.586	48,558
Industry Relative Investment	-0.027	0.072	-0.363	0.690	48,558
Firm Relative Valuation	-0.001	0.506	-3.211	3.310	48,558
Firm New Financing	0.023	0.166	-0.849	1.462	48,558
Firm Relative Investment	0.000	0.357	-2.249	5.246	48,558
Operating Cash Flow Change	-0.011	0.143	-1.447	1.591	45,119
Abnormal Return	0.002	0.176	-1.192	9.25	575,863
		Panel C: Concentrated Industries			
Industry Relative Valuation	0.023	0.199	-1.27	1.20	17,163
Industry New Financing	0.016	0.044	-0.41	0.64	17,163
Industry Relative Investment	-0.006	0.066	-0.57	1.54	17,163
Firm Relative Valuation	-0.002	0.427	-2.13	2.70	17,163
Firm New Financing	0.004	0.110	-0.727	1.37	17,163
Firm Relative Investment	0.000	0.235	-1.60	3.85	17,163
Operating Cash Flow Change	-0.009	0.088	-1.03	1.17	16,192
Abnormal Return	-0.000	0.130	-0.954	4.81	135,447

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. Competitive and concentrated industries are those in the lowest and highest tercile based on this index. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. 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	All Industries 1 Year	All Industries 2 Years
Panel A: Sample-wide results		
Industry Relative Valuation	0.0010 (0.140)	–0.0269 (–3.130)[a]
Firm Relative Valuation	0.0034 (2.480)[b]	–0.0065 (–3.750)[a]
Industry Relative Investment	–0.0394 (–2.900)[a]	–0.0464 (–2.070)[b]
Firm Relative Investment	–0.0027 (–1.070)	–0.0045 (–1.340)
Industry New Finance	–0.0673 (–3.210)[a]	–0.0357 (–1.390)
Firm New Finance	–0.0287 (–2.670)[a]	0.0126 (1.030)
Change in EBITDA	0.0012 (0.340)	–0.0081 (–1.920)[c]
Change in CAPX	–0.0067 (–2.320)[b]	0.0009 (0.290)
Observations	83,974	75,653
Panel B: Competitive Industries		
Industry Relative Valuation	–0.0048 (–0.430)	–0.0509 (–3.720)[a,d]
Firm Relative Valuation	0.0057 (2.790)[a,e]	–0.0038 (–1.420)[d]
Industry Relative Investment	–0.0620 (–2.740)[a]	–0.0514 (–1.480)
Firm Relative Investment	–0.0074 (–2.320)[b,d]	–0.0108 (–2.550)[b,e]
Industry New Finance	–0.0405 (–1.180)	0.0183 (0.430)
Firm New Finance	–0.0352 (–2.560)[b]	0.0130 (0.830)
Change in EBITDA	0.0027 (0.440)	–0.0111 (–1.400)
Change in CAPX	–0.0093 (–1.780)[c]	0.0057 (0.980)
Observations	44,841	39,624
Panel C: Concentrated Industries		
Industry Relative Valuation	0.0123 (2.590)[a]	–0.0023 (–0.370)[d]
Firm Relative Valuation	0.0003 (0.160)[e]	–0.0112 (–4.320)[a,d]
Industry Relative Investment	–0.0122 (–0.860)	–0.0365 (–1.870)[c]
Firm Relative Investment	0.0103 (1.720)[c,d]	0.0116 (1.580)[e]
Industry New Finance	–0.0418 (–1.530)	–0.0326 (–0.870)
Firm New Finance	–0.0079 (–0.510)	0.0202 (1.090)
Change in EBITDA	0.0023 (0.680)	–0.0031 (–0.620)
Change in CAPX	–0.0054 (–1.650)[c]	–0.0004 (–0.090)
Observations	16,169	14,867
Panel D: Industries with Declining Concentration		
Industry Relative Valuation	–0.0236 (–2.850)[a,d]	–0.0534 (–6.060)[a,d]
Firm Relative Valuation	0.0045 (2.310)[b]	–0.0066 (–2.590)[a]
Industry Relative Investment	–0.0596 (–3.180)[a,e]	–0.0635 (–2.060)[b,f]
Firm Relative Investment	–0.0032 (–0.770)	–0.0004 (–0.070)
Industry New Finance	–0.0852 (–3.120)[a,f]	–0.0181 (–0.530)
Firm New Finance	–0.0299 (–1.700)[c]	0.0200 (1.080)
Change in EBITDA	0.0049 (1.280)	–0.0038 (–0.900)
Change in CAPX	–0.0086 (–2.260)[b]	–0.0026 (–0.650)
Observations	36,601	31,328

