Bubble Stock Expectations

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Abstract

We measure expectations during boom-bust episodes of individual US stocks. During the run-up phase, these stocks exhibit (1) higher analyst expectations of long-term earnings growth, (2) higher near-term expected returns, (3) lower short interest, but (4) higher shorting cost. We also study media coverage of these stocks and find that while (5) the frequency of media coverage increases during the run-up, (6) there is no increase in the use of terms such as "bubble" or "overvalued," even after a crash starts. We then perform an ex-ante analysis of run-up episodes, and show that measures of expectations can be used to forecast the probability of a crash: more optimism is associated with higher crash probability. These results are consistent with bubbles being fueled by overly optimistic expectations of fundamentals. Aside from a small fraction of episodes, there seems to be little awareness that a bubble is happening.

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"I'm not saying we can recognize bubbles when they're happening [...] but I do think we can have a pretty good hunch." – Richard Thaler[1]

Historic accounts and behavioral models of stock market bubbles often emphasize the role of investor expectations. Accounts by Bagehot (1873), Kindleberger (1978), and Shiller (2000b) indicate increased optimism and positive sentiment among investors following good news, driving prices well above fundamental value. In more formal models, such as Barberis et al. (2018), the boom-bust cycle of a bubble is driven by investors becoming overly optimistic in response to past returns, and then more pessimistic during the crash. Another approach, which also relies on irrational beliefs, is outlined by Scheinkman and Xiong (2003) who emphasize the importance of investor disagreement coupled with limitations on short selling. The disagreement-based framework helps explain the high trading volumes characteristic of bubbles, exemplified by those during the .com era (Hong and Stein (2007)). Yet another expectations-based narrative of a bubble is that a bubble is a period when investors believe that stocks are overvalued, but buy anyway in anticipation of short-term gains (Shiller (2000a)).

Despite much theory, there has been limited systematic evidence on investor expectations during market bubbles. Shiller (2000b) surveys US and Japanese investors between 1994 and 1999, and Case and Shiller (2003) use survey evidence to gauge whether there is a bubble in the housing market. Greenwood and Shleifer (2014) study investor expectations of the US stock market over time but do not focus on bubbles per se. A number of recent papers, including Giglio et al (2021) survey investors over shorter periods of time. Bybee (2023) leverages a large language model to estimate beliefs and concludes that extrapolative beliefs are a key mechanism behind bubbles. Although there are some documented instances of

[1]Chicago Booth Review June 30, 2016, accessed at https://www.chicagobooth.edu/review/are-markets-efficient

experts recognizing bubbles—such as French and Poterba (1991) identifying the Japanese stock market bubble before its crash and Franco Modigliani referring to the internet sector as a bubble in early 2000s—there remains a lack of systematic evidence on expert beliefs when prices are high.[2]

In this paper we investigate empirically the behavior of beliefs about fundamentals and future returns during 5306 boom-and-bust episodes in individual stock prices in the United States between 1980 and 2023.[3] We leverage several data sources to indirectly measure investor expectations, including: security analyst forecasts, short interest, and media coverage of bubble stocks.

To identify boom-and-bust episodes, we select stocks that experienced (a) a substantial price increase, (b) price-to-sales or price-to-book ratios above 5, and (c) a subsequent crash within 24 months. This method captures well-known cases such as Yahoo! in 1999, GameStop in 2021, and Netflix in 2021, as well as thousands of lesser-known episodes. For each event, defined as the two-year period before and after the price peak, we collect five expectation measures: (i) professional analyst forecasts of future prices and fundamentals, (ii) short interest levels and lending fees, and (iii) media coverage, including mentions of terms like "bubble" or "overvalued."

Our first set of results provides an ex-post analysis of expectations around price peaks. We find that:

1. Analyst expectations remain optimistic at the peak of bubbles. The average one-year expected return is 52%, compared to a market average of 35%. Moreover, analysts predict negative returns for only 7% of bubble stocks at the peak, suggesting a general belief that these stocks remain undervalued.

[2]We thank Owen Lamont for pointing this out to us.

[3]By studying individual stock run-ups and busts, we depart from other studies that have looked at market or industry run-ups, but with the benefit of substantially more statistical power. See Goetzmann (2015) and Greenwood et al. (2019a).

2. Analysts maintain highly optimistic earnings forecasts. At bubble peaks, analysts predict long-term earnings growth exceeding 30%, compared to market averages below 15%. Similar trends emerge for sales growth projections.

3. Short interest is low before the crash but rises afterward. Even three months before the peak, short interest averages 5% of shares outstanding—lower than the market average. Lending fees for boom-bust stocks remain high but increase slightly near the peak, partly due to these stocks' smaller market capitalizations, making them more expensive to short.

4. Media coverage rarely signals awareness of bubbles. Although media attention increases as prices rise, fewer than 10% of articles suggest stocks may be overvalued or in a bubble. More strikingly, this fraction does not increase even after the crash begins. Some exceptions exist—such as GameStop in early 2021, when terms like "bubble" and "mania" were commonly used—but these cases are rare.

To summarize, for the average boom-and-bust in prices, the only evidence we find that people are aware of the bubble comes from short interest, where there is an increase in quantity borrowed (although still at an absolute level that is low) and a slight uptick in lending fees. Analysts, who are presumably experts, are overall optimistic.

However, averages mask meaningful heterogeneity. While in most cases, investors appear unaware of overvaluation, a small subset of events show some recognition of mispricing. GameStop in 2021 stands out as an example where widespread acknowledgment of a bubble coincided with a rapid price surge and crash. Yet, such cases are rare. Only 3% of events in our sample have negative analyst return expectations at the peak, and just 1.6% exhibit expectations below -10%. More common are stocks like Yahoo! in 1999, where analyst optimism, high media attention, and a lack of bubble-related discourse prevailed.

A skeptic might argue that our ex-post findings do not necessarily indicate bubbles. Perhaps these episodes simply reflect periods of excessive optimism that, in hindsight, turned out to be incorrect, rather than irrational pricing ex ante, as argued by Fama (2014). While our goal is not to settle the debate on bubble existence, we address this critique in Part II of the paper. We conduct an ex-ante analysis, identifying 7,887 episodes of rapid price run-ups and high valuation ratios, including 2,581 cases where no crash ends up occurring. This allows us to assess whether investor expectations can help predict future crashes, extending the scope of our analysis beyond purely retrospective evaluations.

We show that various measures of optimism predict an elevated probability of a crash. Specifically, high analyst forecasts of fundamental and price growth are associated with a greater likelihood of a crash. While short interest itself does not significantly predict crashes, high short interest fees do. These results hold even after controlling for other known crash predictors, including volatility, trading volume, issuance, and firm age. The greater the level of optimism, the more likely a run-up can be classified as a bubble.

A number of recent papers empirically study bubbles. Greenwood et al. (2019a) study industry bubbles in the United States and internationally, and show that their characteristics help predict a crash. However, they do not examine investor expectations and focus on industries rather than individual stocks, as we do. Barberis et al. (2018) analyze empirically the predictions of a model with extrapolative investors, but do not study data on expectations. Unlike them, we study individual stocks rather than industries or the market, and measure expectations. Goetzmann (2015) studies Daniel et al. (2023) also study individual stocks that have experienced runups and show that those with low institutional ownership structure experience the lowest returns because they are hard to short. Haddad et al. (2022) suggest that bubbles come from periods of innovation. Many papers studied the rise and fall of .com stocks in the late 1990s (Ofek and Richardson (2003)). Finally, our paper connects

to a large theoretical literature on bubbles, including behavioral models, as well as rational ones (Blanchard and Watson (1982), Tirole (1985), and Abreu and Brunnermeier (2003)).

Our paper is also related to a growing literature on investor expectations, including Shiller et al. (1996), Amromin and Sharpe (2014), Bacchetta et al. (2009), Greenwood and Shleifer (2014), Giglio et al. (2021), and Nagel and Xu (2023).

Section I defines our criteria for identifying boom-bust episodes in stock prices and then studies measures of expectations in event-time, including media coverage. Section II expands the set of episodes to includes run-ups that do not experience a crash, and asks whether expectations help forecast the crash. Section III concludes.

1 Boom-bust episodes in stock prices: Ex-post analysis

1.1 Identifying Bubble Episodes

We identify all episodes of US listed stocks on CRSP with share codes of 10 or 11 between 1980 and 2023 based on four criteria: (a) a 100% run-up in price over the last 6 and 12 months, (b) a positive current-month return, (c) a current-month price-to-sales or price-to-book ratios exceeding 5, and (d) a subsequent crash, defined as a 50% or greater drawdown from peak within the following 24 months. Stocks in a boom-bust episode are excluded for two years before becoming eligible again. These criteria generate 5,306 total events.

These criteria identify many famous boom-bust episodes, such as Gamestop in January 2020, and Yahoo! in December 1999, as well as many lesser known episodes.

Data availability is a key concern. While we identify 5,306 episodes, analyst expectations of long-term growth from IBES are available for only 1,580 cases, with EPS growth and sales growth forecasts available for just 1,192 and 1,440 episodes, respectively. Similar limitations arise when analyzing short interest and press coverage. Throughout the paper, we utilize

all available data, but this approach results in slightly different sample sizes across analyses. In Figure A.1, we show that the IBES subsample follows a similar trajectory in valuations (price-to-sales and price-to-book ratios) and cumulative returns compared to the broader sample.

Figure 1 shows the number of episodes we identify each month between 1980 and 2023. The figure highlights two prominent spikes in bubble activity: the late 1990s, corresponding to the dot-com bubble, and 2020, reflecting the surge in speculative trading and high-growth technology stocks (Pedersen (2022) and Zhou (2023)).

Figure 2 and Figure 3 provide more color on the events we study. Figure 2 shows that the boom-bust episodes experience crashes with heterogeneity in crash timing. The figure shows the percentage of bubble firms that crash in any given month after the bubble peak relative to all bubble firms. The right axis shows the cumulative percentage of bubble firms that crash.

