Bubbles for Fama*

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Abstract

We evaluate Eugene Fama's claim that stock prices do not exhibit price bubbles. Based on US industry returns 1926-2014 and international sector returns 1986-2014, we present four findings: (1) Fama is correct in that a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward; (2) such sharp price increases do predict a substantially heightened *probability* of a crash; (3) attributes of the price run-up, including volatility, turnover, issuance, and the price path of the run-up can all help forecast an eventual crash; and (4) some of these characteristics can help investors earn superior returns by timing the bubble. Results hold similarly in US and international samples.

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"*For bubbles, I want a systematic way of identifying them. It's a simple proposition. You have to be able to predict that there is some end to it. All the tests people have done trying to do that don't work. Statistically, people have not come up with ways of identifying bubbles.*"

-- Eugene F. Fama, June 2016[1]

I. Introduction

The eminent financial economist Eugene F. Fama does not believe that security prices exhibit price "bubbles," which he defines in his Nobel Lecture as an "irrational strong price increase that implies a predictable strong decline" Fama 2014, p. 1475). He calls the term "treacherous." Fama's argument, in essence, is that if one looks at stocks or portfolios that have gone up a lot in price, then going forward, returns on average are not unusually low. Fama's conclusion runs contrary to a long literature studying bubbles historically (e.g., Mackay 1841, Galbraith 1955, Kindleberger 1978, Shiller 2000), as well as many modern theoretical, empirical, and experimental investigations. But is it correct?

In this paper, we seek to address this question. In particular, we look at all episodes since 1928 in which stock prices of a US industry have increased over 100% in terms of both raw and net of market returns over the previous two years. We identify 41 such episodes in US data. We examine the characteristics of these portfolios as well as their performance going forward, just as Fama recommends. We then repeat the exercise for international sector portfolios between 1987 and 2013 to see if the US findings obtain out of sample.

We present four main findings. First, Fama is mostly right in that a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward. Telling a bubble in advance based on a sharp price increase is not possible, in the sense that average returns following a price run-up approximately match those of the broader market in the following two years, and are unremarkable in raw terms as well. The historical accounts are typically based on burst bubbles, and do not take into consideration the fact that many industries that have gone up in price a lot just keep going up. The famed technology bubble of the late

[1] Chicago Booth Review, June 30, 2016. Available at http://review.chicagobooth.edu/economics/2016/video/are-markets-efficient

1990s is one that has actually burst. In contrast, health sector stocks rose by over 100% between April 1976 and April 1978, and continued going up by more than 65% per year on average in the next three years, not experiencing a significant drawdown until 1981.

Second, although sharp price increases do not predict unusually low future returns, they *do* predict a heightened probability of a crash. If we define a crash as a 40% drawdown occurring within a two-year period—a definition that captures many famous price run-ups and their crashes—then going from 50% industry net of market return in the previous 2 years to 100%, the probability of a crash rises from 19% to 54%. If we focus on episodes with a 150% industry net of market return, the probability of a crash rises to 81%. We show that this increase in the likelihood of a crash goes beyond what one would expect based solely on the past volatility of returns, and far exceeds the unconditional probability of an industry crashing. There is indeed a good deal of predictability of a future crash from past industry returns, and Fama's conclusion should be interpreted carefully as it implicitly draws a distinction between future returns and the likelihood of a crash. A policymaker interested in crashes—perhaps because they cause financial fragility or have other adverse effects—might be less interested in whether returns can be timed by a savvy investor.

The reasons for the difference in results between returns and crash probabilities are two-fold. First, as already noted, some industries just keep going up, and do not crash at all. Second, as importantly, bubble peaks are notoriously hard to tell, and prices often keep going up, at least for a while, before they crash, leading to good net returns for an investor who stays all the way through. As Fama (2014, p. 1476) points out, Robert Shiller "called" the US stock price bubble in December 1996, and prices proceeded to double after that. At its low, in 2003, US stock price index was *higher* than when Shiller first called the bubble. In our data, we find that even of the 22 episodes in which a crash does occur ex post, on average prices peak 5.8 months after we first identify the industry as a potential bubble candidate. The average return between the first identification of the price run-up and the peak price is 29%, confirming the adage that it is difficult to bet against the bubble, even if can call it correctly ex ante.

This leads to a third lens through which we evaluate Fama's conclusions. Curiously for the inventor of three forms of market efficiency, Fama only looks at the weak form in his assessment of "bubbles." Of course, investors looking at industries with large price increases

have a good deal of other information at their disposal, such as turnover, issuance, patterns of volatility, and fundamentals. This raises the obvious semi-strong form market efficiency question: in conjunction with an observation of a rapid price increase, can any of this information be helpful for identifying bubbles?

To answer this question, we again distinguish between information relevant for forecasting crashes and information relevant for forecasting future returns. We examine characteristics of industry portfolio growth episodes, most of which have been discussed to some extent in earlier work. These include: volatility, turnover, age of firms in the industry, the return on new companies versus old companies, stock issuance, the book-to-market ratio, sales growth, and the market price-earnings ratio. We also propose a new variable, "acceleration", based on the abruptness of the price run-up.

Our third finding is that many of these characteristics vary systematically between episodes in which prices keep rising, and those in which they ultimately a crash. In particular, run-ups that end in a crash are more likely to have high volatility, stock issuance, especially rapid price increases in a short period, associated increases in the market P/E, and disproportionate price rises among newer firms. We find no ability of fundamentals (as proxied by sales growth) to help distinguish between episodes.

We then investigate whether these characteristics can help a savvy investor earn superior returns by timing the bubble. In other words, with all the difficulties of calling the top, can one still identify characteristics of portfolios that will earn low returns, on average? Our fourth conclusion is that, indeed, some characteristics of sharp price rise episodes do help predict future returns. Looking at the same characteristics as before, we find that, in line with Fama's broad thrust, some of these attributes are *not* predictive of future returns. In particular, share turnover tends to be high in the price run-ups that crash, but also in the price run-ups that do not. Sales growth, which presumably measures fundamentals, does not help identify which episodes will crash. At the same time several variables do help predict which bubbles both crash *and* earn low returns. Volatility, issuance, the relative performance of new versus old firms, and acceleration tend to be predictive characteristics. It is still the case that we cannot call the peak of the bubble, and some of the portfolios we examine keep going up. Nonetheless, investment strategies that condition on high past returns in combination with either volatility, issuance, or acceleration can

on average exceed the returns to a passive buy-and-hold all industries strategy by 10 percentage points or more on a two-year or longer basis.

A significant concern with our analysis is statistical power. Large price run-ups, by nature, are rare—we identify only 41 of them in all of US stock market history since 1925. With the benefit of hindsight, we can surely point to some common elements in these events, with potentially dubious predictive value going forward. Our main response to this concern is to examine international industry data between 1986 and 2013 as an out-of-sample test. We confirm that in the international data as well, Fama is correct that price run-ups do not forecast average returns, but they are associated with a substantially elevated probability of a crash. More importantly, the features of price run-ups that predict crashes in the US – high volatility and share issuance -- have slightly more predictive value in the international data. Trading strategies based on these characteristics also outperform in international data.

To sum up, our evidence suggests that Fama is correct in his claim that a mere price increase does not predict low returns in the future. But even from this perspective, he is not correct that there is no predictability, since sharp price increases do predict a heightened likelihood of a crash. More importantly, returns are in fact predictable, since there are other attributes of well-performing portfolios, such as the sharply differential performance of new and old firms, which in fact help distinguish portfolios that earn low and high returns going forward. Based on this information, there are times when one can call a bubble with some confidence.

Our broad conclusion is one that historians – particularly Kindleberger -- have reached already. There is much more to a bubble than a mere security price increase. There is innovation, displacement of existing firms, creation of new ones, and more generally a "paradigm shift" as entrepreneurs and investors rush toward a new Eldorado. Our contribution is to show that this shift is to some extent measurable in financial data, so one can also identify – imperfectly but well enough to predict returns – asset price bubbles in advance.

We stress that the question of return or crash predictability after an extremely sharp price increase is not a particularly fertile field for testing market efficiency. The reason is that there are very few observations, and as a consequence the statistical power of the tests is low. We present some statistically significant results, but in the end we have only 41 US observations

(that are not even fully independent). Market efficiency is much more effectively tested by looking at the violations of the law of one price (e.g., Lee, Shleifer, and Thaler 1991 for closed end funds, Froot and Dabora 1999 for dual listing stocks, Lamont and Thaler 2003 for spinoffs, or Du, Tepper, and Verdelhan 2016 and Liao 2016 for covered interest parity violations). The evidence on return predictability in the time-series and cross-section as well provides a good deal more power to reject the null (e.g., Lakonishok et al. 1994, LaPorta 1996, Greenwood and Shleifer 2014). Bubbles are interesting not to settle these issues. Rather, they capture imagination and provide stimulating anecdotes, such as Fama's (2014) story about Shiller. But the predictability of crashes is also an important issue for financial stability. A policy maker concerned with financial markets facing high odds of a crash and consequent dislocations might not be comforted to know that expected returns going forward are not abnormally low.

Our paper is related to several lines of research in finance. First, many studies use characteristics to forecast industry returns, especially industry momentum, although we differ by focusing on episodes subsequent to a large price run-up.[2] Daniel, Klos, and Rottke (2016) show that some high momentum stocks subsequently experience violent crashes. Second, there are many empirical studies of individual bubbles, and especially the most recent .com episode of the late 1990s.[3] Our paper helps ask whether some of the findings from these studies (such as patterns of high issuance and trading volume) generalize. Third, some research has tried to forecast market crashes using characteristics such as past skewness, returns, or trading volume (Chen, Hong, and Stein 2001). Fourth, Goetzmann (2015) studies rapid price increases of national stock markets and subsequent returns, but not characteristics of these markets beyond the price run-up. Finally, our paper connects to a theoretical literature on bubbles, including Blanchard and Watson (1982), Tirole (1985), De Long et al (1990), Abreu and Brunnermeier (2003), Scheinkman and Xiong (2003), and Barberis, Greenwood, Jin, and Shleifer (2016).[4]

[2] See Grinblatt and Moskowitz (1999), Asness, Porter and Stevens (2000), Hou and Robinson (2006), Hong, Torous, and Valkanov (2007), Greenwood and Hanson (2012), among others.

[3] Ofek and Richardson (2003), Brunnermeier and Nagel (2004), Pastor and Veronesi (2006), Griffin, Harris, Shu, and Topaloglu (2011),

[4] There is a lot of research in finance on so-called rational bubbles (e.g., Blanchard and Watson 1982, Tirole 1985), but recent evidence has not been kind to this theory (Giglio, Maggiori, and Stroebel 2016).

II. Average Returns after Price Run-ups

We start by identifying in US industry data all episodes in which an industry experienced value-weighted returns of 100% or more in the past two years, in both raw and net of market terms, as well as 50% or more raw return over the past five years. We require high returns at both a 2- and 5-year horizon to avoid picking up recoveries from periods of poor performance. Our database includes returns from February 1926 to March 2014, which allows us to identify every price run-up episode between February 1928 and March 2012 because we require a two-year return to identify price run-ups and a two-year price path afterward to classify collapses and evaluate the performance of trading strategies.

Our choice of 100% returns is meant to conform to Fama and others' notion that a bubble, if it exists, begins with a large price run-up. A return threshold of 100% is able to pick up most episodes that historians have suggested were bubbles ex-post, such as utility stocks in 1929, and .com stocks in the late 1990s. We require both high raw and high net-of-market performance so as to avoid classifying as a potential bubble an industry with modest or flat performance during a time when the market performed poorly. Below we discuss how our conclusions depend on the return threshold we choose.

Our unit of analysis is an industry, identified according to the Fama and French (1997) 49-industry classification scheme (although the precise industry identification scheme is not important for our results)[5]. We use the first 48 of their industries, excluding the residual industry "other", and restrict attention to industries with 10 or more firms, to ensure that the price run-up is experienced by multiple firms. Following standard procedure, returns are measured monthly and based on all stocks with share codes of 10 or 11 in the CRSP database. Stocks are matched to

[5] One subtle complication is that bubbles often tend to be associated with relatively new industries, such as utilities in the 1920s or .com stocks in the 1990s. No single ex ante industry definition is likely to perfectly match to the theme of any particular bubble. For example, Fama and French's 49 industries of "software", "hardware", "chips", and "electrical equipment" all include firms that were ostensibly part of the Technology bubble. We have experimented with different definitions of industries, notably 2-digit SIC code and broader Fama-French industry aggregates, as well as GICS-industry definitions popular among investment professionals.

industries each month using the most recent SIC code on Compustat, or CRSP if not available.[6] Returns are value-weighted across stocks.

