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Real and Financial Industry Booms and Busts

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ABSTRACT

We examine how product market competition affects firm cash flows and stock returns in industry booms and busts. Our results show how real and financial factors interact in industry business cycles. In competitive industries, we find that high industry-level stock market valuation, investment, and financing are followed by sharply lower operating cash flows and abnormal stock returns. Analyst estimates are positively biased and returns comove more. In concentrated industries these relations are weak and generally insignificant. Our results are consistent with participants in competitive industries not fully internalizing the negative externality of industry competition on cash flows and stock returns.

THROUGHOUT HISTORY, INDUSTRIES have gone through cycles in which firms have very high valuations and investment followed by lower subsequent valuations and investment. Periods associated with high valuations are commonly written about as the start of a "new era" in which productivity increases and new products justify very high stock prices and prompt massive investment.[1] This phenomenon is present in many industries over time, and recent examples include the recent real estate boom and late 1990s internet and telecommunications boom.[2] In this paper, we ask whether product market characteristics

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

[2]Our findings are robust to excluding the internet boom of 1998 to 2000. Other industries such as the Winchester disk drive industry and the early railroad industry have similar patterns. Sahlman and Stevenson (1987) note that in mid-1983, the Winchester disk drive industry had a market capitalization of $5.4 billion, but by year's end the industry value fell to $1.4 billion as net income fell 98%. Turning to the railroads, 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. 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 industry competition affect the predictability of real and financial cycles of booms and busts.

We find strong support for the conclusion that market participants in competitive industries do not fully internalize the negative externality of industry competition on cash flows and stock returns. We find that changes in operating performance and future abnormal stock returns 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 these 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 findings are significantly more negative than similar relations in concentrated industries, and cannot be explained by standard size and value/growth proxies. Our results also persist after controlling for recent changes in capital expenditures and potential mean reversion in operating cash flows.[3] 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 3% decline in operating cash flows, and a one standard deviation increase in industry financing is associated with a 5.5% 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 3 percentage points lower than those for a portfolio in the lowest quintile. If we weight by firm rather than by industry, this abnormal return difference exceeds 10% points. In concentrated industries, quintile returns are nonmonotonic, and magnitudes are less than half as large.

Although the effect of competition on cash flows may be natural and expected, the predictability of abnormal stock returns following booms and busts is more puzzling. This predictability remains after adjusting for style characteristics and the Fama and French (1993) factors. We thus investigate whether our evidence is consistent with the predictions of recent rational models of booms and busts that focus on changes in risk (Aguerrevere (2009), Carlson, Fisher, and Giammarino (2004), and Pástor and Veronesi (2009)) and relative wealth concerns (DeMarzo, Kaniel, and Kremer (2007, 2008)).

We find that, consistent with the recent model of Pástor and Veronesi (2009), market betas increase and idiosyncratic risk decreases after industry booms. 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

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

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. Although 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 examine whether the busts we observe are predicted by analyst forecasts of earnings per share (EPS). Using predictive tests of future EPS, we find that analyst estimates are positively biased in competitive growth industries, especially those with high relative valuations. We do not find analogous biases in concentrated industries nor in industries with high market risk.

We also examine whether patenting activity can explain our results given that competition may be intense in order to gain a subsequent product market monopoly (see Sutton (1989), Reinganum (1989)). We find only small differences in our results across levels of patenting activity. High industry financing in low-patent competitive growth industries remains a strong predictor of subsequent negative stock market returns, which is inconsistent with patent competition being used to gain a subsequent product market advantage.

We conclude that although the effect of competition on changes in cash flows may be natural in competitive industries, current theories cannot explain the extent of the predictability of stock returns that we document. Also, these theories cannot explain the biased analyst estimates we find in competitive industries. Overall, our findings in more extreme industries are consistent with stock market participants not anticipating the magnitude of the effects of competition.[4]

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 cascades (early models are Scharfstein and Stein (1990) and Welch (1992)).

What is shared by these papers and our interpretation of this paper's 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. These issues are likely to be most extreme when information about rival firms is

[4]Although not considering the role of industry competition, related empirical work 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. Other articles find low stock returns following high investment (see Titman, Wei, and Xie (2004) and Polk and Sapienza (2009) 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% below the average market-wide returns over time.

costly or difficult to gather, as is likely the case in competitive industries where larger numbers of rival firms exist. Our finding that firm returns comove more in these extreme industries supports this link to high information costs as investors must rely on common, less costly market-wide signals rather than firm-specific signals.

Overall, our results are consistent with a new explanation not previously documented: the externality 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 risk-adjusted stock returns. In contrast, we do not find evidence of predictable busts in concentrated industries. Here, given enhanced pricing power, firms are more likely to internalize the effect of their actions on industry-wide prices, cash flows, and stock returns.

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

I. Industrial Organization and Booms and Busts

In this section, we develop our framework for analyzing how industry competition impacts industry booms and subsequent outcomes. At the end of this section we also consider the implications of risk-based theories of booms and busts, for which we augment our empirical tests.

We postulate that the role of coordination and information is key to understanding why poor outcomes can arise in competitive industries, especially if firms are unable to efficiently gather information about rivals and if valuation uncertainty is high.[5] Schumpeter's early work in 1912 focuses 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 also 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 versus 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

[5]Formal models of entry include Weizsacker (1980), Perry (1984), and Mankiw and Whinston (1986), who formalize how there can be excessive entry relative to the social optimum, as entrants do not internalize all fixed entry costs.

broadly, firms in competitive industries suffer from an inability to coordinate their investment.

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:

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

where $r_{i,j,t}$ is the return of firm i in industry j at time t, $r_{m,t}$ is the market return, $r_{-i,j,t}$ is the return of industry j excluding firm i,[6] and $\epsilon_{i,j,t}$ is a firm-specific shock.

As Chen et al. (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,[7] virtually all theories predict that comovement results in less firm-specific information being impounded into stock prices. Thus, when comovement is high, managers have little information outside of common signals and are likely to make similar investment decisions, especially when information is more costly 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. In these industries, market participants are more likely to rely on common industry price movements than to gather information on individual firms. We abstract from the overall market in equation (1) and do not build a full model of industry competition. Rather, we focus on the cost of gathering information and operationalize the link to industry concentration in the following specification, where $H_{j,t}$ and $r_{-i,j,t}$ denote the industry Herfindahl Index (HHI) and industry return not including firm i:

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

[6] Firm i's return is not included in the industry return, as by construction in concentrated industries it would induce a dependence between the firm's return and the industry return.

[7] Comovement can also be linked to industry herding as discussed earlier, lack of transparency as modeled by Li and Myers (2006), contagion as in Kodres and Pritsker (2002) and Kyle and Xiong (2001), style investing as in Barberis and Shleifer (2003), and investor sentiment as in Barberis, Shleifer and Wurgler (2005).

In industries with few firms, gathering firm-specific information is less costly and thus returns will be related to firm-specific information—the $\epsilon_{i,j,t}$ in the above equation.[8] 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. For example, gathering information about the likely successful introduction of new products by many different firms will be costly relative to the value of this information. 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 ($\eta_{i,j,t}$):

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

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

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

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

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

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 ($r_{-i,j,t}$). In contrast, in concentrated industries monopoly power reduces the dispersion of earnings forecasts (Gasper and Massa (2006)) and expedites the capitalization of private information into prices as modeled by Peress (2009). Firms in concentrated industries will thus rely more on firm-specific information and research ($q_{i,j,t}$ and $\epsilon_{i,j,t}$). The relationship in competitive industries can be amplified by the fact that firms face a noncooperative investment choice, and an optimal response to a new investment opportunity may be to invest before competitors. Therefore, immediate investment is more likely in competitive industries than in concentrated industries. This implies that the elasticity of investment to industry price shocks is also higher than in concentrated industries.

Durnev et al. (2004) and Chen et al. (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.

[8] If observers know the type of competition and whether rivals' actions are competitive or accommodating, gathering information on rivals would yield some information on the firm's returns. However, there will also be firm-specific information, including information on firm strategies and production that will be more valuable and less costly to gather with fewer rival firms.

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. Returns to firms will also depend on their investment relative to its optimal level, as indicated by $(I^*_{i,j,t} - I_{i,j,t})$. There is also an effect from the amount of industry-wide investment, which we capture as the difference between optimal industry investment and actual industry investment excluding firm i $(I^*_{-i,j,t} - I_{-i,j,t})$. 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 lead to subsequent industry busts affecting firm and industry returns and cash flows as follows:

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

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

These two equations motivate our examination of how ex post returns and cash flows depend on ex ante industry returns and investment, and are the basis for considering 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.