Figure 3 shows the average (equal-weighted) path of valuation ratios and cumulative returns, starting 24 months before the peak. The bubble peak is defined as the month with the highest split-adjusted price, occuring in the run-up month or afterward. The figure shows that valuation ratios rise and then fall again. The figure also shows that firms experience significant crashes.

1.2 Expectations of Future Prices and Returns

Figure 4 in the document presents the equal-weighted average expected one-year returns of bubble stocks, the fraction of bubble stocks with negative expected returns, and the value-weighted average expected returns of the overall market.

The expected one-year return is computed as the most recently updated analyst target price divided by the current stock price, minus one. "Market" refers to the mean of this

measure across all stocks, not just those classified as bubble stocks.

The figure highlights that even at the peak of a bubble, analysts maintain a high degree of optimism regarding expected returns. The average expected return for bubble stocks is significantly elevated compared to the overall market, suggesting that analysts do not necessarily anticipate a reversal in price trends. Moreover, only a small fraction of bubble stocks are assigned negative expected returns by analysts at the peak, reinforcing the idea that perceived mispricing is not widely recognized in real-time.

1.3 Expectations of Fundamentals

Panel A of Figure 5 illustrates the equal-weighted average long-term growth (LTG) rate estimates for bubble stocks, tracked in months relative to the peak of the bubble. Analysts' forecasts for LTG exhibit a pronounced increase leading up to the bubble peak, reaching an average of approximately 30% at the peak—roughly double the value-weighted average for all stocks in the market, which remains below 15%.

This optimism persists even after the bubble bursts, with LTG forecasts only gradually declining over the subsequent months. The sustained elevation of growth expectations suggests that analysts remain relatively optimistic about bubble stocks' fundamentals, even as prices begin to collapse. The gap between bubble stocks and the broader market indicates that analysts perceive these stocks as having exceptional long-term potential, consistent with their extreme valuations.

Panel B of Figure 5 presents analysts' expectations for near-term earnings per share (EPS) growth for bubble stocks, also measured in months relative to the peak. The pattern closely resembles that of LTG forecasts, with near-term EPS growth expectations rising steadily as prices surge. At the peak, expected EPS growth rates are significantly higher than the market average, reflecting analysts' optimism regarding the short-term earnings

trajectory of these stocks.

Even as stock prices start to decline post-peak, near-term EPS forecasts remain elevated, showing only a gradual downward adjustment. Notably, it takes nearly a full year after the peak before the expected EPS growth rate for bubble stocks falls below the broader market average. This persistence in optimism suggests that analysts are slow to revise their expectations downward.

Figure 6 performs a similar exercise for analyst expectations of sales growth. Panel A of Figure 6 displays the equal-weighted average expected long-term sales growth for bubble stocks, measured in months relative to the peak. Similar to earnings expectations, analysts forecast exceptionally high sales growth for bubble stocks leading up to the peak, with growth estimates exceeding 30% at their highest point. In contrast, the value-weighted market average remains below 15%, highlighting the significant optimism surrounding these stocks.

Even after the peak, sales growth expectations remain elevated for an extended period before beginning to decline. This persistence suggests that analysts continue to believe in the fundamental strength of these firms, despite the sharp price corrections that occur post-peak. The sustained gap between bubble stocks and the broader market indicates that these stocks are perceived as high-growth firms, even as their valuations undergo rapid adjustment.

Panel B of Figure 6 focuses on analysts' near-term sales growth expectations for bubble stocks, also in months relative to the peak. The pattern mirrors the long-term sales forecasts, with expected near-term sales growth climbing sharply in the lead-up to the peak and remaining significantly above the market average.

Near-term sales growth expectations continue to rise even as prices approach their peak, suggesting that analysts associate the rapid price appreciation with strong underlying business expansion. However, even as stock prices start to decline, near-term sales expectations

remain high, taking nearly a year to fall back toward broader market levels. This delayed adjustment suggests that analysts may be reluctant to downgrade their sales projections immediately, possibly due to a belief that short-term volatility does not reflect a fundamental shift in business performance.

1.4 Did expectations overreact at the height of the bubble?

In Section 1.3, we showed that bubbles identified ex-post exhibit nearly three times higher expected growth in earnings and sales at their peak compared to non-bubble firms. In this section, we assess whether these expectations resulted from an overreaction to news. Specifically, following Coibion and Gorodnichenko (2015), we examine whether forecast revisions at the peak systematically predict negative future forecast errors, which would indicate that forecasts were excessively adjusted upward in response to news.

To implement this test, we use forecasts of earnings and sales for two fiscal years beyond the bubble peak. This ensures that realizations occur 13–24 months after the peak, mitigating the risk that management influences analyst forecasts before financial statements are released. This concern is most relevant for shorter horizons, where management may already have knowledge of upcoming reported fundamentals, potentially biasing results by making forecast revisions less reflective of genuine changes in expectations.

We define the forecast revision, $\Delta F_{i,-1\to 0}$, as the change in the consensus earnings forecast at the bubble peak, $F_{i,0}$, relative to the most recent forecast before the peak, $F_{i,-1}$. Thus, the forecast revision is given by $\Delta F_{i,-1\to 0} = F_{i,0} - F_{i,-1}$. To facilitate cross-sectional comparability, we normalize revisions by the latest available book equity,[4] denoted as $B_{i,0}$.

Accordingly, we define the forecast error as the difference between realized outcomes and the consensus forecast at the bubble peak. The forecast error for firm i is given by

[4] Bouchaud et al. (2019) estimate a similar regression but scale by lagged prices. Scaling by lagged prices in our case introduces additional volatility due to variation in run-up timing and magnitude.

$FE_{i,0\to 24} = (A_{i,24} - F_{i,0})$, where $A_{i,24}$ represents the actual realization 24 months ahead at the end of the second fiscal year. As with forecast revisions, we normalize forecast errors by $B_{i,0}$.

Figure 7 presents the evolution of average forecast revisions and forecast errors in earnings and sales relative to the bubble peak. The first panel shows that both earnings and sales undergo increasingly large upward revisions leading up to the peak, followed by a sharp drop toward zero in the months after, supporting the view that the bubble peak coincides with peak optimism about firm fundamentals. The second panel reveals that these upward revisions are matched by increasingly negative subsequent forecast errors. These results suggest that excessive upward adjustments in expectations led to progressively larger negative forecast errors, with their peak coinciding with the bubble peak.

To more directly test for overreaction, in Table 2, we estimate the following regression cross-sectionally across bubble firms:

$$\frac{FE_{i,0\to 24}}{B_{i,0}} = \alpha + \beta \frac{\Delta F_{i,-1\to 0}}{B_{i,0}} + \epsilon_{i,0\to 24}, \tag{1}$$

where $\beta < 0$ indicates overreaction to news. Estimating Equation (1) using both sales and earnings, we obtain coefficients (t-stats) of -0.62 (-3.21) and -2.02 (-2.06), respectively.

These findings indicate that the elevated growth predictions documented in Section 1.3 were driven by analysts' overreaction at the height of the bubble, only to be sharply disappointed by subsequent realizations. The magnitude of β suggests a misalignment between peak-time expectations and actual fundamentals, consistent with behavioral theories of bubbles that emphasize excessive optimism and the extrapolation of recent trends.

1.5 Short interest

We obtain short interest as a percentage of shares outstanding from Compustat and lending fees from SP Global. Table 1 provides summary statistics. We have coverage on short interest for 2,018 out of the 5,306 stocks, and short interest fees for 1,154 of the stocks.

Figure 8 presents the evolution of short interest and shorting costs for bubble stocks, measured in months relative to the peak of the bubble. The top panel shows the average fraction of shares shorted, while the bottom panel displays the average shorting fee (or lending fee). The figure also includes "Market", which represents the value-weighted average of short interest and shorting costs across all stocks in the sample.

The top panel shows short interest levels. Short interest remains relatively low throughout most of the bubble's run-up phase, indicating that few traders are betting against these stocks even as prices surge. On average, short interest three months before the peak is about 5% of shares outstanding, which is lower than the market average. However, as prices begin to decline post-peak, short interest steadily rises, suggesting that more investors start taking short positions after the bubble bursts.

This delayed increase in short interest implies that short sellers are either constrained during the bubble's expansion (possibly due to high borrowing costs or risk constraints) or that they avoid betting against momentum-driven stocks until clear signs of a reversal emerge.

The bottom panel shows shorting costs. The cost of shorting bubble stocks, measured by the shorting (lending) fee, remains relatively high throughout the bubble period. Unlike short interest levels, which are initially low and increase post-peak, shorting fees are elevated even before the peak and rise slightly as prices approach their highest levels.

This pattern suggests that while outright shorting is limited, those who do attempt to short bubble stocks face significant borrowing costs. The high fees likely reflect strong

demand for short positions in a limited supply environment, where shares are difficult to borrow. The persistence of elevated shorting costs, even as prices decline, suggests that shorting remains costly throughout the bubble cycle, potentially limiting the ability of fundamental traders to correct overvalued prices.

1.6 Is the financial press aware of bubbles?

The previous sections suggest that the experts are split on whether there is a bubble. Overall, analysts do not show much sign of bubble awareness, but there are a few signs in the share lending market. But what about the broader public? In this subsection we investigate how bubble episodes are portrayed in the media. We investigate two questions: (1) does media coverage increase over the course of the bubble, and (b) does the media shown any sign of awareness that a given stock is in a bubble?

We use ProQuest to analyze all articles published in the Wall Street Journal between 1980 and 2023, totaling 3,099,382 documents. We link this dataset to our identified bubble episodes by searching for company name mentions and retain articles associated with stocks undergoing bubble episodes. Since we observe firm legal names from CRSP, such as "Gamestop Corp.", we remove generic words like "Corp.", "Inc" and "LLC" to make firm names more comparable to those mentioned in news articles[5]. This procedure yields a dataset of individual articles that are associated with specific stocks on a given date. We are able to match 70,131 articles to 676 episodes.