We study industries for three reasons. First, most historical accounts of bubbles have a strong industry component. White's (1990, 2007) descriptions of the 1929 stock market boom and subsequent bust, for example, emphasize utilities and telecommunications stocks. Many authors have noted that the stock market boom of the late 1990s was concentrated in .com stocks (Ofek and Richardson 2003). Second, analyzing industries gives us more statistical power than analyzing the entire stock market, although many of the price run-ups we identify occurred during periods of good market performance. Third, by specializing our analysis to industries, we can compare potential bubble industries to other stocks trading at the same time. This is quite important because many of the industry features that we study, such as trading volume, vary substantially over time.

Price run-ups of 100% or more are quite rare: we observe only 41 since 1928. This is not surprising, given that the average price run-up represents a 5.5 standard deviation event[7]. These 41 price run-ups tend to be concentrated during particular periods, a reflection of the relatively fine industry classifications we are using. Because the Fama-French 49 industry definitions are quite narrow, our methodology sometimes separately identifies industries that are part of a broader sectoral bubble. For example, our procedure separately identifies four Fama-French industries with price run-ups in the late 1990s: Computer Software, Computer Hardware. Electronic Equipment and Measure & Control Equipment, but all four were components of the broader .com bubble. Ex post, it might seem reasonable to categorize the industry run-ups into a few number of episodes, each of which encompassed a particular time and theme, such as the 1929 stock market boom which included Automobiles, Chemicals, Electrical Equipment, and

[6] We do not match exactly the industry returns reported by Ken French on his website, because our industries include recently listed firms, which have historically been an important part of stock market bubbles. Fama and French compute industry returns from July of year *t* until June of year *t*+1 based on industry affiliation in June of year *t*. The unconditional correlation between their reported monthly value-weighted industry returns and ours is 97.6%.

[7] Across all episodes, we compute the ratio between returns from *t*-24 to *t* and the square root of 24 times the standard deviation of monthly returns between *t*-36 and *t*-24. The average value of this ratio is 5.5.

Utilities. The trouble with such ex post consolidation is that it limits our ability to use the data for predictive purposes. Nevertheless, we recognize that price run-up episodes are not all independent, and adjust statistical inference by reporting standard errors and *t*-statistics clustered by calendar year throughout.[8] When we study the international data, we cluster standard errors by country-calendar year.

As noted, our definition of a price run-up is based on the industry value-weighted return. This does not mean that the price run-up is limited only to the large firms in the industry. Across the price run-ups that we study, an average of 61% of firms in the industry experience price increases of 100% or more during the run-up period.

We separate the 41 episodes into 22 that crash in the subsequent two years, and 19 that do not. We define a crash as a 40 percent or more drawdown in absolute terms beginning at any point after we have first identified the price increase. This successfully identifies a number of episodes that historians have described *ex post* as having been stock price bubbles, and a few more episodes that are not as well known. Automobiles, Chemicals, and Electrical Equipment were all part of the bubble economy of the late 1920s (White 1990, 2006, 2007). Software, Hardware, and Electrical equipment all denote industries affected by the .com bubble of the late 1990s and early 2000s (Ofek and Richardson 2003). Coal reflects the commodity price run-up during 2006 and 2007, followed by its dramatic collapse in 2008. All of these are cleanly identified as sharing a rapid price run-up and subsequent collapse.[9]

The cutoff of two years for analyzing subsequent performance is meant to set a high bar for calling the bubble. This relatively short window prevents us from, for example, calling an industry a potential bubble in 1996 and claiming vindication when it crashes in 2000.

Because our threshold for a crash is quite high, some of the industries we classify as *not* having crashed nevertheless experience mediocre subsequent returns. For example, airlines

[8] In the Appendix, we also show t-statistics based on standard errors clustered by episode, where "episode" is defined ex post for all run-ups during a two-year time period.

[9] There are many other ways to identify a crash, which all produce similar classifications of our price run-ups into "crashed" and "non crashed." For example, Mishkin and White suggest looking at 20% market declines over horizons of one day, one week, one month, three months, and one year.

experience a large price run-up prior to 1980 and slightly negative returns in the 24 months thereafter, but this performance is not sufficiently poor to be classified as a crash.

Although our criteria of a 40% drawdown does not require the crash to be sudden, in most cases it is: in 18 of the 22 episodes in which there is a crash, the industry experiences a single-month return of -20% or worse during the drawdown period.

Figure 1 summarizes the average returns for the 41 price run-ups. The figure confirms Fama's central claim: a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward. On average, industries that experienced a price run-up continue to go up by 9% over the next year (5% net of market), and 0% over the next two years (-10% net of market). Neither raw nor market adjusted returns are statistically distinguishable from zero.

Figure 1 also shows average *market* returns during and after the industry price run-up. Although industry run-ups tend to coincide with broad market rallies, the presence of an industry run-up is associated with poor average subsequent market returns: across all episodes the value-weighted market earns only 4% in the first year post-run-up, and 0% over two years. After netting out the risk-free return, market excess returns are -1% in the first year, and -10% over two years. The market performs particularly poorly during the episodes that we record as industry crashes: the average two year raw market return in these 22 cases is -25%, the average two year excess market return is -31%. The substantial correlation between large industry crashes and market underperformance supports our approach of studying industry portfolios.

Table 1 summarizes returns for each episode, grouping episodes by whether there was an ultimate crash or not. For the 22 industries that do crash, average returns are -5% (-4% net of market) in the next year and -42% in the next two years (-29% net of market). The 2-year returns are more impressively negative than the one-year returns because the crash does not necessarily come right away. This can be seen in Figure 1, which shows that the crash begins an average of five months after we call a potential bubble. Overall, if we study only the cases in which a crash does occur, the average return experienced between the initial price run-up and the subsequent peak price is 29% (and is as much as 107% in the case of precious metal stocks in the late

1970s). This confirms the adage that it is difficult to bet against the bubble, even if one has correctly identified it as such ex ante.

The second panel in Table 1 shows the list of the 19 industries that experienced a price run-up but no major crash in the subsequent two years. These industries continue to go up by an average of 25% in the subsequent year (16% net of market), and 48% in the next two years (33% net of market).

International Industries

As an out-of-sample test, we repeat our analysis using a sample of all international firms with complete volume and returns in the Compustat Xpressfeed database. Of course, the international data is not a fully independent test, since many of the price run-ups are common across countries. For example, many countries experienced rapid price run-ups in materials and commodities related stocks in 2007 and early 2008. However, even in episodes that are shared across industries in different countries, the timing of the price boom and bust varies substantially.

We use all non-US stocks with complete volume and returns in the Compustat Xpressfeed database. Stocks are matched to sectors based on their GICS-code. The GICS-sector is a broader definition of industry than that of Fama and French (there are 11 sectors vs. 49 Fama-French industries) but this helps ensure that for smaller stock markets such as Sweden, an industry includes a sufficient number of firms to be meaningful. As in the US, we restrict our attention to industries with 10 firms or more. Returns are measured in US dollars (the return in US dollar is 99.9% correlated with the return computed in local currency) terms and are value-weighted within sectors. For these portfolios, the "market" benchmark is the local market value-weighted return, measured in dollars, and the risk-free rate is the dollar return on US Treasury bills. [10] The data begins in October 1985, but 88% of the observations are in 1996 or later. Overall, the starting point is 80,980 sector-months of returns, compared to 50,451 industry-months in our US analysis.

[10] We use dollar returns rather than local currency returns to avoid picking up potential bubbles during high inflation periods in some countries. Stocks are classified by country of their headquarters. We only use securities that are traded on exchanges in their home country, i.e., we exclude ADRs and equivalents.

Following an otherwise identical methodology, we identify 104 price run-ups in 30 countries between October 1987 and December 2013, summarized in Table 2. Of these price run-ups, 51 crash and 53 do not. Average returns to the crashed and non-crashed samples are surprisingly close to those of the US sample despite different industry definitions and sample years. Figure 2 shows that Fama's central claim holds up in the international data as well: a sharp price increase of an industry portfolio does not, on average, predict unusually low returns going forward. Across all price run-ups, these sectors experience an average return of 1% (3% net of market) in the next year, and 7% (0% net of market) in the next two years. In short, our first conclusion drawn from US industries also holds in the international data: Fama is correct about average returns.

Because there are too many international episodes to list them individually, Table 2 summarizes price run-up episodes by country. As before, we start with the episodes in which there was a subsequent crash. For these episodes, average one-year returns following the price run-up are -23% (-5% net of market); average two-year returns are -38% (-13% net of market). These industries experience an average maximum drawdown of -65% in the two-year period following the price run-up. As with the US sample, the drawdown is more severe than average return because the price run-up is not a sufficient statistic to perfectly identify the peak. Consider the .com bubble, which is identified at different times in Germany, the United Kingdom, Japan, France, Hong Kong, Singapore, Norway, and Switzerland. In Germany, we first observe a large price run-up in March 1998, a full 23 months before the bubble peaks in February 2000. In Singapore, Norway, and Switzerland, our price run-up screen of 100% correctly identifies the peak. On average, the period between the initial price run-up and the price peak is 4.1 months, with a 39% subsequent return until the price peak, similar to that in the US sample.

Turning to the international episodes in which there is no crash in the two years post-price-run-up, average one-year returns are 25% (10% net of market); average two-year returns are 51% (12% net of market), and these industries experience an average maximal drawdown of only 22 percent. The best performing industries include IT in India, which experienced a first price run-up of 100% between June 1997 and June 1996, and subsequent returns of 436% until the price peak, in part because the entire stock market boomed; and Consumer related stocks in

Austria, which continue to rise by another 307% (172% net of market) in the two-year period following the initial price run-up.

Sensitivity to Degree of Price Run-up

How sensitive is our conclusion about average returns to the 100% past return cutoff? In Table 3, we list raw, excess (of the risk free rate) and net-of-market returns for the 12- and 24-month period subsequent to the price run-up. Table 3 summarizes average post-run-up returns for both US industries and international sectors based on different return thresholds. As in Table 1 and Table 2, for a given return threshold, we require both value-weighted raw and net of market industry returns to excess this threshold in a two-year period. In the appendix, we provide summary statistics for different ways of identifying price run-ups (such as based on raw returns alone, or based on price run-ups of three standard deviations or greater), with similar results.

Table 3 shows that for return cutoffs under 100%, our conclusion that Fama is correct about average returns does not change. Average net-of-market returns in the 24 months following the price run-up average less than 4%, whether our cutoff for a price run-up is 50%, 75% or 100%. But if we increase the cutoff to 125% or 150%, these returns drop below -13% in US sample. In the 16 incidents of a 150% price run-up in US data, average raw returns over the subsequent 12 and 24 months were -11% and -15%; average net of market returns were -11% and -14%, and average excess returns were -18% and -30%, both one year performance statistically significant at the 10% level. The general pattern is that subsequent returns decrease as the ex-ante threshold goes up.

Panel B in Table 3 shows that we obtain similar findings when we study international sectors. Using a 150% return threshold, we identify 51 price run-ups, with subsequent returns of -15% in 12 months and -17% in 24 months, and excess returns of -18% and -23%, with both statistically below zero at the 10% significance level.

In short, our earlier conclusion that Fama is correct about average returns must be tempered, because following *very* high past returns, a crash is almost certain at some point in the next two years, and excess returns subsequent to the price run-up are reliably poor.

III. Probability of a Crash Following a Price Run-up

While *average* returns following a 100% price run-up are roughly zero, Table 1 shows that slightly more than half of the industries experience a crash in the subsequent two years, with a similar proportion crashing among international sectors. A crash probability of one half is substantially higher than the unconditional probability of a crash in our data. Averaging across all industry-months between 1928 and 2013, the unconditional probability of a crash in any two-year period is 14%, and 11% after 1970, the midpoint in the sample. The unconditional probability of a crash among international sectors is higher, at 25%.

In this section, we show that the probability of a crash is strongly associated with high past returns. In fact, for very high past returns (such as 150% in a two-year period), a crash is nearly certain, although its timing is not.

We start in Figure 3 by showing simple kernel density plots of the probability of a crash conditional on past returns. The underlying sample contains all industry months in which past returns were positive and the industry in question had at least ten firms. Panel C and D repeat the analysis using international sector returns, with nearly identical results.

Panel A shows the probability of a crash as a function of the industry return net of market; Panel B shows the probability as a function of the past raw return. As before, a crash event takes on a value of 1 if the industry experiences a 40% or greater drawdown at any point in the next 24 months. Panel A shows that the probability of such a crash is approximately 20% at past net of market returns of 50% or less, but then rises rapidly to 35% at past net of market returns of 100%, and increases further at higher return thresholds.

Table 3 summarizes the crash probability as a function of past industry return. As in Tables 1 and 2, for a given return threshold, we require both value-weighted raw and net of market industry returns to exceed the return threshold in a two year period.[11] At a past return threshold of 50%, only 19% of episodes crash in US industries and 36% in international country-

[11] Because we require both net of market returns and raw returns to exceed the threshold, the crash probabilities do not exactly match those shown in the kernel density plots in Figure 3, but the overall pattern of crash probability substantially increasing as a function of past returns is evident in both the figure and the table.

sectors, only slightly above the unconditional crash probabilities. However, the probability of a crash increases substantially with past returns, from 19% to 54% in US industries, and from 36% to 49% in international sectors. As we increase the threshold further to 150%, we identify fewer price run-ups of this magnitude, but a higher percentage of them crash. Of the 16 episodes in which there was a 150% price run-up observed in US data, 81% crashed in the subsequent two years. Among international sectors, 67% of the 51 episodes with 150% price run-ups subsequently experienced a crash.