Explanation: We report regression coefficients and t-statistics (in parentheses) for panel data regressions. t-statistics are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. One observation is one firm in one year, and the dependent variable is the firm's change in operating cash flow (operating income / assets) from year t to year t+1. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. Competitive and concentrated industries are those in the lowest and highest tercile based on industry concentration (HHI). Change in EBITDA and CAPX are the past year changes in earnings before interest and taxes plus depreciation and capital expenditures, winsorized at the 1/99% level. * 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 Flow Changes in High Growth Industries

Variable	All Industries 1 Year	All Industries 2 Years
Panel A: High Growth Industries		
Industry Relative Valuation	–0.0214 (–1.930)^{c}	–0.0568 (–4.250)^{a}
Firm Relative Valuation	0.0054 (2.320)^{b}	–0.0032 (–1.100)
Industry Relative Investment	–0.0590 (–2.670)^{a}	–0.0622 (–1.820)^{c}
Firm Relative Investment	–0.0073 (–1.870)^{c}	–0.0132 (–2.660)^{a}
Industry New Finance	–0.0972 (–2.620)^{a}	–0.0341 (–0.740)
Firm New Finance	–0.0279 (–1.800)^{c}	0.0185 (1.060)
Change in EBITDA	0.0080 (1.190)	–0.0097 (–1.320)
Change in CAPX	–0.0122 (–1.930)^{c}	–0.0003 (–0.040)
Observations	33,217	30,939
Panel B: Competitive High Growth Industries		
Industry Relative Valuation	–0.0456 (–2.450)^{b,d}	–0.1124 (–4.820)^{a,d}
Firm Relative Valuation	0.0084 (2.660)^{a,e}	0.0001 (0.040)^{d}
Industry Relative Investment	–0.1023 (–3.030)^{a}	–0.0924 (–1.950)^{c}
Firm Relative Investment	–0.0126 (–2.620)^{a}	–0.0215 (–3.510)^{a,f}
Industry New Finance	–0.0854 (–1.270)	0.0193 (0.240)
Firm New Finance	–0.0318 (–1.730)^{c}	0.0175 (0.840)
Change in EBITDA	0.0128 (1.250)	–0.0136 (–1.180)
Change in CAPX	–0.0156 (–1.550)	–0.0014 (–0.120)
Observations	19,888	18,372
Panel C: Concentrated High Growth Industries		
Industry Relative Valuation	0.0114 (1.310)^{d}	0.0001 (0.010)^{d}
Firm Relative Valuation	0.0005 (0.130)^{e}	–0.0164 (–3.370)^{a,d}
Industry Relative Investment	–0.0101 (–0.430)	–0.0262 (–0.780)
Firm Relative Investment	0.0035 (0.360)	0.0070 (0.620)^{f}
Industry New Finance	–0.0905 (–1.490)	–0.0790 (–0.980)
Firm New Finance	0.0287 (1.190)	0.0443 (1.630)
Change in EBITDA	0.0111 (1.540)	0.0064 (0.770)
Change in CAPX	–0.0102 (–1.370)	–0.0001 (–0.010)
Observations	4,968	4,683
Panel D: High Growth Industries with Declining Concentration		
Industry Relative Valuation	–0.0457 (–3.360)^{a}	–0.0716 (–5.260)^{a,f}
Firm Relative Valuation	0.0052 (1.740)^{c}	–0.0044 (–1.100)
Industry Relative Investment	–0.0632 (–2.320)^{b}	–0.0706 (–1.820)^{c}
Firm Relative Investment	–0.0080 (–1.310)	–0.0082 (–1.260)
Industry New Finance	–0.1325 (–3.150)^{a,e}	–0.0546 (–1.030)^{e}
Firm New Finance	–0.0299 (–1.160)	0.0232 (0.950)
Change in EBITDA	0.0104 (1.420)	–0.0017 (–0.220)
Change in CAPX	–0.0133 (–1.690)^{c}	–0.0045 (–0.560)
Observations	16,348	15,138