Following our examination of cash flows and returns, we examine whether changes in risk can explain our results. Recent work by Hou and Robinson (2005) empirically supports the contention that competitive risk is 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 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. In competitive industries, firms will more aggressively pursue these opportunities, causing their industries to be more procyclical. We thus 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 (2009) 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.

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

Three recent articles offer explanations regarding how boom and bust patterns can develop rationally given effects of risk. Pástor and Veronesi (2009) and DeMarzo et al. (2007, 2008) model how new technological opportunities can play a role in the formation of rational boom and subsequent bust patterns. Although many of these theories are hard to separate from models of excessive competition or herding, we test two hypotheses on the role of risk in booms and busts.

In Pástor and Veronesi (2009), there is a rational boom and bust linked to a switch in uncertainty (risk) from idiosyncratic to systematic. This change in the composition of risk occurs after firms standardize on the winning technology. The increase in systematic risk causes 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 because market participants fail to take into account the effect of product market competition on cash flows.

We test a related hypothesis from DeMarzo et al. (2007, 2008). In these papers, the authors 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.[9] These relative wealth concerns can explain why overinvestment and herding can develop in industries that might provide large fractions of future consumption, and these concerns

[9] Although 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.

should be most relevant when the industry's returns are highly correlated with the market. The main idea is that high systematic risk implies comovement, and hence a more likely outcome that others 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.

II. Data and Methodology

A. Industry Classifications

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).[10]

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 financial firms (SICs 6000 to 6999) and regulated utilities (SICs 4900 to 4999). We also restrict our sample to the years 1972 to 2004, as net equity and debt issuing activity is 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. After applying these filters, our merged CRSP and Compustat database has a total of 108,522 firm-year observations.

We classify industries into competitive and concentrated industries using both public and private firms.[11] 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).[12] The inclusion of BLS data is necessary to cover all industries, as the Department of Commerce Herfindahl data only cover manufacturing industries.

To classify industries by their competitiveness, we calculate an HHI for each industry in each year using a two-step procedure. First, for the subsample of manufacturing industries (where we have actual HHIs including both public and private firms for every fifth year), we regress actual industry HHI from the Commerce Department on three variables: the Compustat public-firm-only

[10]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).

[11]Our initial tables just used Compustat public firms to classify industries. These tables showed similar, slightly stronger findings.

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

Herfindahl,[13] 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 step, 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. Those in the highest tercile are concentrated, and those in the lowest tercile are competitive.

The correlation between actual HHIs, based on the Department of Commerce manufacturing industries, and our fitted HHIs is 54.2%. The correlation between Compustat HHIs using segment data and the actual HHIs is only 34.1%.[14] 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. Overall, we conclude that our fitted HHIs have full industry coverage, and also offer significant improvements relative to the basic Compustat HHI.

We also classify industries into growth and value industries based on industry-average book-to-market ratios in the year prior to the year in which we examine outcomes. We 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.

Lastly, we classify industries by their patenting activity in each year. We use the NBER U.S. Patent Citations data file to measure patenting activity within each industry. This data was extended through 2002 by Bronwyn Hall. When examining outcomes in year t, we measure the industry's patenting activity as the number of patents applied for in the previous year $t-1$ scaled by the industry's year $t-1$ assets in place. We also scale by sales and find similar results. The average firm is in an industry with 480 annual patent applications. This number is 763 for competitive industries and 291 for concentrated industries. After scaling by assets, these averages are 8.6, 7.2, and 5.7, respectively.

[13]We compute Compustat HHI using the firm segment tapes in years the segment data are 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.

[14]In an earlier version of this paper we conducted all of our tests using the Herfindahls computed from Compustat and the Compustat segment tapes. The predictable cash flows and stock returns (significant coefficients) we find are similar to the ones we report in the tables. The earlier results are available in an Internet Appendix.

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 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 (hereafter, relative valuation) using a three-step procedure that is based on the valuation model in Pástor and Veronesi (2003). From Pástor and Veronesi (2003) (PV), we use the empirical model they specify 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 forward-looking measures of return on equity (ROE) and stock returns. We only use lagged data in constructing our measure of relative valuation, as our goal is to examine ex post outcomes, and we wish to avoid having a look-ahead bias. To construct our measure of relative valuation for each firm and industry, we use the following three steps:

(1) We estimate the PV valuation model using data from year $t-10$ to $t-1$ for all firms in industry 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), current firm ROE, and the volatility of profitability (VOLP) for each firm i (we suppress the j subscript, as the equation is estimated separately for each industry). Because VOLP is constant for each firm, we estimate this equation using an unbalanced panel with random firm fixed effects. More specifically, we estimate:

$$\begin{aligned}\log\left(\frac{M}{B}\right)_{i,\tau} &= a + bAGE_{i,\tau} + cDD_{i,\tau} + dLEV_{i,\tau}\\ &\quad + e\log(SIZE_{i,\tau}) + fVOLP_{i,\tau} + gROE_{i,\tau},\\ \tau &= t-10,\ldots,t-1. \end{aligned} \tag{8}$$

The variables above are calculated following PV, and Fama and French (1993). Book equity is constructed as stockholders' equity plus balance sheet deferred taxes and investment tax credit (Compustat item 35) minus the book value of preferred stock. Depending on availability, stockholder's equity is computed as Compustat item 216 or 60 + 130 or 6 − 181, in that order, and preferred stock is computed as item 56 or 10 or 130, in that order. Market equity is computed by multiplying the common stock price at fiscal year-end (item 199) by common shares outstanding (item 25). Firm age is one plus the current year less the first year the firm appears on the CRSP tapes. Leverage is total long-term debt (Compustat item

9) divided by total assets (item 6). ROE is earnings divided by last year's book equity. Earnings are calculated as income before extraordinary items available to common stockholders (item 237), plus deferred taxes from the income statement (item 50), plus investment tax credit (item 51). The volatility of profitability (VOLP) is calculated by regressing the ROE on lagged ROE for all firms in each industry and taking the variance of the residuals. Following PV, we eliminate observations with market equity, book equity, and total assets smaller than 1 million, or with market-to-book ratios outside the range (0.01, 100). We also winsorize VOLP and ROE at the 1/99% level in each year.

(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 (unpredicted) 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:

$$\textit{Relative Valuation}_{i,t} = \log\left(\frac{M}{B}\right)_{i,t} - \textit{Predicted}\left(\log\left(\frac{M}{B}\right)_{i,t}\right). \tag{9}$$

Relative Valuation is winsorized at the 1/99% level within each year.[15] Relative industry-level valuation is the average over all firms in each three-digit SIC industry. Relative firm-level valuation is the total minus this industry-level component.

In the Internet Appendix,[16] we report results for four different alternative valuation models. First, we estimate a simpler version of the PV valuation model where we regress market-to-book on the log of firm size and firm ROE. Second, we report results using models (1) and (3) from Rhodes-Kropf et al. (2005) (RKRV), where log market is regressed on the log of book value of equity and also net income. Lastly, we estimate a version of a price–earnings (PE) model where the log of market value is regressed on the log of the absolute value of net income and a dummy for negative net income. As reported by RKRV, these models have relatively high R^2 values given the fact that the models

[15] We winsorize to ensure that no individual firm value drives the results. Our alternative models presented in the Internet Appendix generate similar results. For these models, winsorizing results in little change to the distribution and also does not affect any results.

[16] An Internet Appendix for this article is online in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp.

are estimated by industry, thus giving them an industry-specific constant and industry-specific coefficients. As discussed later, nearly all of the results we obtain are robust to these other valuation models.

We estimate these models using 10 years of lagged data by industry and we use these coefficients to predict current-period market value using current characteristics. 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 the log of capital expenditures divided by lagged property, plant, and equipment on standard variables from investment models, including lagged Tobin's q, and variables capturing the cash flows of firms (ROE and a dividend paying dummy (DD)). We also include additional variables given the existing literature. Leverage (LEV) captures the debt overhang effect on investment that Hennessy (2004) models. Firm age 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. Taken together, we have:

$$\log\left(\frac{Invest_{i,t}}{PPE_{i,t-1}}\right) = a + bTOBINQ_{i,t-1} + cROE_{i,t} + dDD_{i,t} + eAGE_{i,t} + fLEV_{i,t} + gVOLP_{i,t} + h\log(SIZE_{i,t}). \tag{10}$$

From this model, we calculate relative (unpredicted) 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 minus this industry component.