To test whether the media displays awareness of bubbles, for each firm–month, we count the number of articles containing words indicative of a bubble[6] and compare that to the total number of articles in a given month. If the media becomes aware of a bubble, we would

[5]We also remove symbols like "&" and ".", and remove firms that has names which could be interpreted in contexts unrelated to the firm. Examples of excluded firm names are ´´BE", "GAP" and "At Home".

[6]Words used to identify bubble awareness are "bubble", "overvalued", "speculative", "speculation", "euphoria", "short squeeze", "meme", "frenzy" and "mania".

expect the fraction of articles mentioning **bubble-related words** to increase prior to the bubble's peak and remain elevated beyond the peak compared to the run-up period.

As an example, consider Figure 9, which shows results for Gamestop and Yahoo! in months relative to their bubble peaks[7]. On the left y-axis, we plot the total number of articles mentioning each company, and on the right y-axis, we plot the fraction of those articles mentioning **bubble words**.

For GameStop, we observe a low media coverage in the months leading up to the bubble and then two months before the peak, the total number of articles increase from 10 in November 2020 to more than 200 in January 2021. More importantly, the fraction of those articles mentioning **bubble words** is virtually zero in every month before the peak, but surges to around 60% in the month prior to the peak and settles at 70% in the peak month, suggesting that the media were indeed aware that GameStop was likely in a bubble in that time period. In contrast, for Yahoo!, the fraction of articles mentioning bubble-related words remained essentially unchanged in the year leading up to the bubble peak and in the two years that followed. Importantly, press coverage of Yahoo! almost doubles from 3 months before the peak to the peak, indicating that while there is an increased level of attention towards Yahoo!, there is only limited evidence that the media was aware of a bubble.

In Figure 10, we repeat the same procedure for all 676 episodes and report the average monthly number of articles and average fraction of articles mentioning bubble words. We find that the media coverage tends to increase by 40% from an average of 5 articles per firm 24 months prior to the peak to 7 articles per firm a year before the peak, and staying at that elevated level until a year after the peak More importantly, we find no increase in the average fraction of articles mentioning bubble words either before or after the bubble peak.

[7]The peak of GameStop was in January 2021, and the peak of Yahoo! was in December 1999.

1.7 Is anyone aware of the bubble?

We have already pointed out that the averages obscure substantial heterogeneity among bubble episodes. Our goal in this subsection is to narrow the investigation to the handful of episodes in which market participants seem to be more broadly aware that the price run-up is vulnerable to a crash.

GameStop in 2021 stands out as an example where widespread acknowledgment of a bubble coincided with a rapid price surge and crash. Only 3% of events in our sample have negative analyst return expectations at the peak, and just 1.6% exhibit expectations below -10%.

Table 3 provides a list of the 20 companies in our data with the lowest analyst expectations of returns in the month of the peak price. The table includes some famous examples, such as Microstrategy in 2000, which was widely acknowledged to be an accounting fraud, and AMC Entertainment in June 2021, which was caught up in the meme-stock frenzy.

2 Ex-ante: Expectations and predictability of crashes

Our results document high levels of investor optimism for boom-bust episodes in stock prices. But a skeptic could argue that they are not dispositive on the question of whether bubbles exist, because we have selected events which ex-post experience a crash. More importantly, our analysis in Section I considers all events ordered in event time aligned around the peak in prices, which we only know ex-post. Perhaps these episodes simply reflect periods of excessive optimism that, in hindsight, turned out to be incorrect, rather than irrational pricing ex ante, as argued by Fama (2014).

Our goal in this section is to ask whether the optimism we see ex-post is helpful ex ante for distinguishing price run-ups that crash from those that continue. This exercise is

similar in spirit to Greenwood et al. (2019b) who ask whether characteristics - such as share issuance, volatility, and so on - can help predict industry bubbbles.

To do so, we must expand our sample of 5,306 boom-bust episodes to include stocks that fit the run-up criteria, but that do not experience a crash over the next year. Table 3 describes these stocks. We find 2,581 stocks that meet all of the previous bubble criteria, except that they do not experience a 50% drawdown in the 24-month period after the initial runup is identified. Panel A shows that, at the moment of run-up, these stocks are similar to the rest of the sample, with similar past returns, valuation ratios, and size characteristics.

Panel B of Table 3 summarizes expectations at run-up, and Table 4 compares the crash and non-crash episodes. Table 4 shows that on average, crash episodes have higher long-term growth, higher expectations of future returns, higher short interest fees, similar short interest, and higher forecasts of near term EPS and Sales growth.

Table 6 presents the results of predictive regressions analyzing the relationship between various measures of investor expectations and the likelihood of a stock experiencing a crash. A crash is defined as a 50% or greater drawdown within two years of a price run-up. The table investigates whether analyst expectations of fundamentals, analyst expectations of returns, and features of the short-interest market provide meaningful signals for predicting future crashes. Table 6 presents predictive regressions of the form:

$$\text{Crash}_{i,t+1} = \alpha + \beta \cdot \text{Expectation}_{i,t} + u_{i,t} \tag{2}$$

where the variable $\text{Crash}_{i,t+1}$ is an indicator that equals 1 if stock i experiences a crash, defined as a drawdown of at least 50% in period $t+1$, and 0 otherwise. The parameter α represents the intercept term, while β is the coefficient on the expectation measure of interest. The term $\text{Expectation}_{i,t}$ refers to the expectation measure at time t, which may

include analyst expectations of fundamentals, such as long-term growth (LTG), expected one-year earnings growth, or expected one-year sales growth. It can also capture analyst expectations of returns (ER) or features of the short-interest market, including short interest and short interest fees.

The main findings are as follows. A higher expectation of long-term earnings growth (LTG) is associated with a greater probability of a crash, with a statistically significant coefficient of 0.006 (t = 8.25). This suggests that increased optimism about long-term fundamentals is linked to a higher likelihood of a subsequent price collapse. Analyst expectations of future returns (ER) are also strongly predictive of crashes. A higher expected return significantly correlates with a greater probability of a crash, with a coefficient of 0.061 (t = 10.96), indicating that analysts may systematically overestimate the sustainability of elevated stock prices, particularly for bubble stocks.

Short interest is positively correlated with crash risk, with a coefficient of 0.390 (t = 2.58), suggesting that stocks with higher short interest leading up to the peak are more likely to experience a crash. However, the relatively modest t-statistic implies that this effect is weaker compared to the predictive power of analyst expectations. In contrast, shorting fees (short interest fee) exhibit a strong positive relationship with crash probability, with a coefficient of 0.353 (t = 10.31). A higher cost of shorting is significantly associated with an increased likelihood of a crash, suggesting that constraints on short selling—potentially due to high borrowing costs—prevent arbitrageurs from correcting overvalued prices, allowing bubbles to persist before collapsing.

Near-term expectations of earnings and sales growth show mixed predictive power. Expected one-year earnings growth does not significantly predict crashes (t = 1.00), whereas one-year expected sales growth has a significant positive association with crash probability, with a coefficient of 0.020 (t = 4.07). This result suggests that while analysts' near-term

earnings forecasts may not fully capture crash risk, elevated sales expectations could indicate excessive optimism in firms experiencing rapid revenue growth.

In Table 7, we extend the predictive regression analysis from Table 6 by incorporating additional controls for other known predictors of crashes following price run-ups, following the approach of Greenwood et al. (2019a). Prior studies have identified several firm-level characteristics—such as price volatility, trading volume, share issuance, and firm age—as factors that influence the likelihood of a stock experiencing a sharp price reversal. By including these controls, we test whether long-term growth (LTG) and analyst expectations of returns (ER) continue to forecast an elevated probability of a crash, independent of these other factors.

The results in Table 7 confirm that LTG and ER remain strong predictors of crashes, even after accounting for these additional controls. The coefficient on LTG remains positive and highly significant across specifications, with a coefficient of 0.005–0.006 (t-stats ranging from 4.36 to 4.95), indicating that stocks with higher long-term growth expectations are more prone to subsequent price collapses. Similarly, ER continues to predict a higher likelihood of a crash, with coefficients between 0.055 and 0.063 (t-stats ranging from 7.68 to 8.10), reinforcing the idea that optimistic analyst return forecasts contribute to the formation of bubbles that ultimately burst.

Among the control variables, we find that higher price volatility is significantly associated with a greater probability of a crash, consistent with prior research linking volatility to speculative excesses. The coefficient on volatility is positive and highly significant ($t = 7.67$), confirming that stocks with large fluctuations in price movements are at greater risk of experiencing a sharp correction. Trading volume exhibits a mixed relationship, with some specifications showing a positive correlation with crash probability, while others suggest a slightly negative effect. Stock issuance also appears to be a strong predictor of crashes, with

firms that issue more shares being more likely to experience a price collapse, suggesting that firms take advantage of high valuations to raise capital before the crash occurs. Lastly, firm age is negatively correlated with crash risk, meaning that younger firms—often characterized by high growth expectations—are more likely to experience extreme boom-bust cycles.

These findings highlight that even after controlling for firm characteristics traditionally linked to crash risk, analyst expectations of fundamentals (LTG) and future returns (ER) remain key drivers of speculative price increases that are prone to sharp reversals. The persistence of these effects suggests that bubbles are fueled by excessive optimism from market participants, particularly regarding a firm's future growth prospects. Moreover, the significance of short-term trading volatility and issuance as additional predictors underscores the role of speculative trading dynamics and opportunistic capital raising in the formation and collapse of asset price bubbles.

3 Conclusion

Our study provides systematic evidence on investor expectations during stock market bubbles. Using data on over 5,000 boom-and-bust episodes, we document a striking pattern: during the run-up phase, analysts remain highly optimistic about long-term earnings growth and near-term returns, short interest remains low, and media coverage increases without signaling concerns about overvaluation. Even after a crash begins, there is little indication in the media or among analysts that these stocks were perceived as bubbles.