Explanation: We report regression coefficients and t-statistics (in parentheses) for panel data regressions. t-statistics are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. One observation is one firm in one year, and the dependent variable is the firm's change in operating cash flow (operating income / assets) from year t to year t+1. We restrict the sample to firms in high growth industries, which are those in the lowest tercile based on industry-average book to market ratios (which are first winsorized at the 1/99% level prior to taking industry averages). To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. Competitive and concentrated industries are those in the lowest and highest tercile based on industry concentration (HHI). Change in EBITDA and CAPX are the past year changes in earnings before interest and taxes plus depreciation and capital expenditures, winsorized at the 1/99% level. * 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 VI: Regressions predicting analyst forecast optimism

Variable	All Competitive Industries	Competitive Growth Industries	All Concentrated Industries	Concentrated Growth Industries
		Panel A: Analyst Forecast Optimism		
Industry Relative Valuation	–0.0070 (–0.990)	0.0330 (2.850)^{a}	–0.0051 (–0.510)	0.0154 (0.970)
Firm Relative Valuation	–0.0006 (–0.290)^{f}	0.0019 (0.700)	0.0082 (1.730)^{c,f}	0.0009 (0.110)
Industry Relative Investment	–0.0106 (–0.700)	–0.0099 (–0.530)	0.0159 (0.590)	0.0016 (0.050)
Firm Relative Investment	0.0059 (2.640)^{a}	0.0046 (1.450)	0.0098 (0.930)	–0.0059 (–0.410)
Industry New Finance	0.0149 (0.610)	0.0473 (1.270)	0.0558 (1.680)^{c}	0.1025 (1.940)^{c}
Firm New Finance	0.0098 (1.950)^{c,e}	0.0098 (1.650)^{c}	0.0515 (2.670)^{a,e}	0.0394 (1.060)
Log M/B Ratio	0.0015 (0.940)^{f}	0.0019 (0.790)	0.0081 (2.620)^{a,f}	0.0068 (1.170)
Log Market Value	–0.0062 (–14.000)^{a}	–0.0059 (–9.780)^{a,f}	–0.0057 (–7.790)^{a}	–0.0026 (–1.430)^{f}
Lagged Forecast Error	0.2674 (13.330)^{a,e}	0.2835 (8.950)^{a,e}	0.3713 (8.460)^{a,e}	0.5116 (5.010)^{a,e}
Lagged Forecast Error N/A	–0.0008 (–0.340)	0.0027 (0.760)	0.0039 (0.580)	–0.0044 (–0.310)
Observations	23,945	9,548	4,129	813

Explanation: Regressions examine the effect of relative firm- and industry-level valuation, investment and new finance on analyst forecast optimism. We report regression coefficients and t-statistics (in parentheses) for panel data regression models. t-statistics are adjusted for clustering over time and industry, and corrected for heteroskedasticity. One observation is one firm in one year, and the dependent variable is the analyst forecast optimism. Analyst forecast optimism is defined as the analyst estimate of one year EPS minus the actual outcome of EPS, scaled by price at the time of the estimate (all measures of EPS are adjusted for splits). To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. Competitive and concentrated industries are those in the lowest and highest tercile based on industry concentration (HHI). Growth industries are those in the lowest tercile based on industry-average book to market ratios (which are first winsorized at the 1/99% level prior to taking industry averages). * 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 VII: Regressions predicting monthly firm-level stock returns