The results we have just described may be due in part to industry volatility: highly volatile industries are surely more likely to experience both booms with very high returns and crashes with very low returns, even if a boom is not predictive of a crash. Close inspection of Figure 3 suggests this is not a concern: there is almost no difference in crash probability between episodes with a 0% and a 50% price run-up, but enormous differences between a 50% and 100% price run-up. A simple but more formal way to deal with this concern is through a regression, in which we control for the volatility of returns prior to the price run-up. We do this by estimating regressions of the form

$$Crash_{it} = a + b \cdot [R_{it-1} > X\%] + c\sigma_{it-1} + u_{it}, \qquad (1)$$

where *Crash* takes a value of 1 if the industry experiences a 40% drawdown at any point between month t and month t+24. $[R_{it-1}>X\%]$ denotes a dummy variable that takes a value of 1 if the industry's return (or net-of-market return) is greater than a threshold X, and σ denotes volatility of returns. We estimate (1) using the same data as was used for the kernel plots in Figure 3, and where σ is estimated using one year of monthly industry returns ending just before the run-up period.[12] These regressions are similar in spirit to Chen, Hong, and Stein (2001) who estimate panel regressions to forecast negative skewness at the individual stock level. We estimate equation (1) with and without the volatility term on the right-hand-side. Whether our past return threshold X is 50%, 75%, 100%, 125% or 150%, we find that controlling for lagged volatility slightly attenuates the coefficient on past returns, but the effect is modest. For example, for a return threshold of 100%, controlling for volatility reduces the coefficient on past return

[12] We have experimented with different forms of the volatility control with little effect.

from 0.712 to 0.621. A complete set of results for all return thresholds is presented in the Appendix.

The data thus show that crashes are much more predictable than returns: what explains this? First, as shown in Table 1 and 2, some industries just keep going up, and do not crash at all. This result, in isolation, is reminiscent of results in obtained in the rational bubbles literature, in which the high probability of a crash is balanced with a high probability of continued appreciation of price away from fundamentals.

Second, for the episodes with a crash, prices often keep going up, at least for a while before the crash occurs. This leads to modest returns for an investor who holds the full way through. Figure 4 shows this result more formally across all 22 of our crash episodes. Here we plot "event-time" returns for the 22 episodes in which there was an eventual crash. In each episode, event-time of zero denotes the end of the month in which we first notice a large price run-up. Then, for each price run-up, we mark with a square the month with the peak cumulative return prior to the start of the crash. As can be seen, there is considerable heterogeneity between episodes in how long it takes before the crash starts. Not surprisingly, average returns are much lower for the episodes in which the crash comes sooner. For example, for the 10 episodes in which the crash begins within 3 months, average one-year raw returns are -38%, while for the remaining episodes, average one-year raw returns are 13% --- vastly different experiences for an investor betting against the bubble! At a two-year horizon, the question of when the crash begins is less important: for the 10 episodes in which the crash begins within 3 months, average two-year returns are -48%, compared to -39% for the remaining episodes.

Our findings of elevated crash probabilities following price run-ups are similar to those in Goetzmann (2015), who studies returns following one-year 100% price increases in national stock markets. He too finds an elevated probability of a crash, but the magnitudes are much more modest. Apart from the differences in samples, our results are different from Goetzmann's because we distinguish between a crash and low returns. Our definition of a crash is a 40% drawdown at any point in the subsequent two years. If such a drawdown occurs after continued price run-up, total returns post price run-up may be modest (even positive) despite a crash.

IV. Characteristics of Price Run Ups and Crashes

Investors looking at industries with large price increases have a good deal of information at their disposal beyond price, such as turnover, issuance, patterns of volatility, and fundamentals. In this section, we draw on narrative accounts of bubbles from Mackay (1852), Kindleberger (1978) and others, as well as studies of the .com bubbles of the late 1990s, to systematically construct non-price features of the price run-ups identified in the last section. Our first objective is to establish whether any of these characteristics differ systematically between price run-ups that subsequently crash, and price run-ups that do not. In Section V, we ask whether these additional characteristics can also help forecast future average returns, meaning whether an investor can use the information to time an apparent bubble.

We consider characteristics of six types, all but one motivated by prior accounts of bubbles, and partially driven by data availability (since we require the characteristics to be available as far back 1926 in the US data). Our first set of measures are related to trading volume and volatility, which some studies find to be elevated during recent bubbles (Hong and Stein 2007). Second, many authors have described bubbles as arising from new industries and paradigm shifts (Kindleberger 1978; Garber 1989, 1990; Greenwood and Nagel 2009). We construct a variable "age tilt", defined below, which measures the extent to which the price run-up is concentrated among younger firms. Third, some authors have suggested that during periods of extreme mispricing, firms issue additional equity, both to take advantage of such mispricing and to fund investment opportunities (Ritter 1995; Baker and Wurgler 2000; Pontiff and Woodgate 2008). Fourth, a vast empirical literature shows that scaled price variables (such as P/E or book-to-market ratios) help forecast average return in the cross-section of equities (Fama and French 1992, 1993). Fama and French provide book equity value for firms between 1926 and the 1960s (when they become available more broadly on Compustat), allowing us to compute book-to-market ratios for most industries in our sample. We also include a measure of market valuations, the Shiller cyclically adjusted price-earnings ratio (CAPE). Fifth, we measure fundamentals using sales growth across the industry, beginning in 1951 when the data becomes available from Compustat.

Last, we create a new variable to capture the acceleration of the price path. Here we have in mind that the past 24-month return only coarsely captures the path of prices. A return of 100%

over 3 months may be more likely to end in a crash than one accrued more steadily over a two-year period.

Measuring bubble features systematically is a data challenge, because we must respect secular changes in the data (such as vast increases in trading volume between 1925 and today, or large time-series variation in idiosyncratic volatility (Campbell, Lettau, Malkiel, Xu 2001)), while at the same time comparing episodes that occur at different times. For example, our construction of characteristics must allow us to compare the run-up in utility stocks in 1929 with that of .com stocks in the late 1990s. These concerns loom particularly large for the characteristics of volatility, turnover, and age.

We have experimented with two simple ways to deal with this challenge. The first is to compute the percentage change of that characteristic (say, volatility or turnover) compared to its average value in the year prior to when the price run-up began. The second approach is to use a purely cross-sectional measure of each characteristic by comparing the industry to other industries at the same time. The former emphasizes time-series changes in industry attributes, while the latter emphasizes contemporaneous differences between industries. Both can be heavily impacted by the listings of new firms if the new firms differ in their characteristics from existing firms in the industry. But in practice, both ways of measuring industry characteristics lead us to similar conclusions. For example, as documented by Hong and Stein (2007) and Barberis, Greenwood, Jin, and Shleifer (2016), .com stocks experienced an increase in trading volume between 1997 and 1999, but also had high trading volume compared to other industries in 1999. Below we present results based on cross-sectional comparisons, but the Appendix presents results for time-series adjusted comparisons.

We define the following characteristics:

Volatility: Each month, we compute volatility of daily returns of each stock in the industry. Let X denote the percentile rank of volatility in the full cross-section of firms. Industry volatility is the value-weighted mean of X for that industry. For example, following the 100% price run-up over a two-year period in March 1928, the volatility rank of Automobiles was 0.63, meaning that 63% of firms had lower volatility than the average firm in the Automobile industry at that time.

Turnover: Turnover is shares traded divided by shares outstanding. For Nasdaq stocks, due to the well-known double counting, we divide turnover by two (Anderson and Dyl 2007). To compute industry turnover, we percentile rank monthly turnover for every stock in CRSP, and then compute the value-weighted turnover rank for each industry. For example, turnover of the software industry in March 1999 was 0.86, meaning that value-weighted turnover of the industry was higher than 86% of all listed stocks.

Age: Firm age is measured as the number of years since the firm first appeared on Compustat or on CRSP, whichever of these came first. To compute industry "age", we percentile rank age for every stock in CRSP, and then compute the value-weighted rank for each industry.

Age "tilt": Because industry definitions are imperfect, this variable is meant to capture whether the price run-up occurred disproportionately among the younger firms in the industry. Age tilt is the difference between the equal-weighted industry return and the age-weighted industry return.

Issuance: Percentage of firms in the industry that issued equity in the past year. A firm is said to have issued equity if its split-adjusted share count increased by five percent or more. Issuance was elevated in many, but not all, price run-ups. In March 1999 in the Software industry, Issuance was 48%, meaning that 48% of the firms in the industry had either gone public or issued at least 5% new stock in the most recent year.

Book-to-market ratio: We use book-to-market ratio mainly because we can compute it for all stocks going back to the 1920s, relying on Ken French's book equity data for firms between 1925 and 1965.

Sales growth: For firms with at least two years of revenue data ending in in the month of the price run-up or before, we calculate the one-year sales growth based on the most recent two observations, and then compute the value-weighted rank for each industry. By construction, this this omits information on newly listed firms for which we do not have two years of data.

CAPE: The cyclically-adjusted market price-earnings ratio in the month in which the price run-up is identified, available on Robert Shiller's website. International CAPE series are available through Global Financial Data, covering 29 countries in our sample.

Acceleration: This measures the convexity of the price path. We define it as the difference between the two year return and the return for the first year of that two year period $R_{t\text{-}24\rightarrow t} - R_{t\text{-}24\rightarrow t\text{-}12}$. This measures how much of the price appreciation has occurred most recently.

Because our measures for volatility, age, turnover and sales growth are based on percentile ranks, by construction the equal-weighted mean of each characteristic is 0.50 at all points in time. The remaining variables, have a construction which is more time invariant, and so we use these variables in their natural units.

Figure 5 plots these characteristics in event time for the 41 industry price run-ups that we identify in US data. For each characteristic, the left panel plots means for the industries that crash and compares them to the industries that do not. All plots are done in "event time" where event time of zero corresponds to the end of the month in which we first noticed a 100% price run-up. Looking across the numerous attributes shown, the most stunning patterns in the data occur for the attributes of volatility, age tilt, issuance, the book-to-market ratio, and the market CAPE ratio. For example, Panel A shows that that volatility and turnover tends to be elevated during the price run-ups that subsequently crash, compared to price run-ups that do not crash. Panel H shows that, consistent with our earlier observations, crash episodes tend to be associated with large increases in the market adjusted P/E.

Table 4 summarizes features of price run-ups and crashes. For each characteristic, in columns (1) and (2), as a benchmark we show the mean and standard deviation of that characteristic across all industry-months. In the next two columns, we summarize the characteristic for all price run-ups, and then separately show means for the price run-ups that crashed, and those that did not. Finally, in the last two columns, we show the difference in characteristics between price run-ups with and without a crash, and the *t*-statistics on this difference. As before, standard errors account for the clustering of events in calendar time. Significant values in the last column suggest that, *conditional on a price run-up*, these characteristics may help forecast a potential crash. The top four lines of the table summarize average pre- and post-run-up returns for these subsamples, mirroring our results from Table 1.

We start with volatility. Table 4 shows that in general, price run-ups are associated with highly volatile firms. Industry volatility for price run-ups is 0.51, compared with 0.33 for the full

sample mean. The table shows that the average *level* of volatility is approximately the same among the price run-ups that crash and the price run-ups that do not. However, we see significant differences when we study one-year changes in volatility. On average, industries that crash have experience rapid increases in volatility relative to other industries in the year prior (1-year Δ = 0.08), while industries that do not subsequently crash experience no such increase (1-year Δ = -0.01), with the difference of 0.10 significant at the 5% level.

Proceeding in this way down column (9) in Table 4, we can read the difference between the characteristics of price run-ups that crash, and those that keep going. Changes in volatility, age tilt, issuance, the market CAPE, and acceleration differ between price run-ups that crash and price run-ups that keep going at the 5% level. Firm age and the industry book-to-market ratio also appear predictive, although the results are only significant at the 10% level. In short, price run-ups experiencing increases in volatility, involving younger firms, higher returns among the younger firms, and accelerating faster and in periods of overall good stock market performance, are all more likely to crash.

Surprisingly given the attention paid to trading volume in the most recent .com bubble, Table 4 shows that turnover does not seem to be a characteristic that meaningfully distinguishes the price run-ups that ultimately crash. That is not to say that turnover is not elevated during run-ups: on average, turnover is extremely elevated among the 41 run-ups (an average of 0.68, compared to an unconditional average of 0.55). However, turnover is equally elevated in the run-ups that keep going as it is among the episodes in which the price run-up ultimately crashes.