We define total "new financing" in a given year as the sum of a firm's net equity issuing activity (Compustat annual data item 108 minus item 115) and net debt issuing activity (annual data item 111 minus item 114) in a given year divided by assets. Industry new financing is the summed total amount of new financing over firms in the industry divided by total industry assets. Firm-specific new financing is then the total new financing less the industry component.

These proxies are constructed using known ex ante characteristics, and can thus be used in an unbiased fashion to predict ex post stock returns and real performance.

C. Descriptive Industry Statistics

Table I lists sample industries that have experienced high valuation booms in competitive industries (those in the lowest tercile based on sales HHI using three-digit SIC codes from Compustat) and concentrated industries (those in

Table I

Examples of Industry Booms in Competitive and Concentrated Industries

The table lists sample industries with high relative valuation (valuation less predicted valuation) in each decade for competitive and concentrated industries. Competitive (concentrated) industries are those in the lowest (highest) tercile of the past-year's fitted sales-based HHI. We present each three-digit SIC industry's identifying information and the year in which its 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 in millions. To compute relative valuation, we first fit the following model based on Pástor and Veronesi (2003) (i denotes a firm and t a year):

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

The RHS variables are, respectively, minus the reciprocal of one plus firm age, a dividend dummy, book leverage, log total assets, volatility of profitability, and ROE. 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 10 years. Relative valuations are then winsorized at the 1/99% level within each year. CSTAT concentration is the sales-weighted HHI 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 predicted level of industry concentration from three databases: Department of Commerce manufacturing HHI data, BLS employee data, and Compustat sales data.

Three-Digit SIC Code	Industry Name	Classification	Decade/ Year	Weighted Market to Book	Average Firm Mkt. Value	Weighted Relative Valuation	Relative Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
			1970s						
385	Ophthalmic Goods	Competitive	1978	2.73	22.2	40.8%	49.4%	0.25	0.20
513	Wholesale Apparel	Competitive	1977	0.88	13.4	42.0%	56.7%	0.28	0.20
783	Motion Picture Theaters	Competitive	1976	1.27	22.0	88.1%	70.6%	0.26	0.21
321	Flat Glass	Concentrated	1978	1.16	145.9	82.4%	90.3%	0.60	0.38
422	Public Warehousing and Storage	Concentrated	1979	1.20	201.4	153.0%	148.2%	0.94	0.32

(*continued*)

Table I—*Continued*

Three-Digit SIC Code	Industry Name	Classification	Decade/Year	Weighted Market to Book	Average Firm Mkt. Value	Weighted Relative Valuation	Relative Valuation	CSTAT Concentration (Herfindahl)	Fitted Concentration (Herfindahl)
			1980s						
731	Advertising	Competitive	1982	1.97	175.9	63.1%	70.3%	0.15	0.20
173	Electrical Work	Competitive	1989	2.34	338.2	129.3%	137.8%	0.14	0.18
511	Paper Wholesalers + Paper Products	Competitive	1989	1.49	532.5	55.5%	148.3%	0.12	0.21
322	Glass Containers	Concentrated	1983	1.25	352.0	84.0%	124.0%	0.41	0.32
207	Vegetable and Animal Oils	Concentrated	1987	1.49	2,463.4	148.5%	148.5%	0.14	0.59
			1990s						
737	Business Services	Competitive	1999	20.07	3,038.1	18.8%	31.4%	0.04	0.13
367	Semi-Conductors + Elect. Comp.	Competitive	1999	11.31	4,112.1	50.5%	45.7%	0.04	0.18
519	Flowers, Books + Tobacco Whole.	Competitive	1995	2.74	176.4	54.8%	61.7%	0.15	0.22
306	Fabricated Rubber Goods	Competitive	1994	2.51	117.8	85.1%	131.1%	0.12	0.20
277	Greeting Cards	Concentrated	1994	1.72	937.7	94.6%	118.9%	0.52	0.55
376	Guided Missiles And Space Vehicles	Concentrated	1996	3.29	6,250.2	76.1%	140.6%	0.37	0.64
			2000s						
807	Medical and Dental Laboratories	Competitive	2001	5.61	1,087.7	71.4%	69.8%	0.21	0.22
874	Management and Consulting Services	Competitive	2004	6.99	1,164.9	59.5%	69.8%	0.17	0.18
122	Coal Mining	Competitive	2002	3.50	1,317.9	54.6%	73.2%	0.10	0.23
227	Carpets and Rugs	Concentrated	2004	2.14	2,749.5	78.6%	85.0%	0.63	0.47
516	Wholesale Chemicals + Allied Prod.	Concentrated	2005	1.25	1,219.2	95.9%	85.9%	0.52	0.41

the highest tercile) in each of the following four decades: 1970s, 1980s, 1990s, and in the new millennium through 2005.

Table I shows that in competitive industries, fitted Herfindahl indices are below 0.25. Some of the most extreme competitive industry booms have over 100 publicly traded firms competing in the same SIC code. The business services industry, which includes internet firms, had 843 public firms. Although this last example is part of the late 1990s technology boom, the other examples suggest that high industry valuations are more common. Extreme competitive industries in the 1980s (some having valuations that are more than 100% above predicted levels) deviated just as far from their long-term valuations as those in the 1990s. These earlier booms were not in technology industries, as was the case in the late 1990s. For example, three of the extreme 1970s and 1980s boom industries included apparel, paper, and advertising. Finally, because weighted and unweighted relative valuations are similar, we conclude that both large and small firms alike are prone to industry booms and busts.

Table I also shows that select concentrated industries generally have concentration levels near or exceeding 0.4, and that basic Compustat Herfindahls are generally similar to fitted Herfindahls. Because our tests do not use the concentration measures explicitly, but rather examine high and low competition categories, we thus expect and find similar results using either Herfindahl measure.

One additional conclusion regarding concentrated and competitive industries is that booms appear to be at least as extreme in concentrated industries. For example, Guided Missiles and Space Vehicle firms were 141% above their predicted industry valuations in 1996. The existence of large booms in concentrated industries indicates that sufficient variation 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 persist for several years.

D. Firm-Level Data and Summary Statistics

We compute changes in firm-level operating cash flow (Compustat item 13) scaled by assets (Compustat item 6) in each year. We later examine if they are related to ex ante industry and firm-level relative valuation, investment, and new financing. For robustness, we also estimate our results using the change in operating cash flow scaled by beginning-of-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 et al. (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, where firm size is the CRSP market capitalization on the formation date, the book-to-market ratio uses accounting data from the most recent fiscal-year ending in the last calendar year, and past return is based on the 12-month period ending in May of the formation year.[17] Portfolio breakpoints are based only on NYSE/Amex firms, and we 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 the robustness section).

Table II reports summary statistics for competitive industries (Panel A) and concentrated industries (Panel B). Summary statistics for the full sample are available in the Internet Appendix. Panel A shows that industry relative valuation has a mean that is near zero and a standard deviation that is large at 24.9%. 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 that 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 for example, a one standard deviation change in firm relative valuation is a full 51.7% in Panel A.

For virtually all variables in Panel B (concentrated industries), 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 near 26%. We conclude that industry booms appear to be quite similar in both groups, and so it is unlikely that our comparative tests are biased toward any finding. Hence, our finding that busts are only predictable in competitive industries (documented later) is perhaps especially surprising.

The average returns in Panels A and B are consistent with Hou and Robinson (2005). The annual equivalent difference across the two panels suggests that concentrated industries underperform competitive ones by about 1.5% per year. We find a weak but opposite difference in accounting performance across these two groups, which is also consistent with Hou and Robinson (2005)'s findings.

III. 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 III displays the results of firm-level regressions of the change in operating cash flow on relative valuation, relative investment, and new financing.

[17] This timing ensures that previous fiscal-year accounting data are public information.

Table II

Summary Statistics

The table displays summary statistics for competitive industries (Panel A) and concentrated industries (Panel B). Concentration is based on three-digit SIC codes and is the inferred level of industry concentration from three databases: Department of Commerce manufacturing HHI data, BLS employee data, and Compustat sales data. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's value of this HHI index. To compute relative valuation, we first fit the following model based on Pastor and Veronesi (2003) (i denotes a firm and t a year):

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

The RHS variables are, respectively, minus the reciprocal of one plus firm age, a dividend dummy, book leverage, log total assets, volatility of profitability, and ROE. 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 10 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 financing 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 three-digit SIC industry in year t, and firm variables are set equal to raw quantities less the industry component. Patenting activity for a given industry year is from the NBER U.S. Patent Citations data file. 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 et al. (1997).