Variable	All Industries	Growth Industries Only	High Value Industries Only	High Mkt. Risk Industries Only
		Panel A: All Firms		
Industry Relative Valuation	–0.003 (–1.28)	–0.013 (–3.58)[a]	–0.015 (–3.10)[a]	–0.011 (–3.17)[a]
Firm Relative Valuation	–0.002 (–5.59)[a]	–0.002 (–3.68)[a]	–0.001 (–1.92)[c]	–0.002 (–3.60)[a]
Industry Relative Investment	–0.021 (–3.52)[a]	–0.016 (–2.07)[b]	–0.021 (–1.86)[c]	–0.026 (–3.16)[a]
Firm Relative Investment	–0.003 (–3.93)[a]	–0.003 (–2.66)[a]	–0.003 (–2.04)[b]	–0.003 (–3.20)[a]
Industry New Finance	–0.030 (–4.13)[a]	–0.034 (–2.96)[a]	–0.034 (–3.15)[a]	–0.053 (–3.85)[a]
Firm New Finance	–0.018 (–6.95)[a]	–0.014 (–4.15)[a]	–0.021 (–5.09)[a]	–0.018 (–5.27)[a]
Observations	1,058,751	390,550	324,813	423,461
		Panel B: Competitive Industries Only		
Industry Relative Valuation	–0.004 (–1.01)	–0.020 (–3.76)[a,d]	–0.029 (–3.90)[a,d]	–0.018 (–3.51)[a,d]
Firm Relative Valuation	–0.002 (–4.55)[a]	–0.003 (–3.48)[a,f]	–0.002 (–1.81)[c]	–0.003 (–3.78)[a,e]
Industry Relative Investment	–0.024 (–2.81)[a]	–0.013 (–1.18)	–0.019 (–1.32)	–0.024 (–2.26)[b]
Firm Relative Investment	–0.003 (–3.23)[a]	–0.003 (–2.24)[b,e]	–0.002 (–1.20)	–0.003 (–2.35)[b,f]
Industry New Finance	–0.046 (–3.86)[a,f]	–0.067 (–3.77)[a,d]	–0.054 (–3.09)[a,f]	–0.087 (–4.33)[a,d]
Firm New Finance	–0.017 (–5.64)[a]	–0.014 (–3.66)[a]	–0.021 (–4.55)[a]	–0.017 (–4.46)[a]
Observations	575,863	249,874	181,107	267,305
		Panel C: Concentrated Industries Only		
Industry Relative Valuation	0.001 (0.43)	0.003 (0.68)[d]	0.010 (1.37)[d]	0.005 (1.09)[d]
Firm Relative Valuation	–0.002 (–1.67)[c]	0.000 (0.27)[f]	–0.001 (–0.34)	0.000 (0.35)[e]
Industry Relative Investment	–0.014 (–1.65)[c]	0.007 (0.52)	–0.017 (–1.22)	–0.012 (–0.87)
Firm Relative Investment	–0.004 (–2.00)[b]	–0.008 (–3.40)[a,e]	–0.005 (–1.41)	–0.008 (–3.27)[a,f]
Industry New Finance	–0.016 (–1.12)[f]	0.009 (0.49)[d]	0.001 (0.04)[f]	–0.002 (–0.09)[d]
Firm New Finance	–0.024 (–4.31)[a]	–0.014 (–2.31)[b]	–0.025 (–3.26)[a]	–0.023 (–3.08)[a]
Observations	135,447	40,827	36,577	57,822
		Panel D: Declining Concentration Industries Only)		
Industry Relative Valuation	–0.007 (–1.81)[c]	–0.018 (–2.66)[a]	–0.017 (–2.28)[b,e]	–0.018 (–2.88)[a]
Firm Relative Valuation	–0.003 (–4.02)[a]	–0.003 (–3.00)[a]	–0.002 (–2.38)[b,f]	–0.002 (–2.25)[b]
Industry Relative Investment	–0.019 (–1.90)[c]	–0.008 (–0.62)	–0.032 (–2.10)[b,e]	–0.014 (–1.08)
Firm Relative Investment	–0.002 (–1.45)	–0.003 (–1.73)[c]	–0.002 (–1.63)	–0.003 (–2.10)[b]
Industry New Finance	–0.032 (–2.94)[a]	–0.043 (–2.53)[b]	–0.058 (–3.52)[a,f]	–0.050 (–2.60)[a]
Firm New Finance	–0.015 (–3.31)[a,f]	–0.011 (–1.90)[c,f]	–0.021 (–4.06)[a,e]	–0.013 (–2.20)[b,e]
Observations	367,279	169,804	131,061	172,857

Explanation: We report regression coefficients and t-statistics (in parentheses) for panel data regressions. t-statistics are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. One observation is one firm in one month, and the dependent variable is the firm's monthly abnormal stock return: equal to a firm's raw monthly return less that 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. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year): $log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$
We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. Competitive and concentrated industries are those in the lowest and highest tercile based on industry concentration (HHI). The growth, high valuation, and high market risk industry groupings are based on terciles constructed from industry-average book to market ratios, relative industry valuation, and the industry's average market beta in the past year. * 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 VIII: Regressions predicting firm R-squared (comovement with market and industry)