Table 4 also shows that sales growth, our proxy for fundamentals, is of little use to distinguish between price run-ups that crash and those that continue, because all of the episodes that we study have high sales growth.

Table 5 repeats this analysis for the 104 price run-ups among international sector portfolios. Across all the characteristics we consider, the results in Panel B are broadly consistent, and in some cases statistically somewhat stronger, than our findings in the US, mainly driven by the larger number of observations. For example, the one-year change in volatility is higher among the price run-ups that crash and the price run-ups that do not (a difference of 0.055, t-statistic of 1.5). But unlike in the US, the *level* of volatility of the industry also appears

to be a strong signal that the price run-up will crash: the difference between run-ups with a crash and run-ups without is 15.6 percentile points, with a t-statistic of 5.63.

Much like in the US data, we find that price run-ups experiencing increases in volatility, involving younger firms, higher returns among the younger firms, higher issuance, lower book to market ratios, high market P/E, and faster acceleration, are all more likely to crash. However, issuance is a statistically weaker feature of price run-ups that crash internationally than in the United States. And, as with our results for4 the United States, we find that turnover is elevated during price run-ups, but does not help distinguish between the price run-ups that will crash, and the price run-ups that keep going.

V. Betting on Bubbles

The fact that volatility, age, turnover, issuance and price acceleration are associated with price run-ups that crash does not automatically mean that they can help an investor time the bubble. In this section, we move from static correlates of a price run-up to the returns experienced by an investor who seeks to avoid the crash. The distinction between identifying a bubble correctly and actually earning a positive abnormal return from timing come from three effects. First, even if a bubble is called correctly ex ante, an investor may experience losses as prices continue to rise prior to the crash, particularly at short horizons. Second, in an effort to avoid losses from a potential crashing bubble, the investor may pass up the equity premium for too long, undermining whatever excess returns we may earn during the crash itself. Third, there is tremendous variation in ex post returns, even among the run-ups that crash (from -27% excess returns at a 2-year horizon in Personal Services stocks in 1969 and 1970, to the -77% excess return experienced by Steel stocks in 2001 and 2002.). A trading strategy that helps an investor avoid a minor crash is much less valuable that one that helps the investor avoid a major crash such as the one experienced by Steel stocks in 2001 and 2002.

Our baseline strategy, from which all other strategies are evaluated, is to simply hold the industry following the initial price run-up. From this starting point, we develop trading signals that instruct an investor to exit this holding by conditioning on a price run-up, or a price run-up in conjunction with other characteristics.

We consider two ways to use such a sell signal. In the first, we move capital from the industry into the value-weighted market portfolio. In the second, once a signal has identified a bubble, we move all of the capital into the risk-free asset. Switching to the risk-free asset, rather than the market, is likely to produce better returns only if the bubbles we identify correctly crash during periods of poor market performance.

Table 6 summarizes the returns to simple strategies that, conditional on a price run-up having occurred, monitor characteristics of the industry such as volatility, turnover, or issuance, and decide whether or not to sell *right away* based on that data. This approach corresponds exactly to our previous weak-form tests of returns after a run-up, except we use additional data. To avoid data snooping, all strategies: (1) are based on average characteristic values identified in Table 4 and Table 5; (2) only consider one characteristic at a time; and (3) never buy back the industry once the industry meets the "sell" signal. The Appendix considers additional strategies that re-enter the market *after* a crash has occurred, a tweak that generally improves the performance of an investor who is sitting out the collapse of a bubble.

The table shows that holding all industries with a price run-up leads to compounded total returns of 9% at a one-year horizon, 0% at a two-year horizon, and 10% at a four-year horizon, reflecting exactly ex post performance reported in Table 1 and Table 3. A strategy of simply conditioning on a price run-up of 100% (and thus "selling" all price run-ups) slightly underperforms the passive benchmark by roughly 5% at a one-year horizon. As implied by our earlier results, this is because conditioning on the price increase alone identifies 41 price run-ups, 54% of which turn out to crash, and 46% of which are false positives. As we showed earlier, even when we correctly identify a price run-up that will crash, on average the industry continues to perform well for another 6 months.

At horizons of 2- and 4-years, conditioning on the price run-up alone slightly outperforms the passive benchmark if the proceeds are invested into the market when the bubble is identified. The strategy outperforms more significantly (by 13% at a two-year horizon) if the proceeds are invested in the risk-free asset. The statistical significance is quite limited, however, indicating

that an investor bears significant uncertainty of the future return. We should bear in mind that these tests are based on only 41 observations.[13]

We now turn to strategies that in addition to the price run-up, condition on volatility, turnover, and other characteristics examined in Table 4. Begin with volatility. In Table 4 we showed that price run-ups that crash have higher volatility during the run-up, compared to price run-ups that do not. We can incorporate volatility into the trading strategy by asking whether, at the moment of the price run-up, the volatility is greater than the mean among crashed price run-ups shown in Table 4. Doing so identifies 20 bubble candidates, 65% of which eventually crash, and 35% of which continue to go up or sustain.[14]

Table 6 shows the returns that accrue to an investor who follows strategies of this sort. By conditioning on volatility and switching to the risk-free asset when a bubble is identified, the investor earns 10% at a 1-year horizon, 10% at a 2-year horizon, and 23% at a 4-year horizon. Compared to the passive strategy, this represents outperformance of 1%, 10%, and 13% respectively, with the alphas statistically significant at horizons of 4 years.

Proceeding in this way for the other characteristics (i.e., selling the industry when it reaches a threshold value based on Table 4), Table 6 shows that an investor can condition on characteristics to earn positive abnormal returns relative to the passive strategy. Column (13)-(15) of the table show 1-year, 2-year and 4-year alphas from the "switch into risk-free when bubble identified" strategies. Strategies based on volatility, company age, book-to-market ratio and price acceleration manage to produce excess performance of 10% or more over two years.

At a two-year horizon, conditioning on a price increase *and* characteristics generates outperformance that is comparable to that of conditioning on prices alone. However, in nearly all cases, conditioning on characteristics produces returns with lower standard deviations (and thus

[13] Because standard errors are clustered by calendar year, we break the normal link between t-statistics and the Sharpe ratio on the strategy.

[14] Our choice of threshold for calling the bubble in effect balances type 1 and type 2 error. In general, by setting a very high threshold, we have increasing confidence that the strategy calls the bubble correctly. On the other hand, by setting a very high threshold we also avoid making a call on a larger set of episodes. We use the mean reported in column (5) of Table 4 (and Table 5 for International Sectors) to avoid concerns of data mining. Because we condition on the sample mean, this introduces some look-ahead bias into our portfolio results. But any strategy we consider here is subject to this critique, because for each characteristic we must choose a threshold at which to sell.

greater statistical significance) than conditioning just on prices. This is because characteristics can help an investor avoid the most devastating crashes, but at the cost of also exiting the market in a few cases where there were the largest subsequent price increases.

Another important observation from Panel A of Table 6 is that trading strategies that move capital into the risk-free asset when a bubble is identified tend to perform better than the strategies that move capital into the value-weighted market. This can be seen by comparing column (4) and column (7) at a one-year horizon, column (5) and column (8) at a two-year horizon, and column (6) and column (9) at a four-year horizon. For example, at a two-year horizon, an investor who conditions on age and moves capital into the risk-free earns raw returns of 13% (t-statistic of 2.36), compared to an investor who moves capital into the market, who earns raw returns of only 6% (t-statistic of 1.58).

Panel B of Table 6 shows the corresponding results for international sectors. Conditioning on a price run-up alone, an investor who switches to the risk-free when the bubble is identified earns returns of 3%, 5%, and 9% at horizons of 1, 2, and 4 years. These represent alphas of 3%, -1%, and -31%. Conditioning on characteristics, and particularly volatility, issuance, age, and acceleration (and less so for turnover or age tilt) improves performance, particularly at horizons of 1, and 2 years. Overall, compared to the results in Panel A, the outperformance achieved by conditioning on characteristics is smaller in magnitude, but the overall pattern of results is largely the same.

We draw four conclusions from Table 6. First, at a horizon of one-year, it is virtually impossible to generate outperformance, reflecting our earlier observation that even if we call the bubble correctly, we tend to miss the peak by an average of five months. Second, at a horizon of two years or more, conditioning on the price run-up together with volatility, issuance, and age, age tilt, book-to-market, and acceleration generates statistically significant outperformance, even with our very limited sample of bubble events. Crucially, there is significant variation in the ability of characteristics to help generate performance. Turnover, for example, despite being elevated during many prominent historical bubbles, appears to be of little use in timing the bubble. Third, outperformance tends to be larger, both in terms of economic and statistical significance, for trading strategies in which we switch out of the industry with a price run-up, and into the risk-free asset, compared to the strategies that put the proceeds into the broader

stock market. This reflects our earlier observation that industry price run-ups tend to occur during broader market rallies. If we do call an industry bubble correctly, it is best to avoid the stock market altogether. In fact, the second row of Table 6 Panel A suggests that we can achieve modest outperformance even by conditioning on just the price increase, although the returns are not statistically significant. Fourth, trading strategies that condition on characteristics trade off false positives and false negatives. Conditioning on high issuance, for example, identifies 14 "bubbles" ex ante, 9 of which actually crash—an excellent hit rate – but also fails to call the remaining 13 bubbles that do crash.

VI. Conclusion

In this paper we explored Fama's challenge of whether stock market bubbles can be identified ex ante. We used industry-level data for both the US and internationally, and asked specifically whether we can predict what happens after a 100% industry abnormal return. We presented four findings. First, Fama is largely correct in his claim that returns going forward are largely unpredictable from the mere fact that an industry has gone up 100%. Some of the industries with such run-ups crash, but others keep going up at least for some time. Second, although average returns are hard to predict, the probability of a substantial crash after a 100% return is much higher than it is on average, and in fact rises monotonically as past returns increase. Third, industries with run-ups that subsequently crash exhibit some attributes that are significantly different from those that do not. They have higher volatility, stock issuance, especially rapid price increases, and disproportionate price rises among newer firms. Finally, using these attributes does help to earn abnormal returns through avoidance of some of the crashes. In sum, there are statistically significant ways to predict both the likelihood of a crash, and expected returns, after industry level price increases in both US and international data.

In analyzing this evidence we have followed particularly simple methodologies. We have not tried to search the data to find ex post optimal screens or combinations of variables to predict returns. We have only used variables that the literature has already talked about and we used them one at a time. We have not sought to identify dynamic strategies of optimal exit from the industry, but focused on simply exiting after a run-up. Most importantly, we started from

industries with a very large price increase of 100% above market, which has limited our sample to 41 episodes in US data and 104 in international data. All of this can be perhaps changed to use more sophisticated algorithms, and some of these algorithms would increase the reliability and size of abnormal returns. On the other hand, looking for more complex trading strategies would raise concerns about the lookback bias and data mining that we have tried to avoid.

We should also stress that this paper deals with predicting expected returns and crashes, and not with how to make money to take advantage of predictability. The evidence makes it abundantly clear, and we stressed throughout, that bubble peaks are extremely hard to call and therefore betting against bubbles – especially by selling short – is risky, and especially so for a leveraged investor. An arbitrageur would need to have extremely deep pockets and investors with high tolerance for volatility to make these bets.

To put these points somewhat differently, Fama has set a bar for identifying bubbles. He said one needs to find evidence that crashes and returns can be predicted. We believe that the evidence clears that bar. Of course, the bar can be raised in many ways. Perhaps the future will not be like the past, and the characteristics that helped us identify which price run-ups crash will be different for the next bubble. Perhaps what really matters is arbitrage profits, not predictability. Perhaps portfolios that have gone up sharply in price and exhibit characteristics that entail poor subsequent performance are not "real bubbles". And perhaps even the flat average returns we have documented following price run-ups will be judged to be inconsistent with the logic of conventional asset pricing, in which periods of high risk reward investors with higher returns. We leave the clearing of these much higher bars to future work.

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Figure 1. Returns following 100% Price Run-ups

The figure plots cumulative returns to all US industries that experienced a large price run-up between month *t*-24 and *t*. The sample includes all industries between 1926 and 2012 and is based on Fama and French (1997) 49-industry classifications. We identify 41 episodes in which an industry experiences a raw and net-of-market return of 100% in a two-year period, and a raw return of 50% or more in a five-year period. 22 episodes experienced a subsequent crash, and 19 episodes did not. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. In the figure's horizontal axis, 0 denotes the period in which an industry first experiences a 100% return as described by our screens.