By extending our analysis to an ex-ante setting, we show that measures of optimism—particularly high analyst expectations of fundamental growth—help predict the likelihood of a subsequent crash. While short interest itself does not serve as a strong predictive signal, elevated shorting fees do, suggesting that constraints on arbitrageurs play a role in sustaining bubbles.

These findings reinforce the view that bubbles are fueled by overly optimistic expectations rather than widespread recognition of mispricing.

More broadly, our results highlight the challenges of identifying bubbles in real time. If even professional analysts and media narratives fail to acknowledge overvaluation at the peak, it suggests that recognizing bubbles as they occur is exceptionally difficult. While a small fraction of episodes, such as GameStop in 2021, were widely discussed as potential bubbles, most cases resemble Yahoo! in 1999, where optimism remained unchecked until well after the crash. Understanding the role of investor expectations in bubble formation remains a key area for future research.

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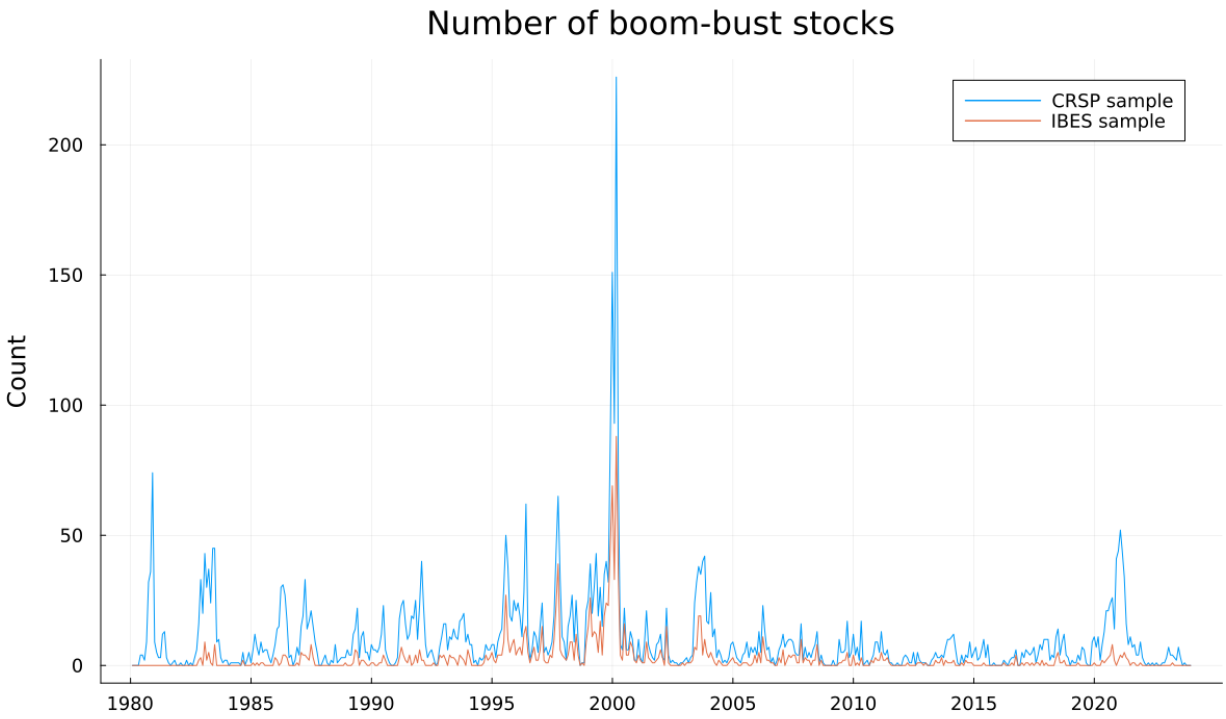


Figure 1: **Number of boom-bust episodes.** The figure shows the number of boom-bust episodes in the CRSP and IBES samples. Stocks are included if, in a given month, they meet all criteria: a return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and a drawdown of at least 50% within the next 24 months. Stocks in a boom-bust episode are excluded for two years before becoming eligible again.

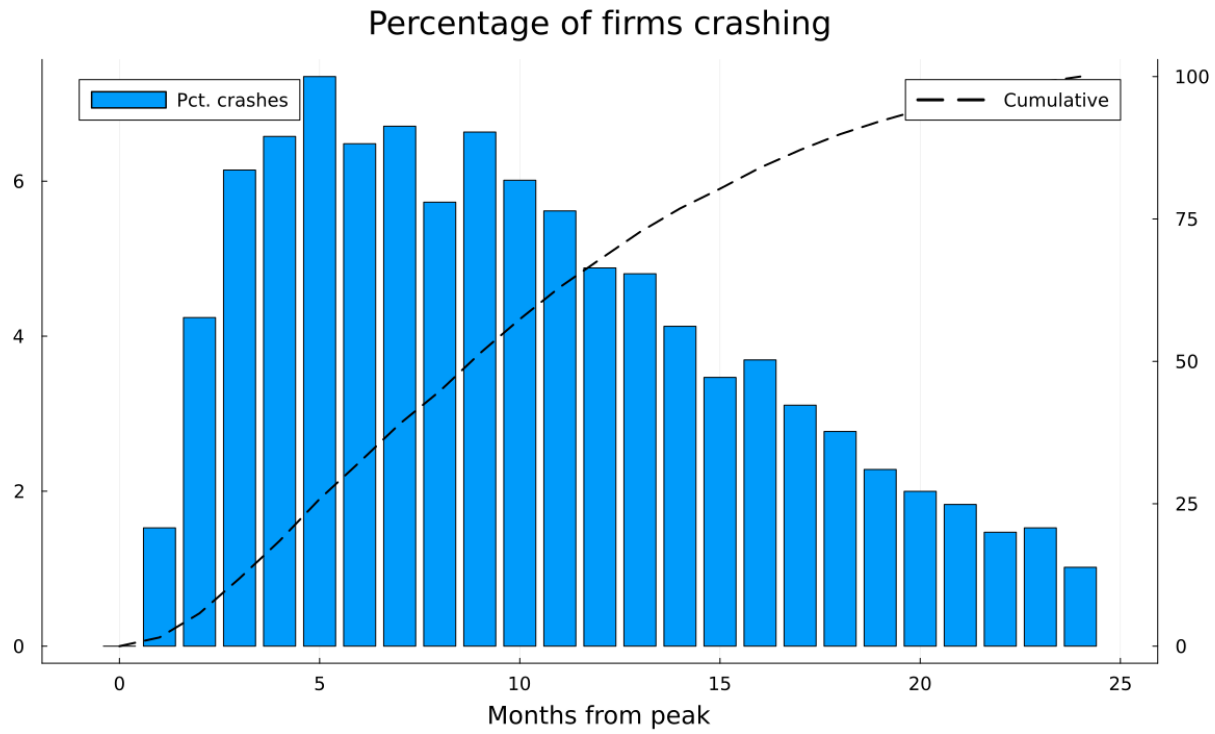


Figure 2: **Timing of crashes.** The figure shows the percentage of bubble firms that crash in any given month after the bubble peak realtive to all bubble firms. The right axis shows the cumulative percentage of bubble firms that crash. Bubble firms are defined as stocks that, in a given month, satisfy all criteria: a return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and a drawdown of at least 50% within the next 24 months. The bubble peak is defined as the month with the highest price between the run-up month and the crash month.

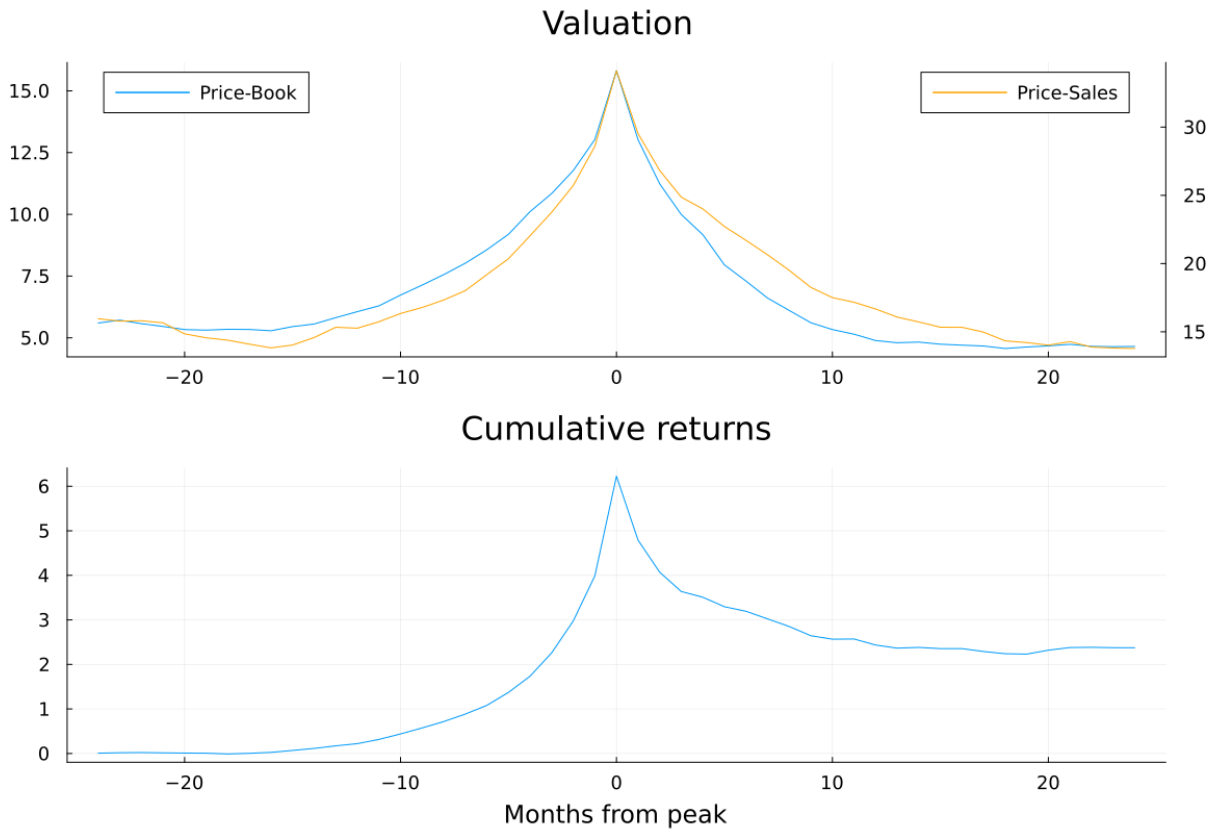


Figure 3: **Sample Selection.** The figure displays the equal-weighted cumulative return, price-to-book ratio, and price-to-sales ratio of bubble stocks, measured in months relative to the bubble peak. The bubble peak is defined as the month with the highest price, occurring in the run-up month or afterward. Stocks are included if, in a given month, they meet all criteria: A return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and a drawdown of at least 50% within the next 24 months. Stocks in a boom-bust episode are excluded for two years before becoming eligible again.