Variable	All Competitive Industries	Competitive Growth Industries	Competitive High Val. Industries	All Concentrated Industries	Concentrated Growth Industries	Concentrated High Val. Industries
			Panel A: R-squared in Market+Industry Return Model			
Industry Relative Valuation	0.0858 (6.430)^{a,d}	0.1185 (4.560)^{a,d}	0.1958 (4.680)^{a,d}	0.0088 (0.670)^{d}	0.0044 (0.230)^{d}	0.0325 (1.430)^{d}
Firm Relative Valuation	0.0312 (14.850)^{a,e}	0.0384 (10.330)^{a,d}	0.0381 (9.060)^{a}	0.0200 (5.650)^{a,e}	0.0077 (1.140)^{d}	0.0282 (3.970)^{a}
Industry Relative Investment	0.0244 (0.980)	0.0073 (0.240)	0.0680 (1.450)	–0.0123 (–0.510)	–0.0105 (–0.200)	–0.0166 (–0.320)
Firm Relative Investment	–0.0067 (–4.480)^{a}	–0.0066 (–2.820)^{a}	–0.0042 (–1.720)^{c}	–0.0060 (–1.340)	–0.0157 (–2.720)^{a}	–0.0141 (–1.700)^{c}
Industry New Finance	0.0889 (2.510)^{b,f}	–0.0123 (–0.220)	0.0627 (0.810)	–0.0319 (–0.750)^{f}	–0.0322 (–0.460)	–0.0468 (–0.690)
Firm New Finance	–0.0200 (–3.690)^{a,d}	–0.0325 (–5.270)^{a,e}	–0.0104 (–1.400)	0.0166 (1.430)^{d}	0.0192 (0.880)^{e}	0.0128 (0.520)
Observations	52,054	21,290	16,209	11,885	3,201	3,201

Explanation: Regressions examine the effect of relative firm- and industry-level valuation, investment and new finance on firm comovement with the market and with its industry. The dependent variable is the R-squared of a regression of each firm's daily stock returns in the given calendar year on the value weighted market index and the firm's value weighted three-digit SIC industry excluding the firm itself. We report regression coefficients and t-statistics (in parentheses) for panel data regression models. t-statistics are from standard errors that are adjusted for clustering over time and industry, and corrected for heteroskedasticity. One observation is one firm in one year. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t denotes a year):

$$log(\frac{M}{B})_{i,t} = a + bAGE_{i,t} + cDD_{i,t} + dLEV_{i,t} + elog(SIZE_{i,t}) + fVOLP_{i,t} + gROE_{i,t}$$

We fit this model once for each industry in each year using firm observations from year $t-10$ to $t-1$. A firm's relative valuation is its $log(M/B)$ in year t less the fitted value using characteristics from year t and the above model estimated using the previous ten years. A firm's relative industry investment is computed in an analogous fashion, except we also include the firm's lagged Tobin's Q as an independent variable. A firm's new finance is the sum of its net debt and equity issuing activity, divided by its assets. For all three quantities, industry variables are the average of the given quantity for all firms in a SIC-3 industry in year t, and firm variables are set equal to raw quantities less the industry component. Competitive and concentrated industries are those in the lowest and highest tercile based on industry concentration (HHI). Growth industries are those in the lowest tercile based on industry-average book to market ratios (which are first winsorized at the 1/99% level prior to taking industry averages). * 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 IX: Regressions predicting annual changes in risk