Variable	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Panel A: Competitive Industries					
Industry Relative Valuation	0.023	0.249	−1.024	1.044	47,226
Industry New Financing	0.024	0.040	−0.188	0.402	47,226
Industry Relative Investment	−0.093	0.256	−1.595	2.113	47,226
Firm Relative Valuation	−0.003	0.517	−2.258	2.441	47,226
Firm New Financing	0.022	0.162	−0.849	1.462	47,226
Firm Relative Investment	0.042	0.828	−3.715	3.032	47,226
Number of Industry Patents	763.6	1,316.6	0.000	6,015	47,226
Industry Patents/Assets	7.17	10.2	0.000	99.7	47,226
Operating Cash Flow Change	−0.011	0.141	−1.447	1.591	43,900
Abnormal Return	0.001	0.175	−1.192	9.25	562,099
Panel B: Concentrated Industries					
Industry Relative Valuation	0.034	0.275	−1.763	1.845	16,791
Industry New Financing	0.016	0.044	−0.408	0.638	16,791
Industry Relative Investment	−0.026	0.281	−1.850	2.426	16,791
Firm Relative Valuation	−0.003	0.459	−2.055	2.126	16,791
Firm New Financing	0.004	0.108	−0.727	1.375	16,791
Firm Relative Investment	0.018	0.685	−3.156	3.014	16,791
Number of Industry Patents	291.0	386.2	0.000	1,472	16,791
Industry Patents/Assets	5.70	11.19	0.000	498.8	16,791
Operating Cash Flow Change	−0.009	0.087	−1.026	1.168	15,843
Abnormal Return	−0.000	0.130	−0.954	5.20	132,862

Table III

Regressions Predicting Firm-Level Operating Cash Flow Changes

We report regression coefficients and t-statistics (in parentheses) for panel data regressions predicting the change in firm-level operating cash flow. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's industry concentration (HHI). One observation is one firm in 1 year, and the dependent variable is the firm's change in operating cash flow (operating income/assets) from year t to year $t+1$ (1 year) or t to $t+2$ (2 years). In the last column, we restrict the sample to firms in high growth industries (lowest tercile based on industry-average book-to-market ratios, which are winsorized at the 1/99% level prior to taking industry averages). To compute relative valuation, we first fit the following model based on Pástor and Veronesi (2003) (i denotes a firm and t a year):

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

The RHS variables are, respectively, minus the reciprocal of one plus firm age, a dividend dummy, book leverage, log total assets, volatility of profitability, and ROE. 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 10 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 financing 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 three-digit SIC industry in year t, and firm variables are set equal to raw quantities less the industry component. Change in EBITDA and CAPX are the past-year's changes in earnings before interest and taxes plus depreciation and capital expenditures, winsorized at the 1/99% level. t-statistics are adjusted for clustering over time and across industries, and are corrected for heteroskedasticity.

Variable	Overall 1 Year	Overall 2 Years	Growth Industries 2 Years
	Panel A: Competitive Industries		
Industry Relative Valuation	−0.0037 (−0.420)[f]	−0.0364 (−3.060)[a,d]	−0.0781 (−4.080)[a,d]
Firm Relative Valuation	0.0104 (5.490)[a,e]	0.0016 (0.650)	0.0025 (0.670)
Industry Relative Investment	−0.0084 (−1.220)	−0.0043 (−0.440)	−0.0220 (−1.280)
Firm Relative Investment	−0.0019 (−1.430)	−0.0046 (−2.750)[a]	−0.0078 (−2.980)[a]
Industry New Financing	−0.0278 (−0.820)	0.0163 (0.380)	0.0445 (0.530)
Firm New Financing	−0.0256 (−1.750)[c]	0.0208 (1.260)	0.0244 (1.140)
Change in EBITDA	0.0029 (0.470)	−0.0105 (−1.360)	−0.0135 (−1.110)
Change in CAPX	−0.0110 (−2.080)[b]	0.0040 (0.680)	−0.0037 (−0.310)
Observations	43,626	38,536	17,861
	Panel B: Concentrated Industries		
Industry Relative Valuation	0.0064 (1.710)[c,f]	0.0000 (−0.010)[d]	−0.0046 (−0.550)[d]
Firm Relative Valuation	0.0036 (1.870)[c,e]	−0.0012 (−0.500)	−0.0036 (−0.800)
Industry Relative Investment	−0.0126 (−3.390)[a]	−0.0135 (−2.710)[a]	−0.0049 (−0.550)
Firm Relative Investment	−0.0025 (−1.600)	−0.0057 (−3.060)[a]	−0.0063 (−1.690)[c]
Industry New Financing	−0.0409 (−1.420)	−0.0333 (−0.860)	−0.0782 (−0.930)
Firm New Financing	0.0015 (0.090)	0.0345 (1.770)[c]	0.0625 (2.120)[b]
Change in EBITDA	0.0008 (0.230)	−0.0055 (−1.070)	0.0050 (0.570)
Change in CAPX	−0.0039 (−1.170)	0.0018 (0.390)	−0.0011 (−0.130)
Observations	15,821	14,540	4,545

(*continued*)

Table III—*Continued*

Variable	Overall 1 Year	Overall 2 Years	Growth Industries 2 Years
Panel C: Industries with Declining Concentration			
Industry Relative Valuation	−0.0149 (−2.350)[b,d]	−0.0342 (−4.710)[a,d]	−0.0432 (−3.770)[a,f]
Firm Relative Valuation	0.0088 (4.730)[a]	−0.0001 (−0.060)	0.0004 (0.090)
Industry Relative Investment	−0.0144 (−2.610)[a]	−0.0108 (−1.470)	−0.0109 (−0.960)
Firm Relative Investment	−0.0026 (−1.660)[c]	−0.0036 (−1.950)[c]	−0.0078 (−2.690)[a]
Industry New Financing	−0.0721 (−2.510)[b]	−0.0165 (−0.440)	−0.0617 (−1.040)[f]
Firm New Financing	−0.0193 (−1.030)	0.0246 (1.260)	0.0297 (1.160)
Change in EBITDA	0.0041 (0.980)	−0.0039 (−0.830)	−0.0012 (−0.140)
Change in CAPX	−0.0086 (−2.140)[b]	−0.0039 (−0.890)	−0.0066 (−0.790)
Observations	35,619	30,469	14,720

*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 the opposing tercile (competitive versus concentrated industries in Panels A and B, and decreasing versus increasing concentration in Panel C) at the 1%, 5%, and 10% levels, respectively.

We examine 1- and 2-year changes in cash flows in columns 1 and 2 for the overall sample. In column 3 we also present the 2-year change in cash flows 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 separate examination is that growth industries likely have higher price uncertainty, and hence the predictions of Hypothesis 1 are likely to be stronger in this subsample.

For each independent variable, we separately examine industry- and firm-specific components as discussed earlier.[18] We focus on the industry variables to directly study the 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 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.[19] 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)

[18]All three firm-level variables are less than 10% correlated with their corresponding industry components, so including both classes does not induce multicollinearity. This low correlation is expected by construction.

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

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 produces negatively biased standard errors in the presence of additional variables at the industry level. We also do not estimate Fama and MacBeth (1973) regressions when examining operating cash flow, as our tests document the existence of firm-level effects (as is common in accounting data), and Petersen (2005) has recently shown that Fama–MacBeth regressions are biased when there is a significant firm-level effect.

Panels A and B of Table III display results for the most competitive and concentrated tercile industries, respectively. Terciles are formed annually based on the fitted Herfindahl discussed earlier.[20] 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 1-year cash flow changes, it predicts 2-year changes at better than the 1% level in 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.

The third column of Panels A and B shows that the coefficients on industry relative valuation are larger for high growth industries than for the set of all industries (second column). For example, the 2-year relative industry valuation coefficient is negative and significant in the third column in Panel A, and this coefficient is at least twice as large as the corresponding coefficient in the second column. 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.

It is especially noteworthy that this coefficient increases in magnitude and significance despite the smaller sample size of high growth firms. It is also interesting that none of these variables is significant for concentrated industries in Panel B. These results strongly support Hypothesis 1 and more broadly confirm that price uncertainty plays an important role.

Panel C shows that relative industry valuation, relative industry investment, and new industry financing are also 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 industry signals.

Although we do find that the mean reversion variable (change in EBITDA) suggests that cash flows do mean revert over longer horizons in some specifications, and that recent investment spikes (change in CAPX) induce

[20]Results in the full sample of all industries (including all three competitiveness terciles) are generally similar to those in Panel A, but coefficients are less significant and are of smaller magnitude. We do not report these results here to conserve space, but they are available in the Internet Appendix.

some shorter-term reversion, our key findings regarding relative valuation, investment, and new financing obtain regardless of whether these controls are included.