Figure 4: **Expected returns.** The figure shows the equal-weighted average expected 1-year returns of **bubble stocks**, the fraction of **bubble stocks** with negative expected returns, and the value-weighted average expected returns of the overall market, measured in months relative to the bubble peak. Expected returns are calculated as the 12-month price target divided by the current price, minus one.

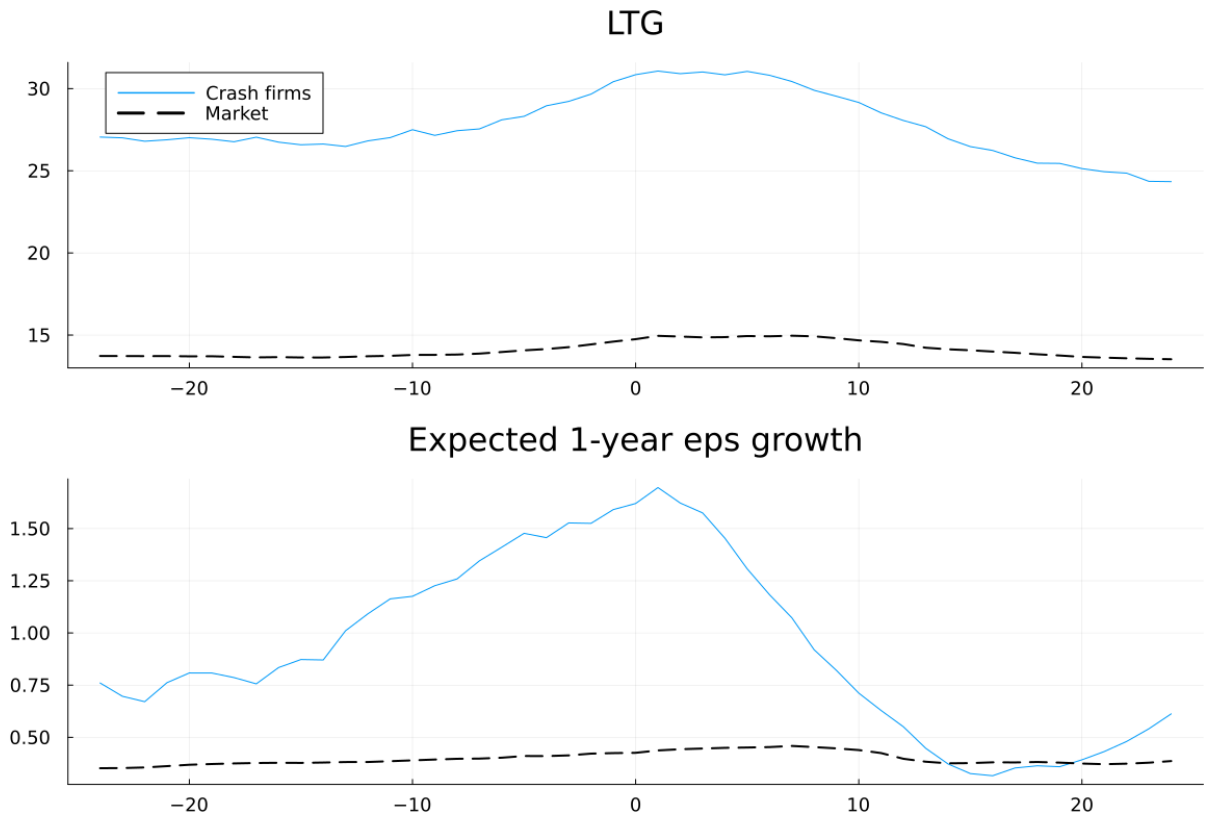


Figure 5: **Expected earnings.** The figure shows equal-weighted averages of expected earnings measures for **bubble stocks**, measured in months relative to the bubble peak. Each panel includes "Market," representing the value-weighted average of all stocks in the sample. Expected one-year EPS growth is calculated as the one-year EPS forecast from IBES divided by the actual earnings for firms with positive actual earnings.

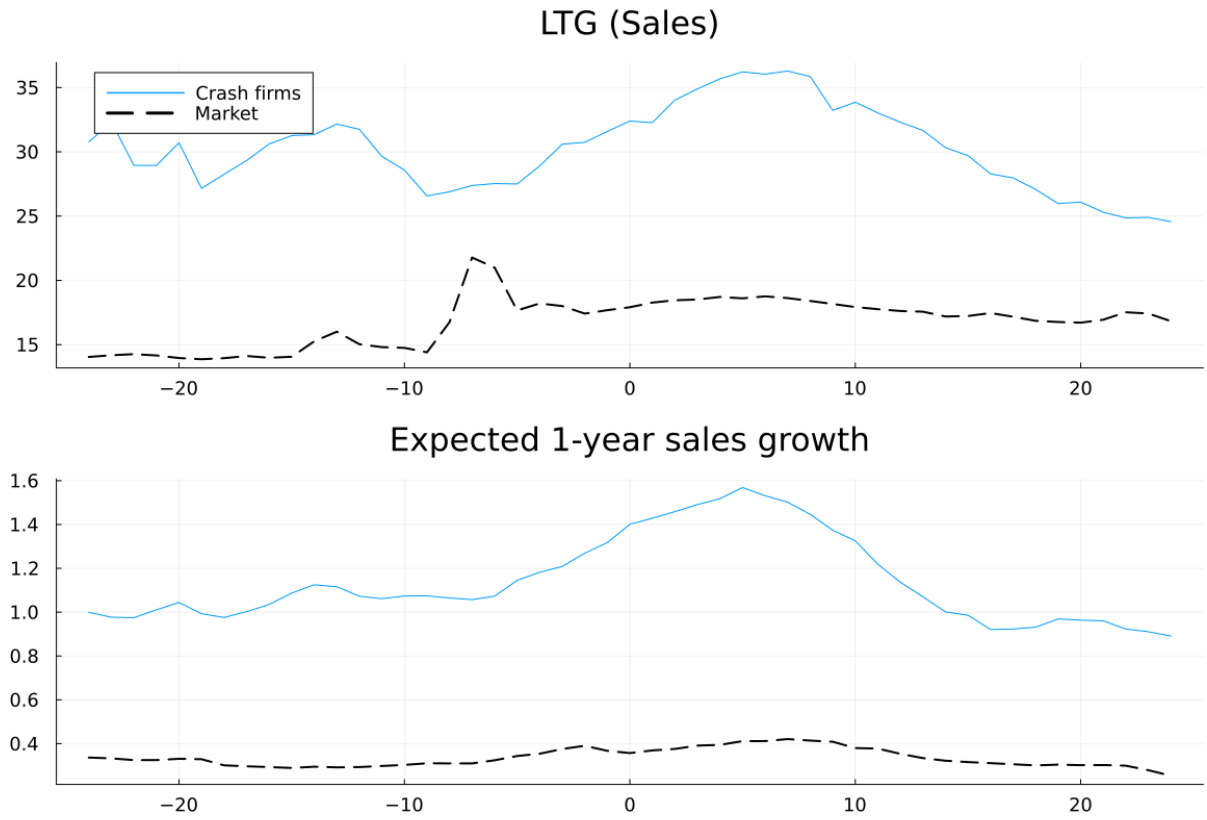


Figure 6: **Expected sales.** The figure shows equal-weighted averages of expected sales measures for **bubble stocks**, measured in months relative to the bubble peak. Each panel includes "Market," representing the value-weighted average of all stocks in the sample. Expected one-year sales growth is calculated as the one-year sales forecast from IBES divided by the latest sales.