Variable	All Competitive Industries	Competitive Growth Industries Only	Competitive High Value Industries Only	Competitive High Mkt. Risk Industries Only
		Panel A: Changes in Market Beta		
Industry Relative Valuation	0.3216 (5.060)[a,d]	0.2984 (2.800)[a]	0.5247 (2.550)[b]	0.2911 (2.840)[a,f]
Firm Relative Valuation	0.0785 (7.610)[a,f]	0.0993 (6.320)[a]	0.1094 (6.580)[a,f]	0.1111 (7.390)[a]
Industry Relative Investment	–0.5388 (–4.600)[a,d]	–0.3769 (–2.550)[b]	–0.4075 (–2.070)[b]	–0.4592 (–3.070)[a]
Firm Relative Investment	–0.0350 (–3.010)[a]	–0.0427 (–2.790)[a]	–0.0280 (–1.660)[c]	–0.0317 (–2.050)[b]
Industry New Finance	0.2747 (1.780)[c]	–0.0496 (–0.230)	0.2268 (0.860)	–0.3059 (–1.270)
Firm New Finance	0.2692 (7.330)[a]	0.2278 (5.130)[a]	0.3277 (6.550)[a]	0.2129 (4.500)[a]
Lagged Market Beta	–0.5930 (–55.280)[a]	–0.5930 (–39.680)[a]	–0.5714 (–34.440)[a]	–0.5870 (–40.940)[a]
Observations	48,878	21,594	15,461	23,000
		Panel B: Changes in Idiosyncratic Risk		
Industry Relative Valuation	–0.0052 (–5.240)[a]	–0.0038 (–2.580)[a]	–0.0005 (–0.270)	–0.0052 (–3.470)[a]
Firm Relative Valuation	–0.0016 (–5.360)[a]	–0.0020 (–4.510)[a,e]	–0.0016 (–4.400)[a]	–0.0019 (–4.630)[a]
Industry Relative Investment	0.0015 (0.550)	0.0028 (0.740)	0.0063 (1.800)[c]	0.0016 (0.400)
Firm Relative Investment	0.0005 (1.460)	0.0007 (1.520)	0.0009 (1.550)	0.0008 (1.750)[c]
Industry New Finance	0.0118 (3.270)[a]	0.0109 (1.860)[c]	0.0182 (3.100)[a,f]	0.0106 (1.750)[c]
Firm New Finance	0.0086 (8.560)[a]	0.0088 (7.130)[a]	0.0076 (6.620)[a]	0.0092 (7.600)[a]
Lagged Idio. Risk	–0.1944 (–9.550)[a]	–0.2319 (–6.870)[a]	–0.2388 (–7.740)[a]	–0.2524 (–7.910)[a]
Observations	48,878	21,594	15,461	23,000

Explanation: Regressions examine the effect of relative firm- and industry-level valuation, investment and new financing on yearly changes in risk. We report regression coefficients t-statistics (in parentheses) for panel data regressions. t-statistics are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. Results in all three panels of this table are restricted to various industry groupings as noted in the column headers. 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 using one year of daily firm level data from July of year t to June of year t+1, and ex-post risk is measured using one year of daily data from July of year t+1 to June of year t+2. Ex-ante and ex-post risk levels are both estimated using the following model (d denotes one trading day in year y and i denotes a firm):

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

The dependent variable in Panel A is based on the market beta ($\beta_{i,y,1}$), and is the ex-post exposure less the ex-ante exposure. Idiosyncratic risk in Panel B is the ex-post standard deviation of the residuals from the above model less the ex-ante standard deviation. The explanatory variables are discussed in Table III. We only examine market betas and idiosyncratic risk because the theoretical predictions we examine only relate to these items. * 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	All Industries	Growth Industries Only	High Value Industries Only	High Mkt. Risk Industries Only
		Panel A: All Firms		
Industry Relative Valuation	0.004 (2.00)^{b}	–0.002 (–0.54)	–0.006 (–1.34)	0.000 (–0.08)
Firm Relative Valuation	–0.002 (–4.50)^{a}	–0.002 (–3.37)^{a}	–0.001 (–1.47)	–0.002 (–2.74)^{a}
Industry Relative Investment	–0.018 (–3.17)^{a}	–0.010 (–1.45)	–0.024 (–2.10)^{b}	–0.027 (–3.32)^{a}
Firm Relative Investment	–0.003 (–3.88)^{a}	–0.003 (–3.03)^{a}	–0.003 (–2.21)^{b}	–0.003 (–3.52)^{a}
Industry New Finance	–0.023 (–3.48)^{a}	–0.026 (–2.50)^{b}	–0.021 (–2.10)^{b}	–0.036 (–2.97)^{a}
Firm New Finance	–0.018 (–6.88)^{a}	–0.016 (–4.41)^{a}	–0.021 (–4.96)^{a}	–0.020 (–5.41)^{a}
Observations	1,005,385	398,424	307,821	403,585
		Panel B: Competitive Industries Only		
Industry Relative Valuation	–0.001 (–0.40)	–0.015 (–2.77)^{a,d}	–0.027 (–3.71)^{a,d}	–0.010 (–1.86)^{c}
Firm Relative Valuation	–0.003 (–5.49)^{a}	–0.003 (–4.13)^{a,f}	–0.002 (–2.34)^{b}	–0.003 (–4.06)^{a,f}
Industry Relative Investment	–0.023 (–2.74)^{a}	–0.012 (–1.09)^{f}	–0.022 (–1.50)	–0.031 (–2.69)^{a}
Firm Relative Investment	–0.003 (–3.31)^{a}	–0.003 (–2.56)^{b,f}	–0.002 (–1.34)	–0.003 (–2.55)^{b}
Industry New Finance	–0.041 (–3.57)^{a}	–0.054 (–3.19)^{a,e}	–0.047 (–2.80)^{a,f}	–0.067 (–3.72)^{a,e}
Firm New Finance	–0.019 (–5.68)^{a}	–0.016 (–3.86)^{a}	–0.023 (–4.72)^{a}	–0.020 (–4.74)^{a}
Observations	536,315	231,069	167,347	249,803