These results are also robust across other specifications including models with random firm effects, and to excluding the technology boom of 1998 to 2000 (see the Internet Appendix).[21] In the Internet Appendix we also present results using the four alternative valuation models discussed earlier, including a simpler version of the PV model, two alternative models from RKRV, and a simpler PE model. Specifically, we report the results for the 2-year change in cash flows (from $t = 0$ to $t = +2$) for each of these alternative models. We report results for both competitive and concentrated industries. The appendix shows that our results are robust to these alternative valuation models. The significance of our relative industry valuation variable across models indicates that the residual, or the unexplained portion of valuation, is what drives our results. Overall, the results support Hypothesis 1, and suggest that cash flows are negatively related to valuation booms in competitive industries, but not in concentrated industries.

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 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 expect industry relative valuations to be associated with positively biased analyst forecasts, 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, and we 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 EPS 1 year before firm i's fiscal year-end in year t, $A_{i,t}$ as the actual EPS ultimately realized at year t's fiscal year-end, and $P_{i,t}$ as 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 IV, 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

[21]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 faced similar fates throughout our sample period.

Table IV
Regressions Predicting Analyst Forecast Optimism

Regressions examine the effect of relative firm- and industry-level valuation, investment, and new financing on analyst forecast optimism. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's industry concentration (HHI). Growth industries are those in the lowest tercile (computed annually) based on the past-year's industry-average book-to-market ratios (which are first winsorized at the 1/99% level prior to taking industry averages). One observation is one firm in 1 year, and the dependent variable is analyst forecast optimism. Analyst forecast optimism is defined as the average analyst estimate of 1-year EPS minus actual EPS, scaled by the price at the time of the estimate (all measures of EPS are adjusted for splits). Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. We also include controls for each firm's ex ante log market-to-book ratio, log market capitalization, and its lagged forecast error from the previous year. We also include a dummy that is one when the lagged forecast error is not available in the I/B/E/S database. We report regression coefficients and t-statistics (in parentheses) for panel data regression models. t-statistics are adjusted for clustering over time and across industries, and corrected for heteroskedasticity.

Variable	Competitive Industries	Competitive Growth Industries	Concentrated Industries	Concentrated Growth Industries
Industry Relative Valuation	−0.0012 (−0.220)	0.0310 (3.370)[a,f]	−0.0069 (−0.950)	0.0066 (0.580)[f]
Firm Relative Valuation	−0.0015 (−0.760)	−0.0007 (−0.270)	0.0059 (1.460)	0.0032 (0.490)
Industry Relative Investment	−0.0107 (−2.280)[b,e]	−0.0084 (−1.170)	0.0068 (1.210)[e]	0.0029 (0.310)
Firm Relative Investment	0.0002 (0.230)	−0.0003 (−0.250)	0.0013 (0.470)	−0.0007 (−0.150)
Industry New Financing	0.0297 (1.300)	0.0610 (1.790)[c]	−0.0113 (−0.370)	0.0199 (0.360)
Firm New Financing	0.0126 (2.560)[b]	0.0125 (2.100)[b]	0.0387 (2.350)[b]	0.0017 (0.060)
log M/B Ratio	0.0014 (0.920)[f]	0.0006 (0.260)	0.0070 (2.400)[b,f]	0.0041 (0.990)
log Market Value	−0.0059 (−13.460)[a]	−0.0060 (−9.630)[a,f]	−0.0052 (−6.980)[a]	−0.0032 (−2.310)[b,f]
Lagged Forecast Error	0.3051 (15.440)[a,e]	0.3210 (9.340)[a,e]	0.3945 (10.580)[a,e]	0.5003 (6.410)[a,e]
Lagged Forecast Error N/A	−0.0009 (−0.350)	0.0007 (0.190)	0.0029 (0.540)	0.0012 (0.140)
Observations	25,675	10,203	6,161	1,378

*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 the opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

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.

Table IV shows that forecasts are biased upwards in the competitive high growth tercile, but not in the concentrated high growth tercile. We find no evidence of an analyst bias based on industry relative valuation in the broader sample of competitive or concentrated industries. There is also some evidence that analyst estimates are biased upwards in competitive industries when there is high industry investment.

We conclude that on average analysts likely anticipate the effects of industry valuation on future earnings accurately 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 are more likely to make predictions based on aggregate price signals, especially when valuation uncertainty is high. The findings in the high growth competitive subsample are consistent with Hypothesis 1.

Taken together, the findings above 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 below and find support. However, the results in more extreme subsamples (those in high growth industries) are more consistent with Hypothesis 1.

IV. 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 V 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. Panels A and B display results for the most competitive and most concentrated tercile industries, respectively. As in earlier sections, we use the fitted concentration measure based on public and private industry data.

Hypothesis 1 predicts that abnormal stock returns will be negative in competitive industries following periods of high valuation and investment. Panel A of Table V confirms that industry relative valuation, relative investment, and new financing are all negatively related to future stock returns in competitive industries. All three coefficients are also 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.

The highly significant and negative coefficients on the firm-level variables affirm the findings of existing studies, and the role of our proxies as valid measures of firm value. Firms have a strong tendency to revert back to their characteristic-implied valuations. Unique to our study is the inclusion of the

Table V

Regressions Predicting Monthly Firm-Level Stock Returns

We report regression coefficients and t-statistics (in parentheses) for panel data regressions predicting monthly firm-level stock returns. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's industry concentration (HHI). The growth, high valuation, and high market risk industry groupings are based on terciles constructed annually from the past-year's industry-average book-to-market ratios, relative industry valuation, and the industry's average market beta. One observation is one firm in 1 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 et al. (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. Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. t-statistics are from standard errors that are adjusted for clustering over time and across industries, and are corrected for heteroskedasticity.

Variable	Overall	Growth Industries	High Value Industries	High Mkt. Risk Industries
Panel A: Competitive Industries				
Industry Relative Valuation	−0.0029 (−0.960)	−0.0133 (−3.170)[a,d]	−0.0279 (−4.450)[a,d]	−0.0125 (−3.260)[a,d]
Firm Relative Valuation	−0.0024 (−4.440)[a]	−0.0025 (−3.170)[a,e]	−0.0027 (−2.720)[a]	−0.0027 (−3.520)[a,e]
Industry Relative Investment	−0.0052 (−2.070)[b]	−0.0080 (−2.430)[b]	−0.0036 (−0.830)	−0.0132 (−3.900)[a]
Firm Relative Investment	−0.0011 (−3.050)[a]	−0.0011 (−1.890)[c]	−0.0005 (−0.810)	−0.0007 (−1.180)
Industry New Financing	−0.0459 (−3.870)[a,f]	−0.0638 (−3.640)[a,d]	−0.0501 (−2.610)[a,e]	−0.0823 (−4.140)[a,d]
Firm New Financing	−0.0178 (−5.360)[a]	−0.0152 (−3.630)[a]	−0.0229 (−4.060)[a]	−0.0187 (−4.340)[a]
Observations	562,099	243,345	154,709	260,770
Panel B: Concentrated Industries				
Industry Relative Valuation	0.0014 (0.650)	0.0026 (0.710)[d]	0.0021 (0.340)[d]	0.0043 (1.200)[d]
Firm Relative Valuation	−0.0015 (−1.620)	0.0020 (1.360)[e]	−0.0012 (−0.720)	0.0011 (0.780)[e]
Industry Relative Investment	−0.0051 (−2.460)[b]	−0.0021 (−0.590)	−0.0055 (−1.620)	−0.0061 (−1.750)[c]
Firm Relative Investment	−0.0015 (−2.160)[b]	−0.0008 (−0.740)	−0.0021 (−1.810)[c]	−0.0005 (−0.490)
Industry New Financing	−0.0112 (−0.780)[f]	0.0131 (0.650)[d]	0.0176 (0.680)[e]	0.0047 (0.250)[d]
Firm New Financing	−0.0251 (−4.210)[a]	−0.0198 (−2.980)[a]	−0.0314 (−3.310)[a]	−0.0263 (−3.450)[a]
Observations	132,872	40,173	36,221	57,086

(continued)

Table V—*Continued*

Variable	Overall	Growth Industries	High Value Industries	High Mkt. Risk Industries
Panel C: Industries with Declining Concentration				
Industry Relative Valuation	−0.0029 (−0.950)	−0.0089 (−1.760)[c]	−0.0142 (−2.560)[b,e]	−0.0119 (−2.490)[b]
Firm Relative Valuation	−0.0024 (−3.460)[a]	−0.0023 (−2.100)[b]	−0.0037 (−3.230)[a,d]	−0.0019 (−1.850)[c]
Industry Relative Investment	−0.0062 (−2.480)[b,e]	−0.0134 (−4.610)[a,d]	−0.0047 (−1.300)[e]	−0.0128 (−3.810)[a,e]
Firm Relative Investment	−0.0013 (−2.610)[a]	−0.0014 (−1.650)[c]	−0.0002 (−0.250)	−0.0012 (−1.480)
Industry New Financing	−0.0276 (−2.550)[b]	−0.0310 (−1.860)[c]	−0.0418 (−2.300)[b]	−0.0372 (−1.960)[b]
Firm New Financing	−0.0145 (−3.120)[a,f]	−0.0112 (−1.910)[c,e]	−0.0215 (−3.720)[a,f]	−0.0133 (−2.220)[b,e]
Observations	359,097	166,367	117,197	169,267

*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 the opposing tercile (competitive versus concentrated industries in Panels A and B, and decreasing versus increasing concentration in Panel C) at the 1%, 5%, and 10% levels, respectively.

industry-level variables, and our finding that they are especially relevant in competitive industries.