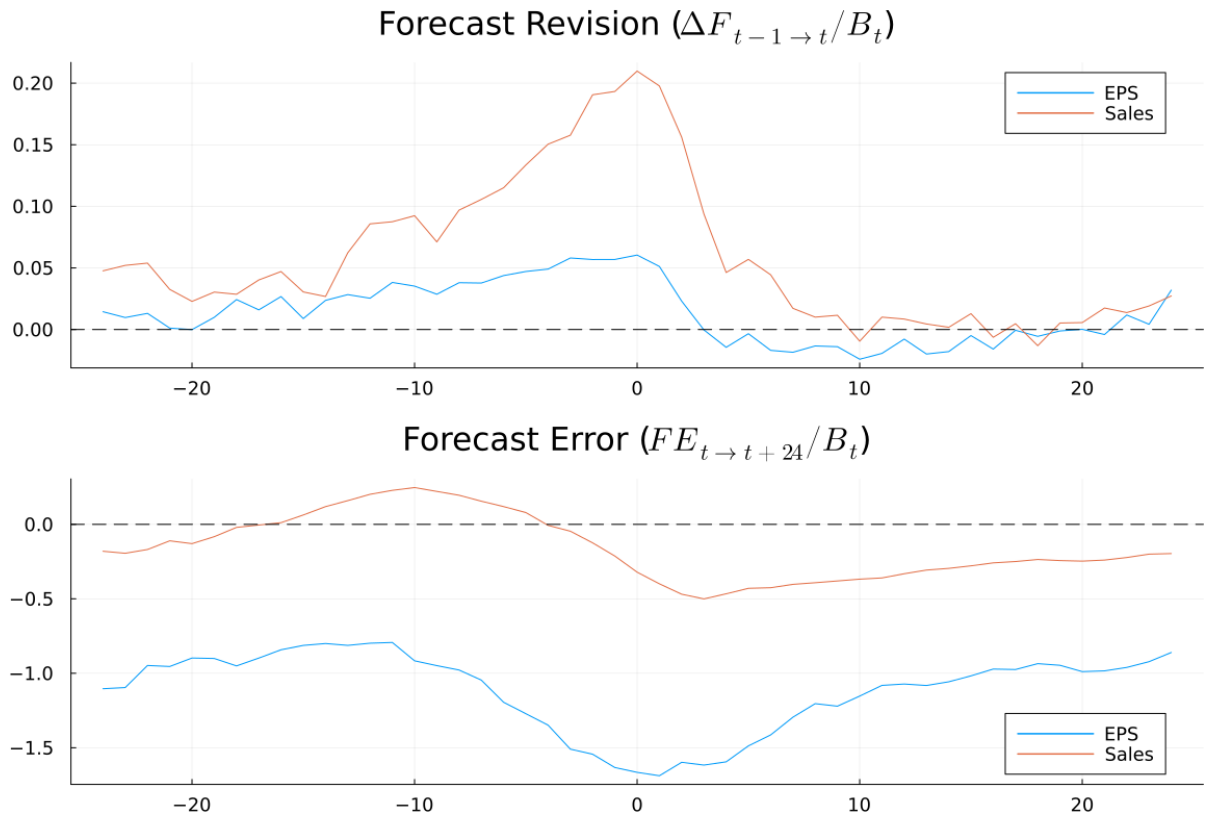


Figure 7: **Forecast revisions and errors.** The figure shows the average forecast revision and forecast error of bubble stocks, measured in months relative to the bubble peak. Forecast revision is the difference between the latest forecast at t and the previous one at $t-1$ scaled by book-equity B_t. Forecast error is the realized outcome (sales or earnings) 24 months ahead minus the forecast made at time t.

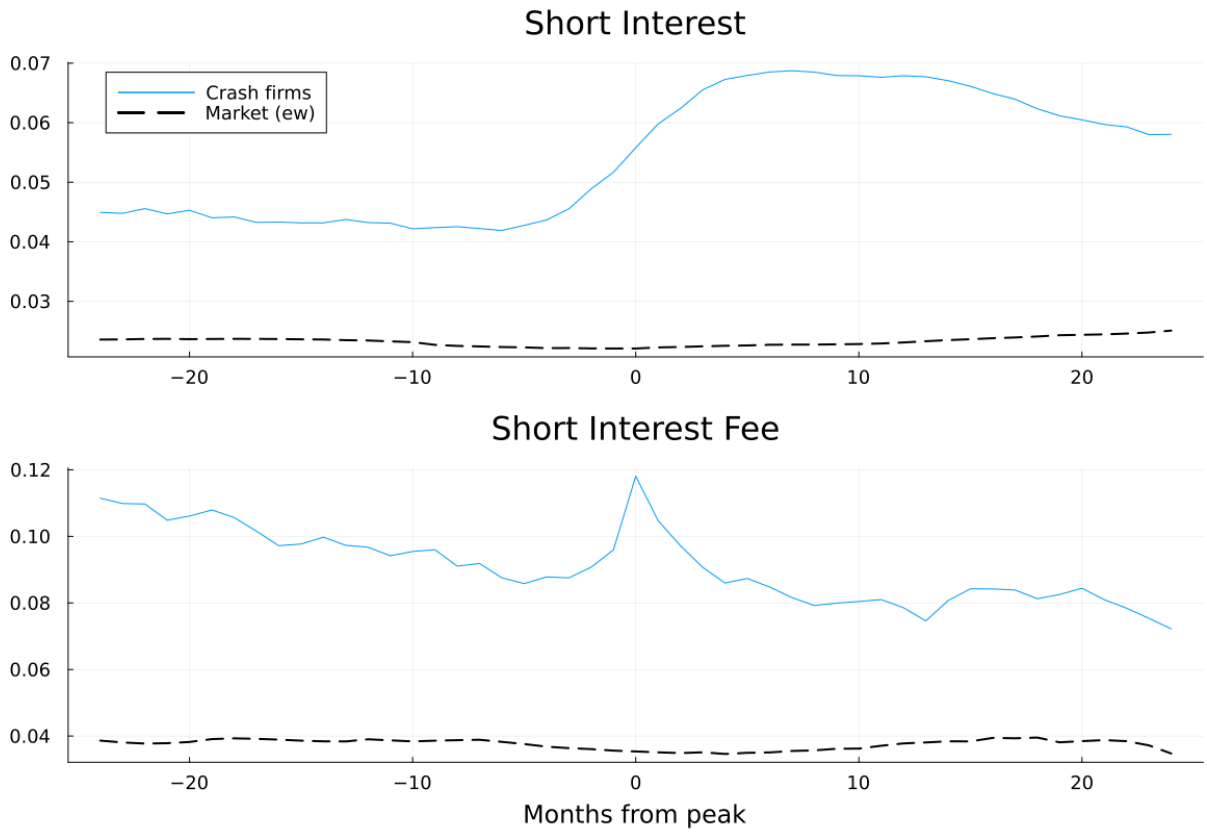


Figure 8: **Short interest.** The figure shows the average shorting amount and price for **bubble stocks**, measured in months relative to the bubble peak. The top panel displays the average fraction of shares shorted, while the bottom panel shows the average cost of shorting. "Market" represents the value-weighted average fraction of shares shorted and the price for all stocks in the sample.

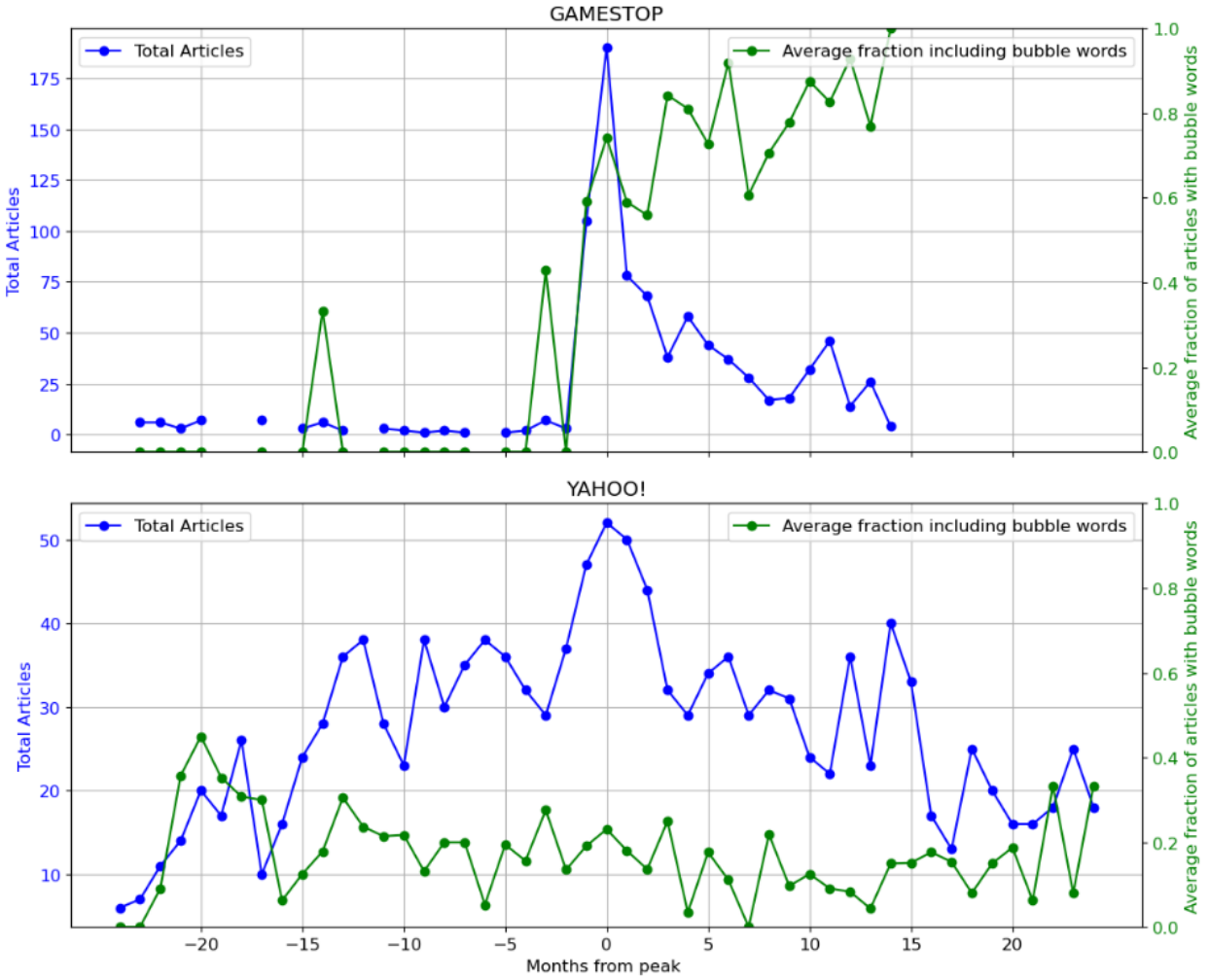


Figure 9: **Bubble awareness and the media: Gamestop and Yahoo!.** The figure shows the total number of articles from Wall Street Journal mentioning Gamestop and Yahoo! as well as the fraction of those articles containing any bubble-related words. Results are shown in months relative to their bubbles peaks. The peak for Gamestop was in January 2021, and the peak of Yahoo! was in December 1999.