Explanation: Regressions examine the effect of relative firm- and industry-level valuation, investment and new finance on changes-in-risk-adjusted firm-level monthly abnormal stock returns. We report regression coefficients and t-statistics (in parentheses) for panel data regressions. t-statistics are from standard errors that are adjusted for clustering over time and industry, and are corrected for heteroskedasticity. One observation is one firm in one month, and the dependent variable is the firm's changes-in-risk-adjusted monthly abnormal return. To compute this variable, we start with the standard abnormal return, which is a firm's 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). To adjust for changes in risk, we use a two-step procedure. Frist, 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. * 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 quintile portfolio abnormal returns

	Firm Level Returns					*Industry Level Returns*				
Variable	1	2	3	4	5	1	2	3	4	5
					Panel A: Sample-wide results					
Industry Relative Valuation	0.467	2.245	2.161	1.262	–2.228	–0.274	–1.041	–0.897	–0.135	–1.339
Firm Relative Valuation	3.164	1.386	0.578	0.439	–0.728					
Industry Relative Investment	3.287	1.193	0.738	1.238	–2.627	–0.093	–0.421	–0.630	–0.737	–1.812
Firm Relative Investment	2.562	1.880	1.398	0.125	–1.152					
Industry New Finance	0.873	0.761	3.610	0.554	–2.526	–1.123	–0.308	0.239	–0.517	–1.984
Firm New Finance	3.305	2.903	2.635	0.439	–4.449					
					Panel B: Competitive Industries					
Industry Relative Valuation	0.079	4.730	4.064	2.586	–4.293	–1.001	–0.359	–0.671	0.187	–2.240
Firm Relative Valuation	4.259	2.887	1.143	0.995	–0.277					
Industry Relative Investment	4.827	1.751	1.686	2.310	–4.331	–0.834	0.734	–0.649	–0.384	–2.857
Firm Relative Investment	3.128	2.692	2.741	0.743	–0.306					
Industry New Finance	1.134	1.438	6.122	1.349	–3.400	–0.252	0.620	–0.205	–0.306	–3.173
Firm New Finance	3.661	4.225	4.450	1.336	–4.293					
					Panel C: Competitive Growth Industries					
Industry Relative Valuation	6.493	6.809	3.012	–2.073	–8.581	0.154	1.255	–0.055	–4.158	–3.495
Firm Relative Valuation	4.595	3.707	2.320	1.286	–1.142					
Industry Relative Investment	6.679	–1.926	6.188	–0.366	–1.076	–1.317	–1.321	1.374	–1.682	–3.099
Firm Relative Investment	3.739	1.703	3.427	1.001	0.736					
Industry New Finance	2.455	0.793	7.590	2.048	–8.690	–1.129	–0.545	0.484	0.644	–5.514
Firm New Finance	4.351	3.636	5.051	1.862	–3.783					

Explanation: The table presents average risk-adjusted stock returns for various portfolios based on quintiles of key boom and bust variables noted in the first column. Reported abnormal returns are monthly returns (multiplied by twelve for convenience) reported as percentages. Results are based on the entire sample (1972 to 2004), and we report both firm-level (one observation is one firm) and industry level (one observation is one industry) average returns. 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. Panel A includes all industries, Panel B includes competitive industries only (lowest fitted HHI tercile), Panel C includes competitive growth industries only (lowest fitted HHI tercile and lowest B/M ratio tercile).