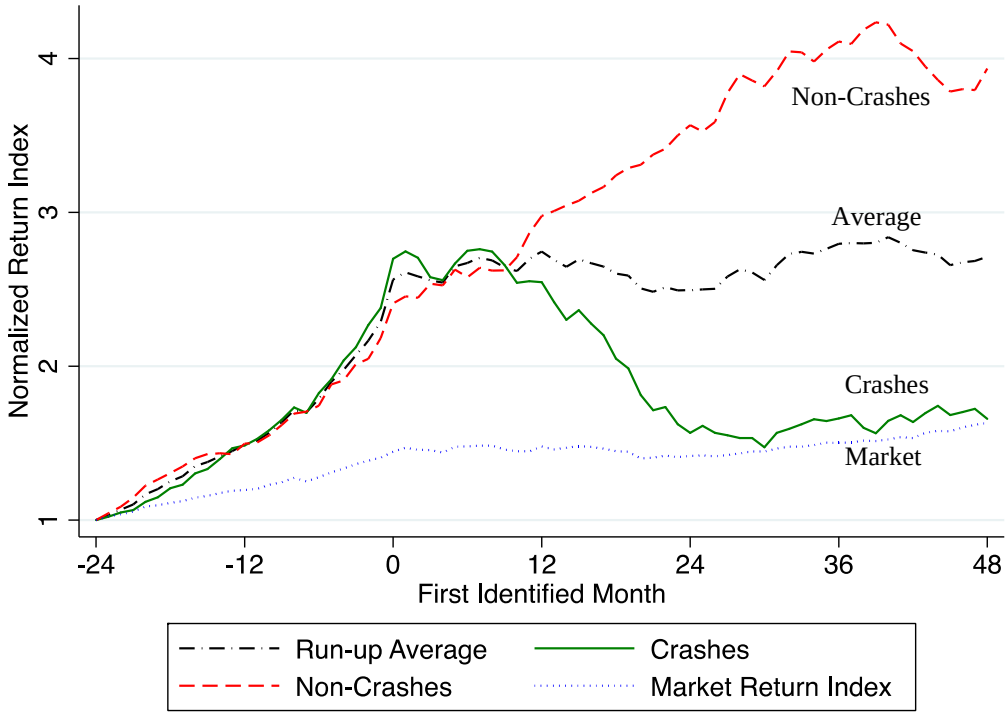


Figure 2. Returns following 100% Price Run-ups: International Data

The figure plots cumulative returns to all country-sectors that experienced a large price run-up between month *t*-24 and *t*. The sample includes all sectors between 1985 and 2013 and is based on two-digit GICS sector classifications. We identify 104 episodes in which an industry experiences a raw and net-of-market return of 100% in a two-year period, and a raw return of 50% or more in a five-year period. 51 episodes experienced a subsequent crash, and 53 episodes did not. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. In the figure's horizontal axis, 0 denotes the period in which an industry first experiences a 100% return as described by our screens.

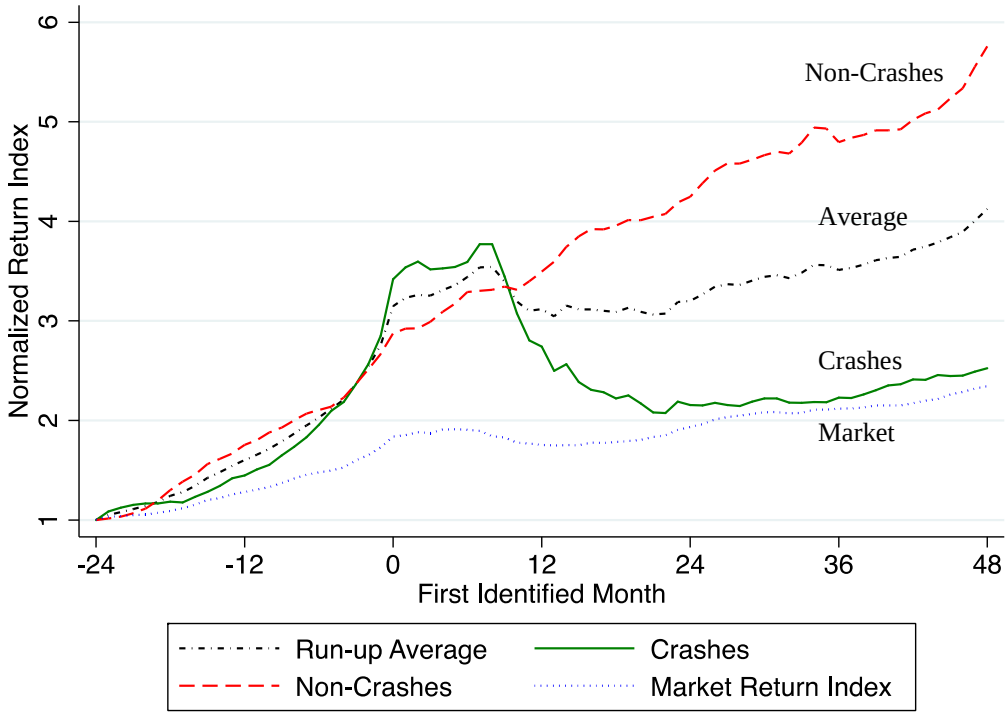
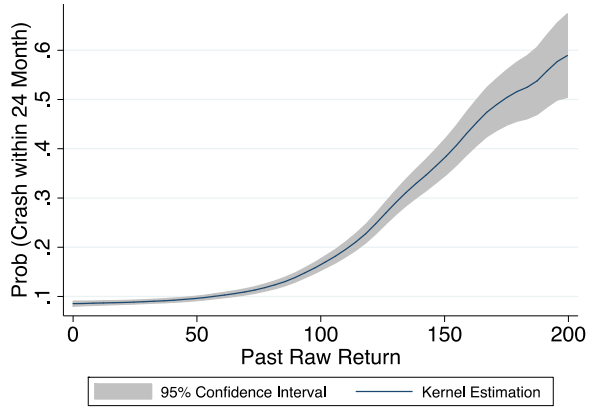


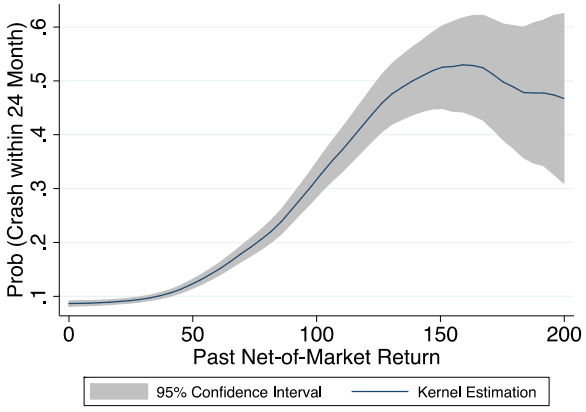
Figure 3. The Role of Past Returns in Predicting Crashes

The figure estimates the subsequent probability of crash as a function of past two-year raw and net-of-market returns in both US industries and international country-sectors. Panel A and B are based on monthly Fama-French 48 US industry panel data 1926-2014 with no less than 10 firms and positive past raw or net-of-market return ("Other" industry is excluded). Panel C and Panel D are based on monthly country-sector panel data 1985-2015 with no less than 10 firms and positive past raw or net-of-market return. Crash for any month is defined as a 40% drawdown from any point in the two years after the specific month. The shaded area represents the 95% confidence interval. Epanechnikov kernel is assumed in non-parametric estimation.

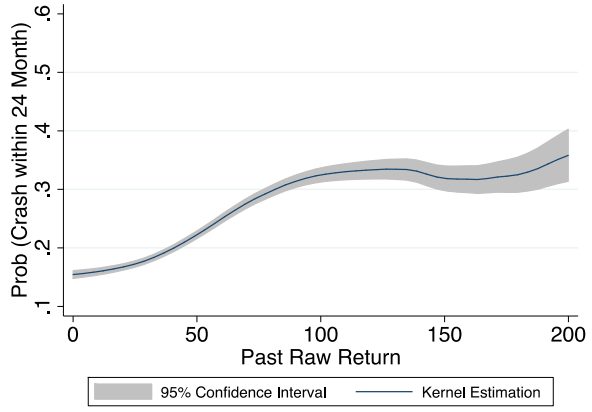
Panel A: US Industries
Predictor Variable: 2-year Raw Past Return



Panel B: US Industries
Predictor Variable: 2-year net-of-market Return



Panel C: International Sectors
Predictor Variable: 2-year Raw Past Return



Panel D: International Sectors
Predictor Variable: 2-year net-of-market Return

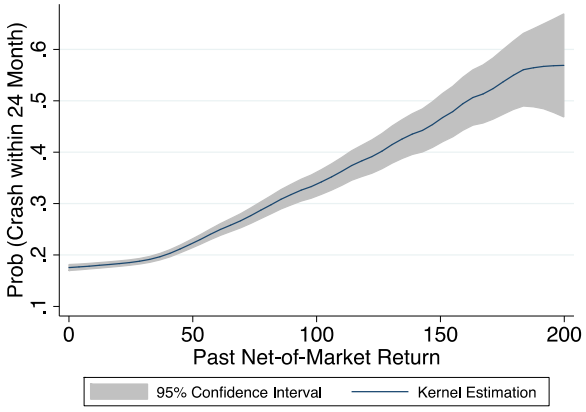
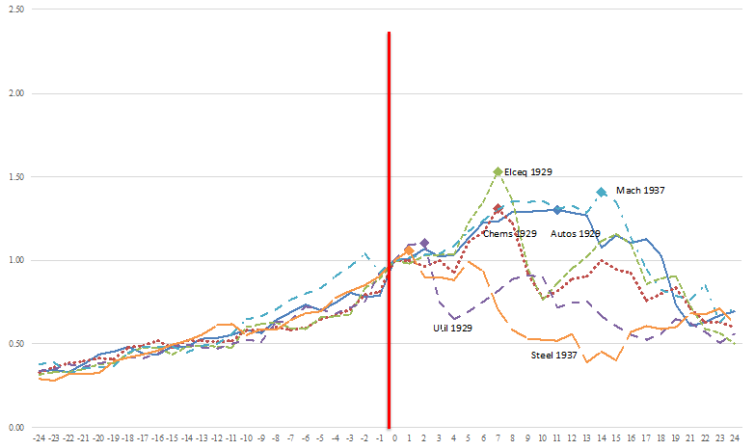


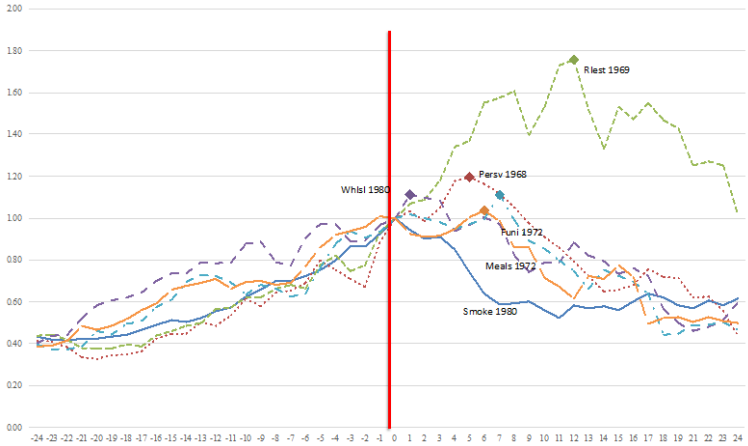
Figure 4. Bubble Peaks Following the Run-up

The figure shows cumulative returns for the 22 episodes for which there was a subsequent crash following price run-up. Event time of 0 denotes the month when price run-up is first identified. All price run-ups have been normalized to have a total return index of 1 at this time. We separate the episodes into four figures for visibility.