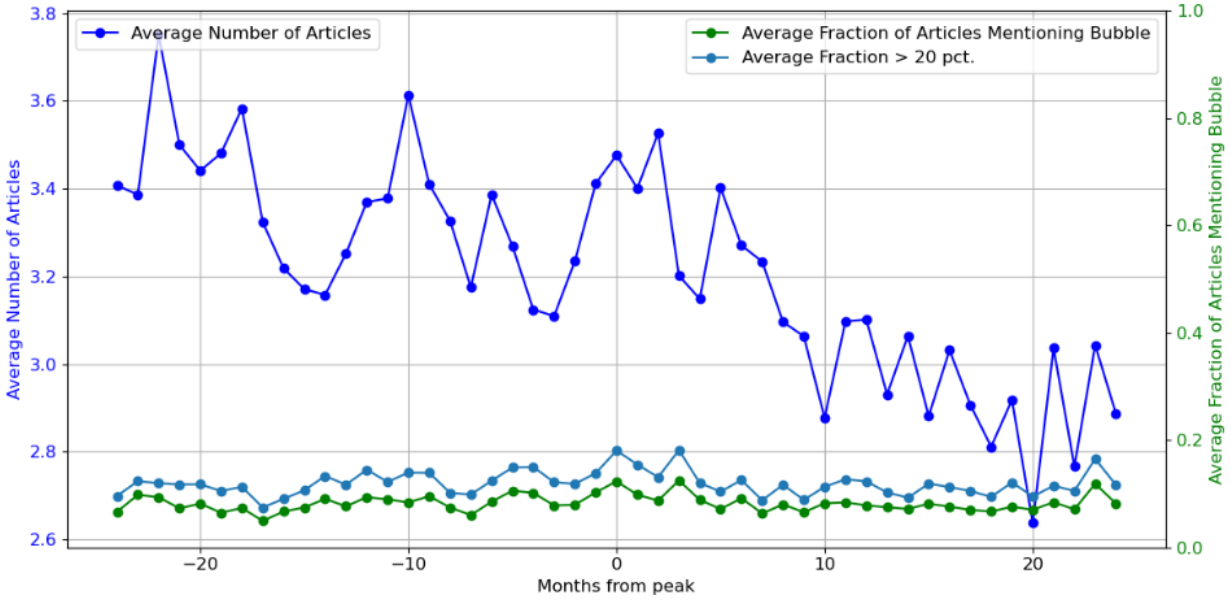


Figure 10: **Bubble awareness and the media.** The figure shows the total number of articles from Wall Street Journal mentioning any bubble stocks as well as the fraction of those articles containing any bubble-related words. Results are shown in months relative to their bubbles peaks.

	Obs	Mean	Std. Dev.	Min	p1	p25	p50	p75	p99	Max
Panel A: Characteristics at peak										
Past 12 month return	5306	3.543	4.337	0.009	0.274	1.536	2.383	3.973	20.375	106.536
Past 12 month market return	5306	0.246	0.159	-0.429	-0.173	0.166	0.249	0.319	0.679	0.679
Past 24 month return	5306	3.674	5.637	-0.969	-0.569	1.140	2.282	4.279	26.592	131.375
Future 12 month return	5306	-0.581	0.289	-1.000	-0.970	-0.751	-0.610	-0.470	0.330	5.450
Future 12 month market return	5306	0.032	0.172	-0.429	-0.317	-0.108	0.057	0.162	0.391	0.648
Price-Book at peak	5122	15.814	11.637	0.528	2.093	6.856	11.247	21.689	39.255	39.255
Price-Sales at peak	5019	34.131	53.673	0.032	0.410	3.639	8.875	31.362	174.304	174.304
Future 24 month maximum drawdown	5306	0.728	0.130	0.500	0.506	0.620	0.723	0.831	0.984	1.000
Size decile at peak	5306	5.969	2.413	1	1.000	4.000	6.000	8.000	10.000	10
Panel B: Expectations at peak										
LTG	1580	30.848	12.978	-22.100	2.416	22.000	30.000	40.000	60.000	60.000
ER	1220	0.524	1.194	-0.249	-0.249	0.139	0.245	0.437	7.239	7.239
Short interest	2018	0.056	0.063	0.000	1.205e-05	0.011	0.035	0.079	0.293	0.493
Short interest fee	1154	0.118	0.278	0.002	0.002	0.004	0.009	0.087	1.270	2.468
EPS growth	1192	1.620	2.290	-1.570	-1.570	0.487	0.899	1.708	10.217	10.217
Sales growth	1440	1.401	2.360	-0.693	-0.693	0.297	0.653	1.308	10.440	10.440
Forecast revision	2788	0.035	0.202	-0.547	-0.547	0.000	0.000	0.025	0.681	0.681
Forecast error	2541	-1.665	4.883	-20.738	-20.738	-0.727	-0.194	-0.022	4.396	4.396
Number of articles per firm at peak	676	3.47	9.49	1.0	1.0	1.0	1.0	3.0	35.5	190
Fraction of articles mentioning bubble at peak	676	0.123	0.274	0.0	0.0	0.0	0.0	0.0	1.0	1.0

Table 1: **Ex-post boom-bust sample 1980-2023.** The table shows summary statistics of boom-bust episodes. Stocks are included if, in a given month, they meet all criteria: a return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and a drawdown of at least 50% within the next 24 months. Stocks in a boom-bust episode are excluded for two years before becoming eligible again. The bubble peak is defined as the month with the highest price between the run-up month and the crash month.

	FE (earnings)	FE (sales)
	(1)	(2)
(Intercept)	-1.459***	-0.234***
	(-10.866)	(-4.994)
ΔF (earnings)	-2.024*	
	(-2.057)	
ΔF (sales)		-0.619**
		(-3.205)
N	1,452	889
R^2	0.013	0.028

Table 2: **Overreaction to news.** In column (1), we regress the two-year earnings forecast error $\frac{FE_{i,0\to 24}}{P_{i,-6}}$ on the forecast earnings revision between dates $t = -1$ and $t = 0$, that is, $\frac{\Delta F_{i,-1\to 0}}{P_{i-6}}$. In column (2), we regress the perform a similar regression using sales instead of earnings. Standard errors are adjusted for heteroscedascity and autocorrelation. t-statistics are in parentheses. $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

Date Identified	Company	MV ($)	P/B	Expected ILTG (%)	
Feb-00	MICROSTRATEGY INC	2,746,947,500	40.0	-87.6%	50
Feb-07	G T X INC	647,689,213	17.3	-82.9%	
May-11	G T X INC	220,322,952	5.9	-79.5%	
Jun-21	A M C ENTERTAINMENT HOLDINGS INC	11,761,313,978	0.0	-75.4%	
Feb-00	R F MICRO DEVICES INC	6,464,610,000	43.3	-71.4%	50
Jan-04	ZIX CORP	250,515,308	20.6	-55.0%	
Mar-04	STILLWATER MINING CO	1,091,240,351	1.6	-53.1%	
May-06	TRANSMERIDIAN EXPLORATION INC	502,643,083	10.1	-51.2%	
Jun-21	VIRGIN GALACTIC HOLDINGS INC	7,517,466,880	16.7	-47.7%	
Jan-14	HALOZYME THERAPEUTICS INC	1,716,849,644	36.7	-40.8%	
Feb-00	TERAYON COMMUNICATION SYSTEMS	2,619,253,000	31.1	-40.0%	50
Jan-21	FUELCELL ENERGY INC	3,601,286,215	69.5	-33.5%	
Jan-21	APPIAN CORP	6,316,809,247	28.5	-32.2%	
Mar-14	MAGNUM HUNTER RESOURCES CORP	1,442,324,959	6.7	-28.2%	
Jul-23	UPSTART HOLDINGS INC	3,001,272,025	9.2	-23.4%	
Nov-05	MIDWAY GAMES INC	1,664,574,827	13.0	-23.3%	15
Feb-04	EMISPHERE TECHNOLOGIES INC	135,612,347	4.3	-22.0%	
Jan-21	BLOOM ENERGY CORP	3,963,878,599	0.0	-21.9%	25
Jul-07	BOLT TECHNOLOGY CORP	247,284,605	7.2	-21.0%	
Jan-21	SUNPOWER CORP	4,369,773,816	905.7	-20.3%	
Jul-13	OVERSTOCK COM INC DEL	669,721,818	21.2	-18.5%	24.3

Table 3: **Stocks with bubble awareness** The figure shows stocks for which analyst expected returns were negative.