We next compare Panel A (competitive industries) to Panel B (concentrated industries). In the broad sample (first column), we find that industry new financing is more important in competitive industries in Panel A than in concentrated industries in Panel B, consistent with Hypothesis 1. This coefficient is negative and significant at the 1% level in Panel A, and is not significant in Panel B. The difference in coefficients is also significant. This result is also economically meaningful. For example, the industry new financing coefficients are roughly two to three times larger in some specifications in Panel A than in Panel B. The relative industry valuation and relative industry investment variables are not significantly different in the 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 cases, we continue to find that industry new financing matters, but we also now find that relative industry valuation is significantly different across competitive (Panel A) and concentrated industries (Panel B). The sign on this variable even reverses in concentrated 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 predicted by Hypothesis 1, and that this result is most noteworthy in extreme industries where it is likely that valuation uncertainty is high.

Panel C 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. However, these results are weaker than those for high competition in general (Panel A), suggesting that valuation in ex ante competitive industries matters most.

The significance of both firm- and industry-level variables suggests that, as is the case for operating cash flows, more extreme firms have more negative outcomes.

DeMarzo et al. (2007) (DKK) (Hypothesis 2D) present a theory of investment and relative wealth concerns, and suggest that predictable bust patterns should be largest following high investment in high systematic risk industries. The high market risk tercile in the last column of Table V tests this prediction. In Panel A, we find that the industry relative investment variable in the high market risk tercile is indeed more negative than in other subsamples, providing some support for Hypothesis 2D. However, this result is weak, as the coefficients on industry relative investment are not significantly different for competitive and concentrated industries.

In our Internet Appendix, we present additional results analogous to Table V but using the four alternative valuation models discussed earlier, including a simpler version of the PV model, two alternative models from RKRV and a simpler PE model. We present the results separately for competitive industries and concentrated industries, and we indicate whether the results are statistically different both from zero and also from the opposing competition-based tercile (competitive versus concentrated industries). The results and inferences from these alternative models are similar to those presented here and show sharp differences between competitive and concentrated industries. In particular, all of the coefficient estimates on industry relative valuation in competitive growth and high value industries are negative and statistically different from zero and, with only one exception, from their corresponding coefficient in concentrated industries. The results for the concentrated industries show that most of the coefficient estimates are small and insignificantly different from zero. Both RKRV models and the PE model also show stronger support for DKK in competitive growth industries, where the industry relative investment coefficient in competitive industries is significantly different from that in concentrated industries.

B. Patenting Activity

In Table VI, we examine the effect of high patenting activity on our previous results. We classify industries into patenting activity terciles. We do this by summing the patenting activity in an industry and then dividing by the total industry assets. We then group industries into terciles in each year based on the result of this calculation in the previous calendar year. In results reported in the Internet Appendix we also scale industry patenting activity by sales. These additional results are qualitatively similar to those presented here.

Table VI shows that our results do differ some for growth industries based on patenting activity but do not differ much for high relative valuation industries, where we previously document our strongest results. In high valuation industries, we see that in both high and low patenting activity industries, there is a significant negative relation between industry relative valuation and subsequent abnormal stock returns in competitive industries but not in concentrated industries. Note that for the simpler PV valuation model discussed earlier, this negative relation only persists for the high patenting activity industries.

We also find that in competitive, low patenting activity industries, there is a significant negative relation between industry financing and subsequent abnormal stock returns. High industry financing in these more commodity-like competitive high-value industries with low patenting activity is followed by negative abnormal stock returns. This last result for high industry financing also persists for competitive growth industries with low patenting activity, and is robust to using the simpler PV valuation model.

Overall, we conclude that the largest differences still obtain as differences between competitive and concentrated industries, consistent with industry competition and not with patenting activity driving the largest differences we see in the data. These results combined with the earlier-mentioned weaker results on changes in competition suggest that theories of endogenous competition (Shaked and Sutton (1983) and Sutton (1989)), where firms compete

Table VI

Patenting Activity and Subsequent Monthly Firm-Level Stock Returns

We report regression coefficients and t-statistics (in parentheses) for panel data regressions predicting monthly firm-level stock returns. One observation is one firm in 1 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 et al. (1997). Patenting activity for a given industry year is computed using the NBER U.S. Patent Citations data file, and is the number of patents applied for in the previous calendar year in the given industry scaled by the industry's previous calendar year assets in place. For monthly abnormal return observations between July of year $t+1$ and June of year $t+2$, independent variables are constructed using accounting data with fiscal-years ending in year t. The growth and high valuation industry groupings are based on terciles constructed annually from the past-year's industry-average book-to-market ratio and relative industry valuation, respectively. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's industry concentration (HHI). Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. t-statistics are from standard errors that are adjusted for clustering over time and across industries, and are corrected for heteroskedasticity.

Variable	Low Patent, Growth Industries	High Patent, Growth Industries	Low Patent, High Value Industries	High Patent, High Value Industries
		Panel A: Competitive Industries		
Industry Relative Valuation	−0.0045 (−0.730)	−0.0155 (−2.090)[b,f]	−0.0244 (−2.430)[b,e]	−0.0294 (−2.240)[b]
Firm Relative Valuation	−0.0030 (−1.260)[f]	−0.0031 (−3.330)[a,f]	−0.0060 (−2.580)[a,e]	−0.0024 (−1.800)[c]
Industry Relative Investment	−0.0007 (−0.150)	−0.0101 (−1.800)[c]	0.0019 (0.360)	−0.0086 (−1.030)
Firm Relative Investment	−0.0021 (−1.600)	−0.0011 (−1.490)	−0.0018 (−1.630)	−0.0002 (−0.190)
Industry New Financing	−0.0690 (−2.790)[a,e]	−0.0455 (−1.640)	−0.0729 (−2.510)[b,d]	−0.0362 (−1.150)
Firm New Financing	−0.0085 (−0.890)	−0.0133 (−2.900)[a]	−0.0186 (−1.680)[c]	−0.0220 (−3.430)[a]
Observations	19,099	175,665	19,425	86,534
		Panel B: Concentrated Industries		
Industry Relative Valuation	0.0067 (0.790)	−0.0001 (−0.010)[f]	0.0040 (0.510)[e]	−0.0029 (−0.350)
Firm Relative Valuation	0.0043 (1.350)[f]	0.0016 (0.720)[f]	0.0024 (0.740)[e]	−0.0028 (−0.920)
Industry Relative Investment	−0.0118 (−2.200)[b]	−0.0021 (−0.520)	−0.0058 (−1.160)	0.0026 (0.600)
Firm Relative Investment	0.0002 (0.080)	−0.0013 (−0.790)	−0.0004 (−0.150)	−0.0028 (−1.430)
Industry New Financing	0.0252 (0.980)[e]	−0.0079 (−0.180)	0.0818 (2.620)[a,d]	−0.0185 (−0.420)
Firm New Financing	−0.0130 (−0.810)	−0.0176 (−1.910)[c]	−0.0323 (−1.430)	−0.0358 (−2.150)[b]
Observations	7,001	20,621	7,949	13,662

*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 the opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

aggressively to keep rivals out (through high R&D or limit pricing), likely do not explain the broad results we observe.

C. 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 et al. (2007), Roll (1988), and Durnev et al. (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 VII, the dependent variable is the R^2 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 across industries, and are corrected for heteroskedasticity. One observation corresponds to one firm 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.