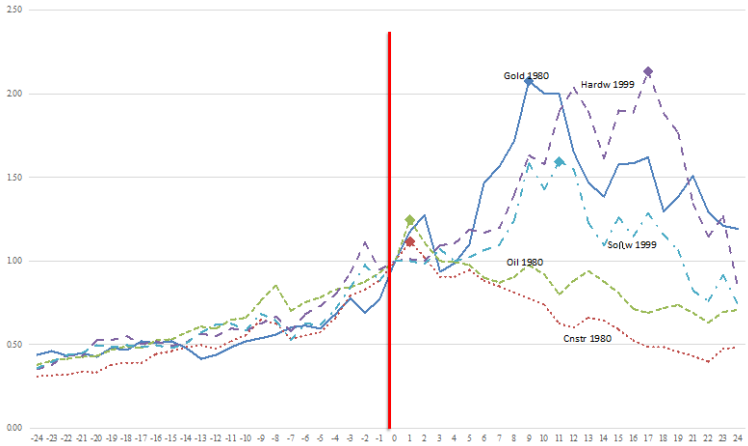
Panel A: Crashes in 1927-1937



Panel B: Crashes in 1937-1980



Panel C: Crashes in 1980-1999



Panel D: Crashes in 1999-2012

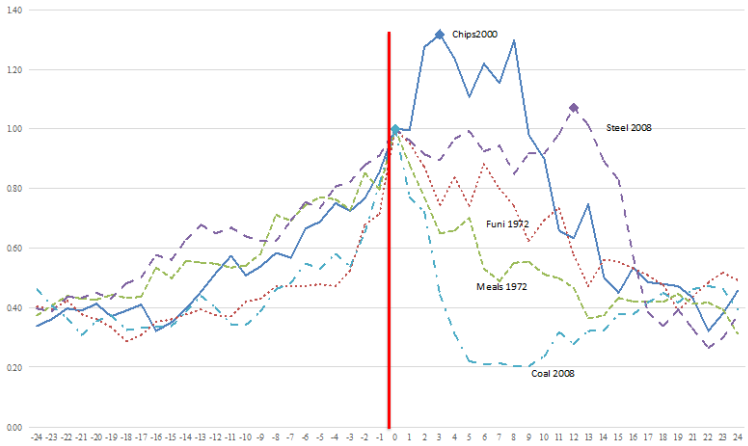
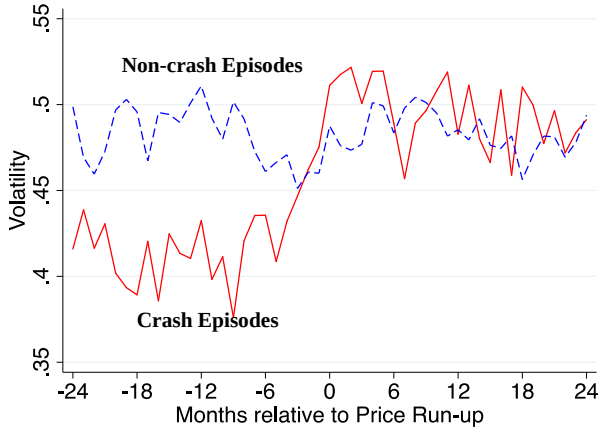
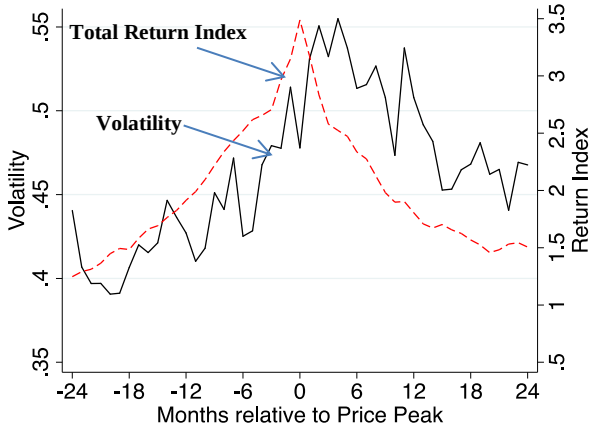


Figure 5. Features of Price Run-ups

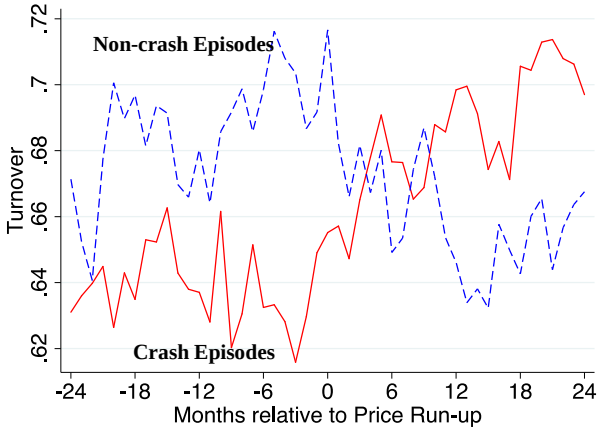
The figure shows the characteristics for price run-ups, separated by those that crash (solid line) and those that do not (dashed). The figures in the left-column show event time plots of these characteristics, which include volatility, turnover, age, age tilt, issuance, the book-to-market ratio, sales growth, and the market cyclically adjusted P/E from Shiller. Construction of the characteristics and their aggregation to the industry level is described in the text. The right column shows these same characteristics for the crash events only, and plotted in "peak time" where period 0 denotes the month end just before the start of the crash. Identical figures for international sectors are presented in Appendix Figure 1.