	Obs	Mean	Std. Dev.	Min	p1	p25	p50	p75	p99	Max
Panel A: Characteristics at runup										
Past 12 month return	2581	2.033	1.374	1.000	1.002	1.269	1.620	2.306	7.407	19.126
Past 12 month market return	2581	0.210	0.160	-0.337	-0.241	0.133	0.208	0.300	0.648	0.679
Past 24 month return	2581	1.815	2.099	-0.913	-0.666	0.667	1.370	2.408	9.685	35.890
Future 12 month return	2581	0.367	0.910	-0.530	-0.453	-0.111	0.102	0.560	3.831	12.462
Future 12 month market return	2581	0.116	0.144	-0.385	-0.268	0.044	0.133	0.203	0.459	0.679
Price-Book at runup	2581	10.765	9.344	0.000	0.000	5.437	7.341	12.214	39.255	39.255
Price-Sales at runup	2581	16.585	36.670	0.000	0.000	1.784	4.700	10.666	174.304	174.304
Future 24 month maximum drawdown	2581	0.329	0.141	-0.000	0.000	0.262	0.367	0.438	0.498	0.500
Size decile at runup	2581	6.018	2.357	1	1.000	4.000	6.000	8.000	10.000	10
Panel B: Expectations at runup										
LTG	934	25.001	13.494	-100.000	-5.254	18.000	24.500	30.000	60.000	60.000
ER	683	0.280	0.480	-0.249	-0.249	0.075	0.179	0.336	2.080	7.239
Short interest	1235	0.041	0.049	0.000	4.687e-05	0.006	0.024	0.057	0.230	0.383
Short interest fee	583	0.035	0.117	0.002	0.002	0.003	0.004	0.012	0.760	1.042
EPS growth	748	1.452	2.235	-1.570	-1.570	0.399	0.707	1.439	10.217	10.217
Sales growth	760	0.812	1.766	-0.693	-0.693	0.147	0.348	0.704	10.440	10.440
Forecast revision	1511	0.030	0.138	-0.547	-0.460	0.000	0.000	0.018	0.681	0.681
Forecast error	1141	-0.203	2.326	-20.738	-14.553	-0.036	0.017	0.086	4.396	4.396

Table 4: **Ex-ante non-crash sample 1980-2023.** The table shows summary statistics of US stocks that satisfy all our run-up criteria but do not crash. Stocks are included if, in a given month, they meet the following criteria: a return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and they do not experience a drawdown of at least 50% within the next 24 months. Stocks previously included are excluded for two years before becoming eligible again. The runup month is defined as the first month where all the above criteria are satisfied.

		Non-crash	Crash	Crash minus Non-Crash
1	Number of episodes	2581	5306	2725
2	Past 12m return (ew)	2.033	2.327	0.293
3	Forward 12m return (ew)	0.367	-0.136	-0.503
4	Price-Sales	16.585	26.529	9.945
5	Price-Book	10.765	12.671	1.907
6	LTG	25.001	29.358	4.357
7	ER	0.280	0.583	0.304
8	Short interest fee	0.035	0.134	0.099
9	Short interest	0.041	0.045	0.005
10	1-year EPS growth	1.452	1.563	0.111
11	1-year Sales growth	0.812	1.174	0.362

Table 5: **Crashing firms vs. non-crashing firms.** This table reports the average returns, valuations, expectations, and other outcomes in the run-up month for firms that experience a crash and those that do not. The number of episodes refers to the number of run-ups for which return and valuation data are available. For all other characteristics, averages are computed using a smaller sample that includes all non-missing observations.

	Crash					
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.439***	0.610***	0.596***	0.623***	0.560***	0.592***
	(19.465)	(51.247)	(54.131)	(49.839)	(39.181)	(48.059)
LTG	0.006***					
	(8.250)					
ER		0.061***				
		(10.963)				
ShortInt			0.390**			
			(2.583)			
ShortIntFee				0.353***		
				(10.312)		
1-year expected earnings growth					0.005	
					(1.002)	
1-year expected sales growth						0.020***
						(4.065)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	2,344	1,890	3,188	1,709	1,730	1,959
R^2	0.026	0.018	0.002	0.035	0.001	0.007

Table 6: **Predicting crashes.** The table shows predictive regressions of crashes on different expectations. All regressions are performed cross-sectionally in the run-up month, using expectations that were available at the run-up. Crash is a dummy, equaling one if a firm experienced a drawdown above 50% within two years of the runup month and zero otherwise. Standard errors are adjusted for heteroscedascity and autocorrelation. t-statistics are in parentheses. $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

	Crash								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	0.628***	0.670***	0.639***	0.703***	0.375***	0.467***	0.476***	0.528***	0.450***
	(78.911)	(123.390)	(93.853)	(98.605)	(8.237)	(14.352)	(12.382)	(13.128)	(7.345)
Volatility	0.595***				1.993*				1.653
	(7.668)				(2.529)				(1.933)
Trading volatility		0.000***				-0.000***			-0.000***
		(32.957)				(-10.052)			(-7.057)
Issuance			0.129***				0.107		0.090
			(7.266)				(1.817)		(1.539)
Age				-0.005***				-0.005**	-0.004
				(-6.410)				(-2.888)	(-1.764)
LTG					0.005***	0.005***	0.003*	0.004***	0.003*
					(4.357)	(4.949)	(2.466)	(4.150)	(2.154)
ER					0.055***	0.058***	0.063***	0.057***	0.058***
					(7.863)	(8.106)	(7.685)	(8.101)	(7.129)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
N	7,562	7,562	6,167	7,562	909	909	802	909	802
R^2	0.013	0.001	0.007	0.006	0.059	0.051	0.035	0.057	0.050

Table 7: **Controlling for known bubble predictors.** The table shows predictive regressions of crashes on LTG and ER controlling for known bubble predictors. All regressions are performed cross-sectionally in the run-up month, using expectations that were available at the run-up. Crash is a dummy, equaling one if a firm experienced a drawdown above 50% within two years of the runup month and zero otherwise. Standard errors are adjusted for heteroscedascity and autocorrelation. t-statistics are in parentheses. $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

	$r_{0\to24}$					
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.130*	-0.014	-0.012	-0.012	0.125***	0.018
	(2.261)	(-0.594)	(-0.515)	(-0.401)	(4.034)	(0.664)
LTG	0.000					
	(0.095)					
ER		-0.080***				
		(-5.959)				
ShortInt			-0.386			
			(-1.233)			
ShortIntFee				-0.576***		
				(-7.535)		
1-year expected earnings growth					0.004	
					(0.343)	
1-year expected sales growth						-0.029***
						(-3.418)
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
N	2,344	1,890	3,188	1,709	1,730	1,959
R^2	0.000	0.008	0.000	0.017	0.000	0.003

Table 8: **Predicting returns.** The table shows predictive regressions of future two-year returns, $r_{0\to24}$ on different expectations. All regressions are performed cross-sectionally in the run-up month, using expectations that were available at the run-up. Standard errors are adjusted for heteroscedasticity and autocorrelation. t-statistics are in parentheses. $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

Appendix

A Additional Empirical Results

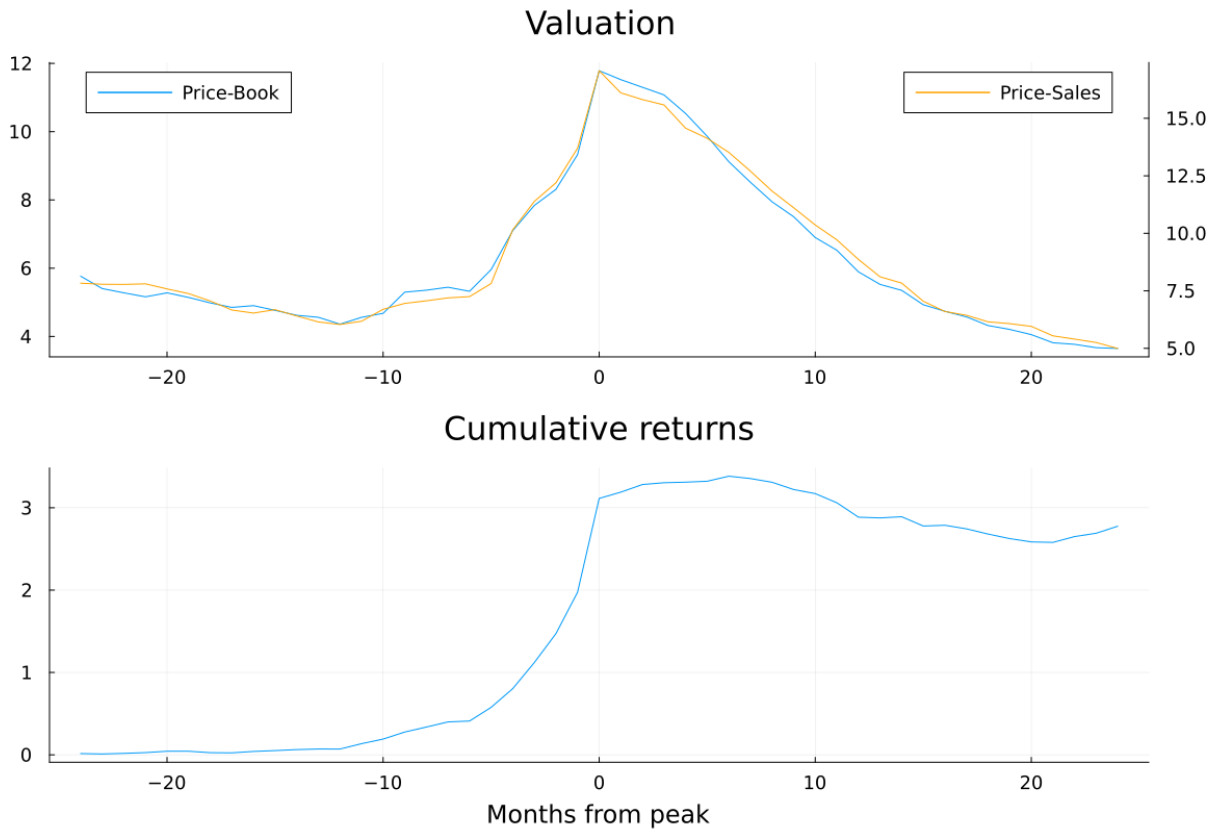


Figure A.1: **Sample selection on IBES subsample.** The figure displays the equal-weighted cumulative return, price-to-book ratio, and price-to-sales ratio of bubble stocks, measured in months relative to the bubble peak, where the bubble peak is defined as the month with the highest price, occurring in the run-up month or afterward. Stocks are included if, in a given month, they meet all criteria: a return exceeding 100% over the last 12 and 6 months, a positive current-month return, a price-sales or price-book ratio above 5, and a drawdown of at least 50% within the next 24 months. Stocks in a boom-bust episode are excluded for two years before becoming eligible again. Stocks must have non-missing LTG in the month of the bubble peak to be included.