The first column in Table VII 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 1% level. The fourth column shows that this relationship is much smaller in concentrated industries. A comparison of the first three columns also illustrates that this result is larger in high relative valuation industries, as the high relative valuation coefficient increases from 0.07 in column 1 to nearly 0.18 in column 3. We also find positive comovement between returns and industry new financing in competitive industries in column 1. However, this finding does not persist in growth or high valuation industries in columns 2 and 3.

Overall, these results are consistent with high valuations and information acquisition costs being important to predictable busts in competitive industries. The absence of a significant relation in concentrated industries is consistent with lower information gathering costs due to the smaller number of rival firms, and hence returns comove less with aggregate price changes.

D. Changes in Systematic and Idiosyncratic Risk

Pástor and Veronesi (2009) posit that high valuations and subsequent busts are due in part to levels of systematic risk that can increase over time. Our findings regarding stock returns in the high market risk tercile in Table V 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

Table VII

Regressions Predicting Firm R^2 (Comovement with Market and Industry)

Regressions examine the effect of relative firm- and industry-level valuation, investment, and new financing on firm comovement with the market and with its industry. The dependent variable is the R^2 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. One observation is one firm in 1 year. The growth and high valuation industry groupings are based on terciles constructed annually from the past-year's industry-average book-to-market ratio and relative industry valuation, respectively. Competitive and concentrated industries are those in the lowest and highest tercile based on the past-year's industry concentration (HHI). Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. 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 across industries, and are corrected for heteroskedasticity.

Variable	All Competitive Industries	Competitive Growth Industries	Competitive High Val. Industries	All Concentrated Industries	Concentrated Growth Industries	Concentrated High Val. Industries
Industry Relative Valuation	0.0705 (6.350)[a,d]	0.0900 (4.650)[a,d]	0.1767 (4.630)[a,d]	0.0139 (1.590)[d]	0.0052 (0.400)[d]	−0.0055 (−0.330)[d]
Firm Relative Valuation	0.0271 (12.690)[a,d]	0.0346 (9.320)[a,d]	0.0385 (8.440)[a,e]	0.0158 (4.610)[a,d]	0.0125 (2.020)[b,d]	0.0204 (3.050)[a,e]
Industry Relative Investment	0.0099 (1.250)	−0.0014 (−0.100)	0.0196 (1.280)	0.0005 (0.080)	−0.0010 (−0.070)	−0.0075 (−0.680)
Firm Relative Investment	0.0088 (11.060)[a,f]	0.0124 (8.920)[a,d]	0.0090 (5.840)[a,e]	0.0054 (3.320)[a,f]	0.0000 (0.010)[d]	0.0008 (0.220)[e]
Industry New Financing	0.0750 (2.140)[b,f]	−0.0325 (−0.590)	0.0847 (1.090)	−0.0358 (−0.840)[f]	−0.0328 (−0.490)	−0.0247 (−0.340)
Firm New Financing	−0.0252 (−4.650)[a,e]	−0.0357 (−5.730)[a,e]	−0.0066 (−0.800)	0.0081 (0.730)[e]	0.0171 (0.840)[e]	0.0278 (1.390)
Observations	50,807	20,771	13,864	11,661	3,137	3,187

*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 the opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

for their rise in systematic risk (Hypotheses 2B and 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 1st of each year, and ending on June 30 of the following year. Letting d denote one trading day in year y, we then regress the daily stock returns associated with firm i in each year on the three Fama and French (1993) factors plus momentum as follows (one regression per firm year):

$$r_{i,d} = \alpha_i + \beta_{i,1} MKT_d + \beta_{i,2} HML_d + \beta_{i,3} SMB_d + \beta_{i,4} UMD_d + \epsilon_{i,d}. \qquad (12)$$

We define a firm year's idiosyncratic risk as the standard deviation of the residuals from this regression. We next focus on the specific theoretical predictions regarding the market beta ($\beta_{i,1}$) 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 V, here we only present results for competitive industries (we only find predictable industry returns for this subsample); results for concentrated industries are in the Internet Appendix. For independent variables collected in 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 level 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 et al. (2001)).

Table VIII 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 (i.e., 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 (2009).

Panel B helps to clarify the ambiguity associated with interpreting the results in Panel A. The results in Panel B support the Pástor and Veronesi (2009) predictions in the broad sample, and in the high systematic risk subsample, as idiosyncratic risk falls whereas market risk increases. However, high industry

Table VIII

Regressions Predicting Annual Changes in Risk

Regressions examine the effect of relative firm- and industry-level valuation, investment, and new financing on yearly changes in two measures of risk (changes in market beta and changes in idiosyncratic risk). Results in both panels are based on competitive industries. One observation is one firm in 1 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 1 year of daily firm-level data from July of year t to June of year $t+1$, and ex post risk is measured using 1 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 estimated once for each firm in each year (d denotes one trading day and i denotes a firm):

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

The dependent variable in Panel A is based on changes in market beta ($\beta_{i,1}$), 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. We include a control for the past-year's risk exposures as risk exposures are known to mean revert. We only examine market betas and idiosyncratic risk because the theoretical predictions we examine only relate to these items. Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. 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 across industries, and are corrected for heteroskedasticity.

Variable	Competitive Industries	Competitive Growth Industries	Competitive High Value Industries	Competitive High Mkt. Risk Industries
	Panel A: Changes in Market Beta			
Industry Relative Valuation	0.2601 (5.050)[a,d]	0.2437 (2.940)[a,e]	0.2616 (1.450)	0.2301 (2.800)[a,e]
Firm Relative Valuation	0.0700 (7.090)[a,e]	0.0925 (6.250)[a]	0.1165 (6.380)[a,f]	0.0935 (6.470)[a]
Industry Relative Investment	−0.1444 (−4.140)[a,d]	−0.1532 (−2.700)[a,e]	−0.1147 (−1.880)[c]	−0.1711 (−3.670)[a,d]
Firm Relative Investment	−0.0043 (−0.820)	−0.0088 (−1.070)	−0.0135 (−1.270)	0.0007 (0.100)
Industry New Financing	0.2930 (1.900)[c]	−0.0341 (−0.160)	0.3840 (1.330)	−0.1418 (−0.600)
Firm New Financing	0.2653 (7.170)[a]	0.2319 (5.370)[a]	0.3307 (5.750)[a]	0.2151 (4.590)[a]
Lagged Market Beta	−0.5914 (−53.530)[a]	−0.5960 (−38.880)[a]	−0.5705 (−28.830)[a]	−0.5866 (−39.580)[a]
Observations	47,681	21,040	13,238	22,272

(continued)

Table VIII—*Continued*

Variable	Competitive Industries	Competitive Growth Industries	Competitive High Value Industries	Competitive High Mkt. Risk Industries
Panel B: Changes in Idiosyncratic Risk				
Industry Relative Valuation	−0.0036 (−4.580)[a]	−0.0023 (−1.980)[b]	0.0003 (0.150)	−0.0033 (−2.790)[a]
Firm Relative Valuation	−0.0013 (−4.480)[a]	−0.0016 (−3.920)[a,e]	−0.0012 (−2.750)[a,f]	−0.0017 (−4.190)[a]
Industry Relative Investment	−0.0003 (−0.430)[f]	−0.0012 (−0.990)[e]	−0.0003 (−0.300)	−0.0014 (−1.090)[e]
Firm Relative Investment	−0.0003 (−1.410)	−0.0005 (−1.330)[e]	0.0001 (0.320)	−0.0006 (−1.620)
Industry New Financing	0.0128 (3.650)[a]	0.0131 (2.280)[b]	0.0190 (2.950)[a,e]	0.0135 (2.220)[b]
Firm New Financing	0.0090 (8.270)[a]	0.0092 (6.840)[a]	0.0085 (6.070)[a]	0.0099 (7.330)[a]
Lagged Idio. Risk	−0.1845 (−8.760)[a]	−0.2224 (−6.510)[a]	−0.2550 (−7.080)[a]	−0.2499 (−7.500)[a]
Observations	47,681	21,040	13,238	22,272

*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 the opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

valuation is not related to ex post changes in idiosyncratic risk in the high valuation subsample (column 3). 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 industries.

We do not find support for Hypothesis 2C for the high industry investment coefficient. In particular, the industry relative investment coefficient is negative instead of positive for ex post market risk and is not significant for idiosyncratic risk. We also find little support for Hypothesis 2C based on the industry new financing variable. The coefficient for industry new financing is positively related to the change in market risk in column 1 (although not in columns 2 to 4) but is only significant at the 10% level and is not significantly different from the analogous coefficient for concentrated industries.