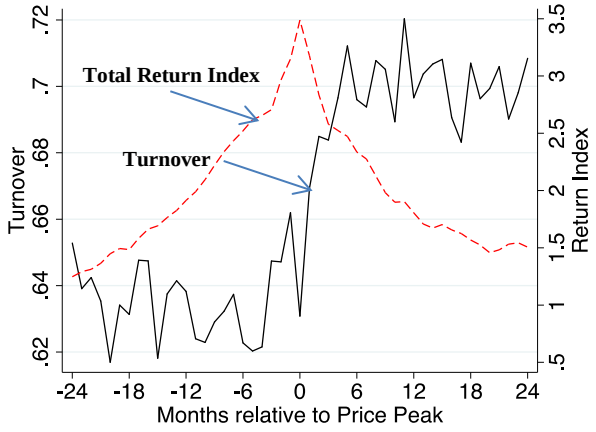
Panel A: Volatility



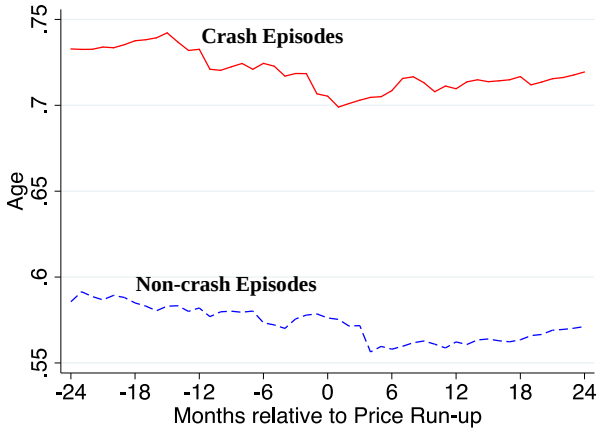


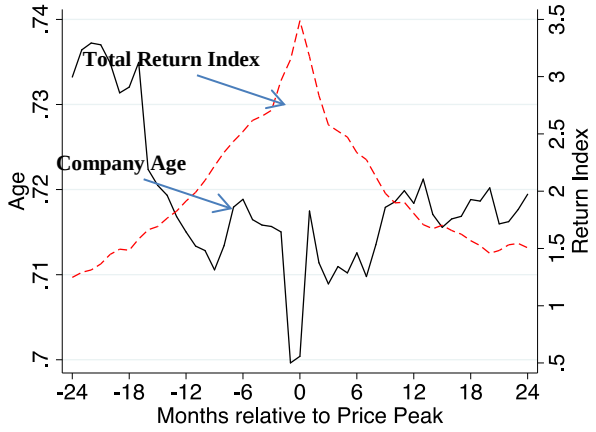
Panel B: Turnover



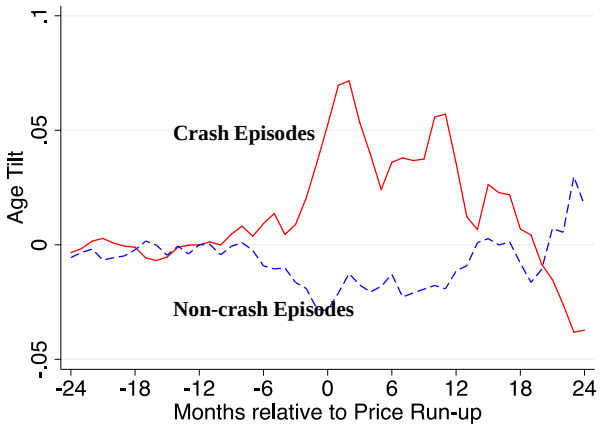


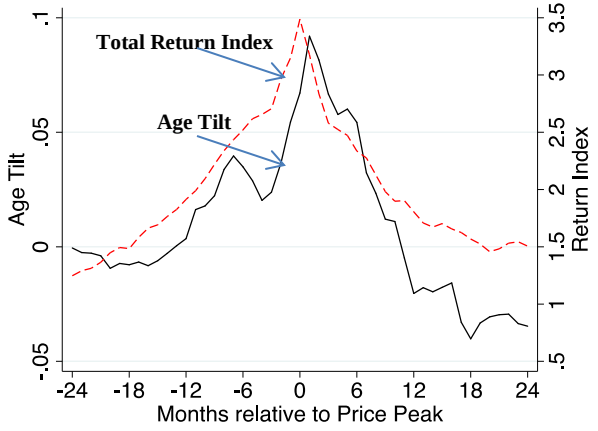
Panel C: Company Age



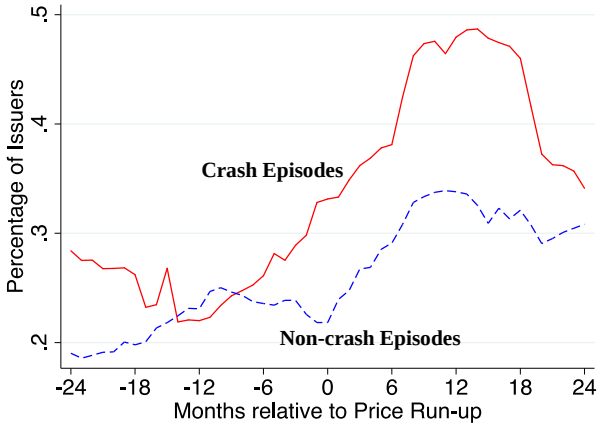


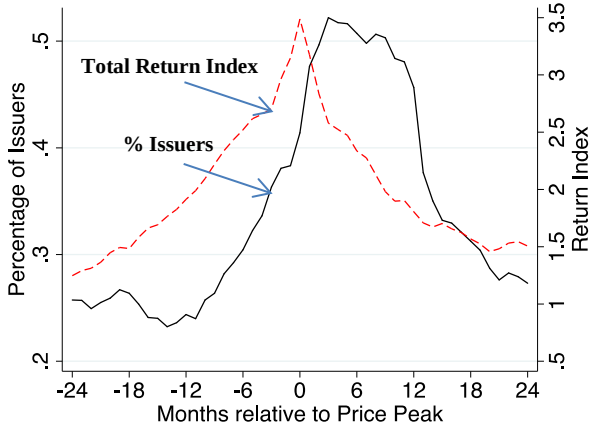
Panel D: Age Tilt



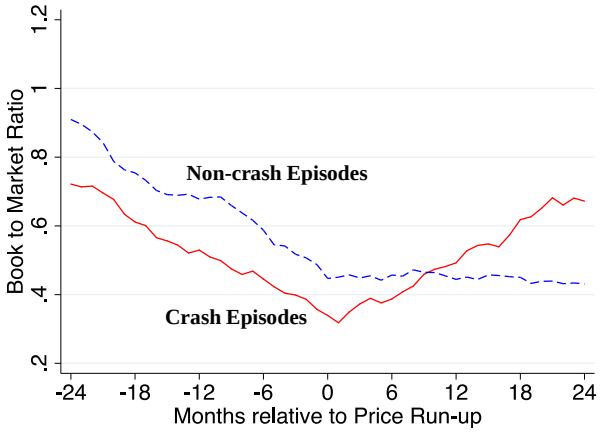


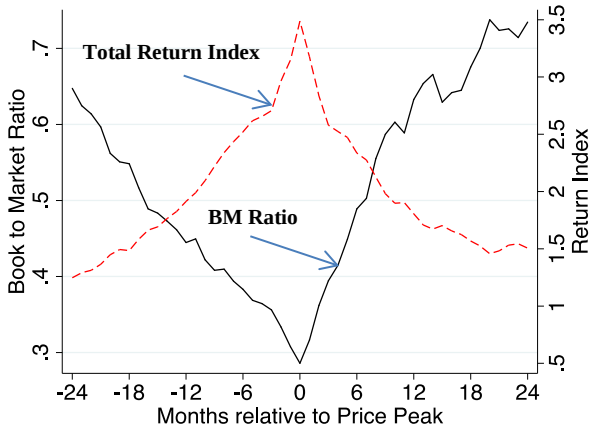
Panel E: Issuer Pecentage



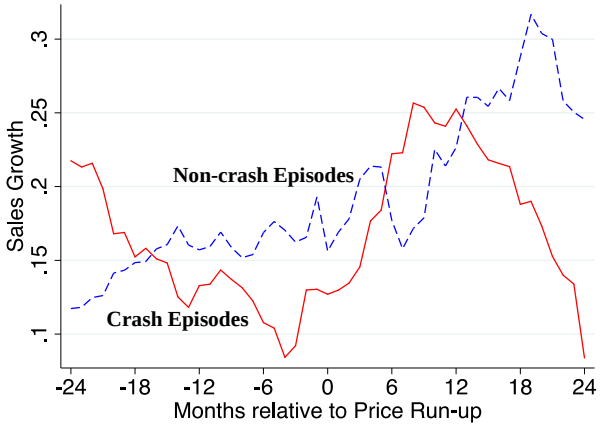


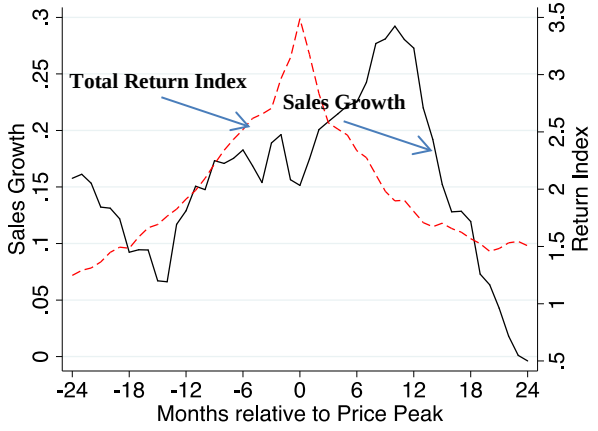
Panel F: Book-to-Market Ratio



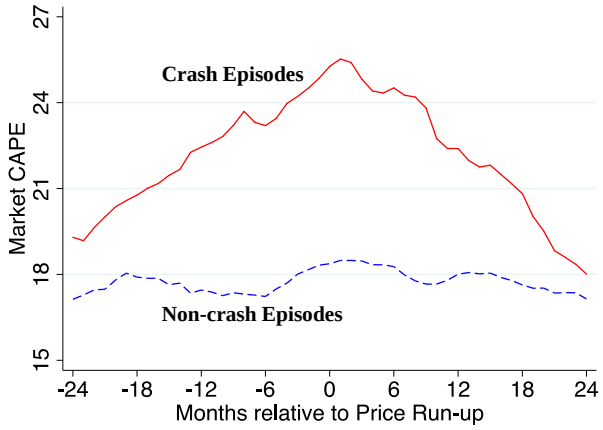


Panel G: Sales Growth





Panel H: Market CAPE Ratio



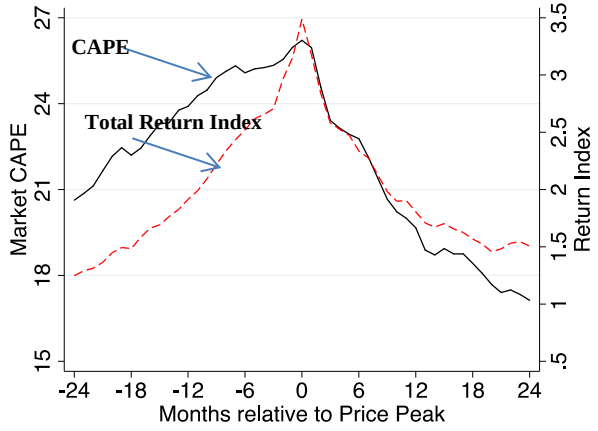


Table 1. Returns after Industry Price Run-ups, US industries 1928-2012

We list all price run-ups of Fama-French 49 industries, defined as any incident with (1) 100% raw and value-weighted return over the past two years (2) 100% net-of-market returns over the past two years, and (3) 100% raw return over the past five years. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. We document subsequent performance for all price run-ups, including raw/net-of-risk-free/net-of-market return, maximal price drawdown within 24 months, number of months to price peak (for crashes only) and raw return to price peak (for crashes only).

Panel A. Run-ups that Subsequently Experienced a Crash

Industry Name	Number of Firms	Price Run-up first observed:	Subsequent Performance & Maximal Drawdown over next 2-years								
			12mo Raw Return (%)	24mo Raw Return (%)	12mo net-of-RF Return (%)	24mo net-of-RF Return (%)	12mo net-of-market Return (%)	24mo net-of-market Return (%)	24mo Maximal Drawdown	Months to Price Peak	Return to Peak
Automobiles and Trucks	42	1928/03	29%	-22%	25%	-30%	-6%	-58%	-53%	11	30%
Chemicals	13	1929/01	-5%	-47%	-10%	-55%	3%	-15%	-67%	7	53%
Electrical Equipment	18	1929/01	-11%	-41%	-16%	-48%	-3%	-8%	-55%	7	31%
Utilities	23	1929/07	-26%	-47%	-29%	-52%	-1%	2%	-54%	2	11%
Machinery	37	1936/05	32%	-34%	32%	-34%	15%	-3%	-55%	14	41%
Steel Works	61	1937/02	-44%	-35%	-44%	-36%	-10%	-11%	-63%	1	6%
Tobacco Products	13	1961/11	-42%	-42%	-45%	-48%	-32%	-52%	-44%	0	0%
Real Estate	12	1968/05	-21%	-63%	-27%	-76%	-29%	-46%	-69%	5	20%
Personal Services	24	1968/05	76%	-14%	70%	-27%	68%	3%	-51%	12	76%
Wholesale	52	1968/10	-12%	-45%	-18%	-59%	-9%	-31%	-59%	1	11%
Entertainment	24	1972/05	-25%	-54%	-30%	-67%	-24%	-39%	-60%	7	11%
Restaurants &Hotels	40	1972/06	-39%	-53%	-44%	-67%	-39%	-39%	-55%	6	4%
Precious Metals	14	1979/12	65%	8%	53%	-19%	32%	-18%	-48%	9	107%
Petro and Natural Gas	51	1980/10	-40%	-40%	-55%	-68%	-41%	-58%	-64%	1	11%
Construction	272	1980/10	-12%	-25%	-27%	-53%	-13%	-43%	-49%	1	24%
Computer Hardware	190	1999/03	103%	-32%	99%	-43%	85%	-25%	-68%	17	113%
Computer Software	551	1999/11	54%	-36%	50%	-47%	36%	-29%	-60%	11	59%
Electronic Equipment	347	1999/12	-37%	-56%	-43%	-66%	-28%	-37%	-75%	3	32%
Meas. & Control Equipment	129	2000/02	-42%	-51%	-48%	-61%	-34%	-35%	-59%	0	0%
Steel Works	77	2000/08	-53%	-70%	-58%	-77%	-29%	-33%	-66%	0	0%
Steel Works	48	2007/05	7%	-59%	4%	-63%	14%	-22%	-75%	12	7%
Coal	13	2008/06	-72%	-64%	-73%	-65%	-46%	-49%	-74%	0	0%
Crash Mean	**93**	**N/A**	**-5%**	**-42%**	**-11%**	**-53%**	**-4%**	**-29%**	**-60%**	**5.8**	**29%**
All Run-up Mean	**67**	**NA**	**9%**	**0%**	**4%**	**-10%**	**5%**	**0%**	**-42%**	**N/A**	**N/A**

[Table 1 Continued]

Panel B. Run-ups without a Crash in the next 2 years

Industry Name	Number of Firms	Price Run-up first observed:	Subsequent Performance & Maximal Drawdown over next 2-years						
			12mo Raw Return (%)	24mo Raw Return (%)	12mo net-of-RF Return (%)	24mo net-of-RF Return (%)	12mo net-of-market Return (%)	24mo net-of-market Return (%)	24mo Maximal Drawdown
Aircraft	12	1939/10	-11%	-8%	-11%	-8%	-2%	8%	-27%
Textile	21	1946/05	-35%	-4%	-36%	-5%	-13%	1%	-32%
Aircraft	21	1954/12	27%	50%	26%	46%	-4%	11%	-17%
Pharma. Products	17	1958/11	35%	31%	32%	25%	20%	18%	-14%
Aircraft	31	1965/11	-3%	36%	-8%	27%	6%	27%	-26%
Industrial Mining	31	1966/01	3%	32%	-2%	23%	7%	26%	-28%
Meas. & Control Equipment	28	1967/04	6%	14%	2%	4%	-1%	-3%	-21%
Construction	19	1967/06	56%	40%	51%	29%	42%	26%	-17%
Entertainment	27	1967/06	45%	34%	41%	23%	32%	19%	-29%
Restaurants &Hotels	23	1967/11	61%	55%	56%	43%	43%	49%	-19%
Aircraft	33	1976/09	4%	70%	-1%	58%	8%	63%	-12%
Healthcare	36	1978/04	39%	136%	30%	115%	28%	114%	-26%
Computer Software	14	1978/08	15%	124%	5%	103%	3%	92%	-28%
Healthcare	35	1980/04	102%	69%	90%	42%	70%	47%	-32%
Computer Software	205	1992/10	16%	42%	13%	36%	1%	23%	-8%
Textile	49	1992/10	16%	-3%	13%	-10%	2%	-23%	-21%
Recreation	44	1992/10	29%	21%	26%	15%	15%	2%	-15%
Construction	51	2003/10	21%	68%	20%	65%	11%	49%	-13%
Industrial Mining	12	2005/02	41%	110%	37%	101%	32%	88%	-12%
Non-crash Mean	**37**	**N/A**	**25%**	**48%**	**20%**	**39%**	**16%**	**33%**	**-21%**
All Run-up Mean	**67**	**NA**	**9%**	**0%**	**4%**	**-10%**	**5%**	**0%**	**-42%**

Table 2. Returns after Industry Price Run-ups, International Country Sectors 1987-2013

We list all price run-ups of international country-sector industries (Two-digit GICS code), defined as any incident with (1) 100% raw and value-weighted return over the past two years (2) 100% net of market returns over the past two years, and (3) 100% raw return over the past five years. Our International data covers 37 countries with more than 8 years of data available in Compustat. We identify 104 country-sector price run-ups in 30 countries.

Panel A. Run-ups that Subsequently Experienced a Crash

Country	Number of Episodes	Country-means: Subsequent Performance & Maximal Drawdown over next 2-years across all episodes									
		Average Number of Firms	12mo Raw Return (%)	24mo Raw Return (%)	12mo net-of-RF Return (%)	24mo net-of-RF Return (%)	12mo net-of-market Return (%)	24mo net-of-market Return (%)	24mo Maximal Drawdown	Average Months to Price Peak	Average Return to Peak
Australia	1	27	-53%	-79%	-59%	-89%	-40%	-71%	-84%	4	19%
Austria	1	17	46%	5%	42%	-4%	-2%	-95%	-56%	12	46%
Belgium	1	13	-46%	-53%	-46%	-53%	-37%	-73%	-63%	5	21%
Brazil	7	33	-19%	-53%	-23%	-59%	10%	4%	-71%	8	42%
Switzerland	2	14	-41%	-51%	-45%	-56%	-25%	-42%	-63%	1	9%
China	5	175	-34%	-31%	-37%	-34%	-2%	-4%	-62%	2	14%
Germany	1	15	-14%	81%	-19%	71%	-15%	45%	-48%	23	107%
France	2	51	-41%	-55%	-45%	-61%	-12%	-25%	-69%	4	5%
Greece	3	26	-3%	-48%	-8%	-58%	17%	3%	-80%	4	141%
Hong Kong	4	37	5%	-33%	1%	-38%	-11%	-15%	-65%	4	48%
India	3	101	43%	-18%	38%	-26%	58%	10%	-68%	5	155%
Italy	2	38	-47%	-61%	-53%	-71%	-26%	-22%	-59%	0	0%
Japan	1	350	-30%	-60%	-36%	-70%	-8%	-15%	-73%	3	27%
Korea	3	89	-44%	-36%	-45%	-38%	-8%	-13%	-59%	1	4%
Malaysia	2	75	-37%	-37%	-43%	-47%	-12%	-15%	-62%	2	30%
Norway	1	16	-37%	-11%	-37%	-11%	-38%	-22%	-52%	6	25%
Portugal	1	15	-79%	-90%	-85%	-100%	-51%	-42%	-88%	0	0%
Singapore	2	30	-66%	-15%	-68%	-17%	-20%	-3%	-69%	3	2%
Sri Lanka	3	45	12%	-26%	12%	-26%	-21%	-19%	-47%	6	23%
Sweden	1	39	-33%	-68%	-39%	-78%	-10%	-27%	-85%	2	47%
Thailand	2	35	-47%	-42%	-53%	-52%	0%	2%	-57%	1	16%
Taiwan	2	52	-34%	-11%	-38%	-18%	4%	17%	-46%	4	4%
UK	1	137	-34%	-73%	-40%	-83%	-21%	-50%	-87%	3	52%
Crash Mean	**2.3**	**64**	**-23%**	**-38%**	**-27%**	**-44%**	**-5%**	**-13%**	**-65%**	**4.1**	**39%**
All Run-up Mean	**2.3**	**64**	**1%**	**7%**	**-1%**	**2%**	**3%**	**0%**	**-43%**	**N/A**	**N/A**