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 Pástor and Veronesi (2009) and Aguerrevere (2009), can explain part of the link between high industry valuations and subsequent returns in competitive industries. However, these theories are not able to explain our findings in extreme industries 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 such as 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 the extent of product market competition.

E. 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 new financing to predict ex post stock returns in competitive industries.[22] The idea we examine here is whether market participants anticipate future risk changes. Ex post risk changes might be important if our return results are due to market participants reacting to ex post 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 nonpredictive, 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 IX displays the results for competitive industries, and for subsamples based on high growth, high relative valuation, and high market risk. The coefficients in each specification can be compared to analogous models based on standard abnormal returns in Panel A of Table V. We omit concentrated industries to conserve space, and because there is no return predictability to explain in Table V for this subsample, but these results are available in the Internet Appendix. Pástor and Veronesi (2009) (Hypothesis 2C) predict that changes in risk will explain all or part of the return predictability we report in earlier tables, whereas Hypothesis 1 and other alternatives including DKK (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.

Comparing the coefficients and significance levels in Table IX with those in Table V yields some support for the Pástor and Veronesi (2009) prediction that changes in risk can explain some of the return predictability we find. In the high market risk sample in column 4, for example, we find that controlling for changes in risk reduces the industry relative valuation coefficient from 0.0125 (Table V) to 0.0070 (Table IX). However, in other extreme subsamples, changes in risk are considerably less influential. For example, the high relative industry valuation coefficient barely declines from 0.028 to just 0.026 in the high valuation subsample.

[22]We thank Ľuboš Pástor for this suggestion.

Table IX

Regressions Predicting Change in Risk-Adjusted Monthly Firm-Level Stock Returns

Regressions examine the effect of relative firm- and industry-level valuation, investment, and new financing on monthly firm-level abnormal stock returns adjusted for changes in risk. Results are based on competitive industries. One observation is one firm in 1 month, and the dependent variable is the firm's monthly abnormal return adjusted for changes in risk. 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 et al. (1997). To adjust for changes in risk, we use a two-step procedure. First, 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 nonpredictive, 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. Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III. 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 across industries, and are corrected for heteroskedasticity.

Variable	Overall	Growth Industries	High Value Industries	High Mkt. Risk Industries
		Competitive Industries		
Industry Relative Valuation	−0.0012 (−0.400)	−0.0090 (−2.200)^{b,e}	−0.0261 (−4.190)^{a,d}	−0.0070 (−1.720)^{c,f}
Firm Relative Valuation	−0.0030 (−5.370)^{a}	−0.0033 (−3.920)^{a,e}	−0.0034 (−3.270)^{a}	−0.0031 (−3.700)^{a,e}
Industry Relative Investment	−0.0054 (−2.110)^{b}	−0.0088 (−2.470)^{b,f}	−0.0060 (−1.340)	−0.0158 (−3.900)^{a,e}
Firm Relative Investment	−0.0010 (−2.540)^{b}	−0.0012 (−1.850)^{c}	−0.0002 (−0.310)	−0.0007 (−1.080)
Industry New Financing	−0.0414 (−3.610)^{a,f}	−0.0519 (−3.160)^{a,e}	−0.0462 (−2.580)^{a,f}	−0.0620 (−3.410)^{a,e}
Firm New Financing	−0.0199 (−5.510)^{a}	−0.0175 (−3.800)^{a}	−0.0253 (−4.330)^{a}	−0.0223 (−4.720)^{a}
Observations	523,380	225,506	142,428	243,094

*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 the opposing tercile (competitive versus concentrated industries) at the 1%, 5%, and 10% levels, respectively.

Overall, our findings support Hypothesis 1 in competitive industries where valuation uncertainty is high, and support Hypothesis 2C in broader industry groupings and in samples where systematic risk (ex ante market beta) is high.

Table IX also shows that accounting for changes in risk does not explain the return predictability of other variables including industry relative investment. Because 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 show that there is still a large negative coefficient on industry relative valuation in column 4, consistent with Hypothesis 2D (and Hypothesis 1, which is also silent regarding whether changes in ex post risk explain stock returns cross-sectionally). Regarding the industry new financing term, we also continue to see unchanged strong negative coefficients when we adjust returns for changes in risk.

F. Economic Magnitude of Stock Market Returns

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

In Table X, we calculate abnormal returns for quintile portfolios based on ex ante relative industry valuation, industry investment, and industry new financing. One observation is one firm, and 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 et al. (1997).

Table X 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, in Panel B, the highest quintile of relative industry valuation underperforms the lowest quintile by over 5 percentage points annually. The results are more than twice as large in Panel C, where we further condition on the high growth subsample. Here, relative industry valuation creates a more than 13 percentage point spread in annual returns in competitive industries. We find similar results for relative industry investment and industry new financing.

Although we do not report results for concentrated industries to conserve space (see the Internet Appendix for the results), we do not find economically meaningful return differences across quintiles in concentrated industries. Although also not reported to conserve space (again, see the Internet Appendix), we compute quintile returns at the industry level. These results are analogous to our firm-level results with smaller magnitudes. The differences between high and low valuation quintiles exceed 3 percentage points. It is also relevant to note that in most specifications, we find the most extreme return differences in the outermost quintiles. This finding is consistent with our earlier results, in which predictable booms and busts are most profound in more extreme industry groupings.

Table X

Average Quintile Portfolio Abnormal Returns

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 12 for convenience) reported as percentages. Results are based on the entire sample (1972 to 2004). One observation is one firm in 1 month, and quintiles are formed in each 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 et al. (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. Panel A includes all industries, Panel B includes competitive industries only, and Panel C includes competitive growth industries only. Industry and firm relative valuation, investment and new financing variables are defined in Tables II and III.

Variable	Lowest	2	3	4	Highest
Panel A: Sample-wide Results					
Industry Relative Valuation	−0.010	1.504	3.403	0.532	−2.482
Firm Relative Valuation	2.843	1.212	1.175	0.442	−0.963
Industry Relative Investment	1.767	2.885	0.959	−0.285	−2.093
Firm Relative Investment	2.925	2.318	1.083	0.205	−1.802
Industry New Financing	0.819	0.840	3.490	0.581	−2.611
Firm New Financing	3.297	2.839	2.619	0.539	−4.566
Panel B: Competitive Industries					
Industry Relative Valuation	−0.471	2.671	6.616	1.385	−5.597
Firm Relative Valuation	3.881	2.269	2.375	0.888	−0.612
Industry Relative Investment	2.138	5.211	1.664	−0.164	−4.396
Firm Relative Investment	3.389	3.159	2.002	1.505	−1.105
Industry New Financing	0.821	1.629	5.941	1.517	−3.781
Firm New Financing	3.522	4.156	4.550	1.392	−4.455
Panel C: Competitive Growth Industries					
Industry Relative Valuation	4.199	8.116	3.462	−4.823	−9.242
Firm Relative Valuation	4.383	3.171	4.023	1.401	−0.968
Industry Relative Investment	8.564	5.058	−0.229	−0.862	−9.559
Firm Relative Investment	3.964	3.743	3.422	1.310	−0.358
Industry New Financing	3.198	2.415	7.718	1.062	−8.401
Firm New Financing	4.175	3.355	6.119	2.392	−3.678

G. Additional Robustness Tests

We also examine whether our results are robust to using abnormal returns based on an adjustment proposed by Mitchell and Stafford (2000). We first define a firm year as July to June. We then regress each firm year's 12-monthly stock returns on four factors: the three Fama and French (1993) factors plus momentum.[23] From these time-series regressions, we extract a database of yearly firm-specific intercepts describing each firm's abnormal return in the given year. We define a firm's "Mitchell/Stafford alpha" as its yearly intercept

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

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 return (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 nonlinear. The results from these tests reveal that our main findings 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 and MacBeth (1973) method. Our inferences do not depend on the chosen specification.

V. Conclusions

Our paper examines real and financial outcomes of industry booms and busts and analyzes whether these outcomes are related to industry-level competition. 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 EPS are biased upwards in these industries. 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% ex post decline in operating cash flows. In the stock market, risk-adjusted abnormal stock returns for a competitive high growth industry portfolio in the highest quintile of ex ante relative industry valuation are over 3 percentage points lower than a similar portfolio in the lowest quintile using industry-weighted returns. Using firm-weighted returns, abnormal stock returns in competitive growth industries are more than 10 percentage points lower in the highest industry valuation quintile than 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 do not explain our findings for 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.

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