[Table 2 Continued]
Panel B. Run-ups without a Crash in the next 2 years

Country	Number of Episodes	Country-means: Subsequent Performance & Maximal Drawdown over next 2-years across all episodes							
		Average Number of Firms	12mo Raw Return (%)	24mo Raw Return (%)	12mo net of Risk-Free (%)	24mo net of Risk-Free (%)	12mo net of Market Return (%)	24mo net of Market Return (%)	24mo Maximal Drawdown
Australia	1	108	27%	71%	22%	62%	6%	4%	-11%
Austria	1	15	97%	156%	96%	153%	23%	-1%	-6%
Belgium	2	11	-21%	-24%	-23%	-29%	-2%	-21%	-35%
Brazil	2	31	26%	108%	23%	101%	41%	87%	-25%
Switzerland	2	24	19%	42%	18%	40%	11%	11%	-20%
China	2	228	-8%	-24%	-8%	-24%	-3%	-3%	-36%
Denmark	2	18	10%	23%	6%	17%	0%	-26%	-22%
ESP	1	12	-19%	-18%	-24%	-28%	-14%	-16%	-38%
Finland	5	26	30%	66%	29%	62%	28%	43%	-15%
France	1	19	14%	68%	8%	58%	2%	14%	-12%
UK	2	85	5%	9%	3%	4%	3%	-3%	-31%
Greece	1	20	71%	22%	67%	12%	21%	-1%	-40%
Hong Kong	2	232	-14%	-12%	-14%	-12%	-3%	-11%	-30%
India	5	119	20%	69%	19%	65%	3%	5%	-26%
Korea	2	177	24%	77%	19%	67%	3%	12%	-31%
Mexico	1	12	-7%	21%	-7%	21%	-2%	4%	-26%
Malaysia	2	64	15%	-29%	12%	-35%	-10%	-21%	-11%
Netherlands	1	40	33%	53%	30%	45%	13%	11%	-14%
New Zealand	1	10	40%	39%	35%	32%	40%	22%	-10%
Singapore	6	38	2%	20%	1%	18%	-1%	-9%	-21%
Thailand	9	37	64%	105%	63%	103%	19%	43%	-20%
South Africa	2	62	46%	95%	45%	92%	15%	-4%	-17%
Non-crash Mean	**2.4**	**64**	**25%**	**51%**	**23%**	**46%**	**10%**	**12%**	**-22%**
All Run-up Mean	**2.3**	**64**	**1%**	**7%**	**-1%**	**2%**	**3%**	**0%**	**-43%**

Table 3. Price Run-ups & Crashes

We experiment different price run-up thresholds (X = 50%, 75%, 100%, 125%, 150%), classify the identified episodes and document their subsequent performance. We define a price run-up as occurring when an industry or sector experiences a raw *and* net of market return of X% in a two-year period, and a raw return of 50% or more in a five-year period. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. For each specific pick-up threshold, we report likelihood of a subsequent crash, drawdown and subsequent average returns. Our data samples include (1) Panel A: US Industry 1928-2012 (2) Panel B: International sectors 1987-2013. T-statistics are shown in the brackets. Standard errors are clustered by calendar year in Panel A, by sector-calendar year in Panel B.

						Subsequent Average Returns					
	Likelihood of a Subsequent Crash & Drawdown					Raw Return		Net of Risk-Free Returns		Net of Market Returns	
Pick-up Threshold	Number of Run-ups Identified	Number of Crashes	% Crashes	Drawdown of Crashes (%)	Average Drawdown (%)	12-month Raw Return (%)	24-month Raw Return (%)	12-month Net of Risk-Free Return (%)	24-month Net of Risk-Free Return (%)	12-month Net of Market Return (%)	24-month Net of Market Return (%)
Panel A: US Industries 1928-2012											
50%	165	32	19%	-53%	-27%	12%	22%	7%	11%	3%	3%
				[-28.19]	[-12.93]	[3.23]	[3.66]	[1.94]	[1.94]	[0.96]	[0.72]
75%	76	28	37%	-54%	-34%	12%	13%	7%	2%	4%	3%
				[-33.79]	[-10.86]	[2.54]	[1.77]	[0.48]	[0.28]	[1.29]	[0.61]
100%	41	22	54%	-60%	-42%	9%	0%	4%	-10%	5%	0%
				[-32.62]	[-8.82]	[1.26]	[-0.01]	[0.55]	[-0.94]	[1.12]	[-0.03]
125%	21	16	76%	-60%	-51%	-5%	-17%	-11%	-30%	-6%	-14%
				[-17.27]	[-9.94]	[-0.60]	[-0.98]	[-1.31]	[-1.72]	[-1.00]	[-1.04]
150%	16	13	81%	-62%	-56%	-11%	-15%	-18%	-30%	-11%	-14%
				[-17.48]	[-11.65]	[-1.40]	[-0.69]	[-2.40]	[-1.42]	[-1.79]	[-0.86]
Panel B: International Sectors 1987-2013											
50%	228	81	36%	-62%	-36%	12%	21%	9%	16%	5%	5%
				[-27.59]	[-12.84]	[3.31]	[3.37]	[2.61]	[2.62]	[2.55]	[1.86]
75%	148	61	41%	-62%	-39%	7%	15%	5%	10%	4%	5%
				[-27.33]	[-14.03]	[1.67]	[2.21]	[1.12]	[1.52]	[1.76]	[1.44]
100%	104	51	49%	-65%	-43%	1%	7%	-1%	2%	3%	0%
				[-23.16]	[-11.86]	[0.22]	[0.81]	[-0.24]	[0.24]	[0.83]	[0.01]
125%	73	39	53%	-68%	-47%	-4%	-2%	-6%	-7%	-2%	-7%
				[-23.39]	[-11.24]	[-0.58]	[-0.20]	[-1.00]	[-0.71]	[-0.51]	[-1.42]
150%	51	34	67%	-70%	-54%	-15%	-17%	-18%	-23%	-6%	-14%
				[-23.31]	[-10.60]	[-2.13]	[-1.49]	[-2.55]	[-1.94]	[-1.48]	[-2.27]

Table 4. Features of Price Run-ups and Crashes: US Industries

The table summarizes features of price run-ups of US industries in the first-identified month, all industry-month average of the features and the difference between the run-ups with subsequent crash and run-ups without. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. The features include: (1) Past return (2) Value-weighted volatility and its 1-year change (3) Value-weighted percentile ranked turnover and its 1-year change (4) Value-weighted percentile ranked firm age (5) Age tilt: equal-weight 1-year gross return minus age-weighted 1-year gross return. (6) Percentage of issuers and its 1-year change. An issuer is defined as a company that issued 5% or more shares or IPO within one year (7) Value-weighted book to market ratio (8) Value-weighted percentile ranked sales growth (9) Market CAPE (10) Acceleration: 2-year gross return minus first half 1-year gross return. *t*-statistics are based on standard errors clustered by calendar year.

	All industry-years		Run-ups		Run-ups with Crash		Run-ups with no Crash		Crash minus no Crash	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Difference**	**[t-stat]**
Past 2-year Return	0.272	(0.42)	1.563	(0.32)	1.697	(0.34)	1.408	(0.22)	0.289	[2.62]
Excess Past 2-year Return	0.023	(0.32)	1.120	(0.15)	1.136	(0.17)	1.101	(0.13)	0.035	[0.02]
Turnover and Volatility:										
Volatility (VW)	0.328	(0.14)	0.500	(0.12)	0.511	(0.11)	0.488	(0.12)	0.024	[0.50]
Volatility (VW)- 1yr-Δ	-0.002	(0.10)	0.031	(0.14)	0.079	(0.16)	-0.023	(0.10)	0.102	[2.07]
Turnover (VW)	0.545	(0.19)	0.684	(0.15)	0.655	(0.16)	0.717	(0.14)	-0.061	[-1.12]
Turnover (VW)- 1yr-Δ	0.002	(0.09)	0.027	(0.09)	0.018	(0.09)	0.036	(0.10)	-0.018	[-0.60]
Age:										
Firm Age (VW)	0.740	(0.17)	0.645	(0.21)	0.705	(0.22)	0.576	(0.17)	0.129	[1.68]
Age tilt	-0.002	(0.06)	0.015	(0.12)	0.052	(0.14)	-0.029	(0.07)	0.081	[2.73]
Issuance:										
% Issuers	0.245	(0.18)	0.279	(0.17)	0.331	(0.17)	0.218	(0.14)	0.113	[1.78]
Fundamentals vs. Price:										
Book to Market (VW)	0.747	(0.65)	0.389	(0.21)	0.339	(0.28)	0.447	(0.21)	-0.108	[-1.59]
Sales Growth	0.515	(0.14)	0.632	(0.15)	0.624	(0.28)	0.640	(0.13)	-0.016	[-0.30]
CAPE	18.272	(7.56)	22.073	(9.47)	25.266	(0.28)	18.375	(5.54)	6.891	[1.90]
Acceleration:										
Acceleration	N/A	N/A	1.073	(0.35)	1.213	(0.31)	0.911	(0.33)	0.302	[2.54]

Table 5. Features of Price Run-ups and Crashes: International Sectors

The table summarizes features of price run-ups of international sectors in the first-identified month, all industry-month average of the features and the difference between the run-ups with subsequent crash and run-ups without. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. The features include: (1) Past return (2) Value-weighted volatility and its 1-year change (3) Value-weighted percentile ranked turnover and its 1-year change (4) Value-weighted percentile ranked firm age (5) Age tilt: equal-weight 1-year gross return minus age-weighted 1-year gross return. (6) Percentage of issuers. An issuer is defined as a company with more than 5% share issuance within one year. (7) Value-weighted book to market ratio (8) Value-weighted percentile ranked sales growth (9) Market CAPE (10) Acceleration: 2-year gross return minus first half 1-year gross return. *t*-statistics are based on standard errors clustered by sector and calendar year.

	All industry-years		Run-ups		Run-ups with Crash		Run-ups with no Crash		Crash minus no Crash	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Difference**	**[t-stat]**
Past 2-year Return	0.278	(0.67)	2.140	(0.94)	2.419	(1.18)	1.872	(0.53)	0.548	[3.20]
Excess Past 2-year Return	0.041	(0.45)	1.302	(0.55)	1.453	(0.75)	1.158	(0.13)	0.295	[2.42]
Turnover and Volatility:										
Volatility (VW)	0.363	(0.16)	0.498	(0.16)	0.578	(0.15)	0.422	(0.13)	0.156	[5.51]
Volatility (VW)- 1yr-Δ	-0.003	(0.16)	0.057	(0.17)	0.085	(0.17)	0.029	(0.17)	0.055	[1.50]
Turnover (VW)	0.605	(0.16)	0.576	(0.16)	0.581	(0.17)	0.572	(0.15)	0.010	[0.27]
Turnover (VW)- 1yr-Δ	0.004	(0.10)	0.029	(0.12)	0.043	(0.12)	0.016	(0.11)	0.027	[1.30]
Age:										
Firm Age (VW)	0.585	(0.19)	0.593	(0.19)	0.550	(0.21)	0.633	(0.17)	-0.083	[-1.94]
Age tilt	-0.015	(0.42)	0.438	(1.95)	0.820	(2.21)	0.055	(1.57)	0.766	[1.85]
Issuance:										
% Issuer	0.437	(0.39)	0.484	(0.48)	0.537	(0.55)	0.433	(0.39)	0.104	[1.16]
Fundamentals vs. Price:										
Book to Market (VW)	0.659	(1.22)	0.338	(0.22)	0.260	(0.20)	0.412	(0.23)	-0.153	[-3.54]
Sales Growth	0.537	(0.16)	0.582	(0.15)	0.597	(0.14)	0.566	(0.16)	0.031	[1.07]
CAPE	20.02	(8.83)	25.088	(12.42)	30.664	(14.07)	19.744	(7.49)	10.92	[4.88]
Acceleration:										
Acceleration	N/A	N/A	1.546	(0.91)	1.972	(1.07)	1.135	(0.45)	0.837	[5.53]

Table 6 Betting Against Bubbles Using Bubble Features

The table reports the performance of trading strategies with selling signals based on the features identified in Tables 4 and 5. "Hold" strategy denotes the benchmark for portfolio evaluation. In all strategies, an investor chooses to either hold the industry or to exit and hold another asset, alternatively the broader market or the risk-free rate. The "sell" signal for each strategy is to exit the industry if the feature reported in column (1) is greater (or smaller for special cases) than the corresponding mean of among crashed price run-ups in Tables 4 and 5. Column 2 reports the number of price run-ups identified as potential bubbles by the strategy. Column 3 reports the percentage of the identified run-ups followed by a subsequent crash. Column 4-9 report the raw returns of the strategy in 1-year, 2-year and 4-year horizon. Column 10-15 report the net of benchmark returns and the corresponding *t*-statistics in parenthesis. All numbers in bold are the returns of strategies beating the benchmark at 90% significance level. In Panel A, we specifically set "sell" signal as "smaller than mean" for book-to-market ratio in the spirit of Table 4. *t*-statistics are based on clustered standard errors by calendar year. In Panel B, we set "sell" signal as "smaller than mean" for book-to-market ratio and firm age in the spirit of Table 5. *t*-statistics in Panel B are based on standard errors clustered by sector and calendar year.

Panel A: US Industries

Strategy	# Price Run-ups Identified as potential bubbles	% Identified run-ups with a subsequent crash	Raw Returns						Net of Benchmark Returns					
			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified		
			1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Hold = Benchmark	0	0	9%	0%	10%	9%	0%	10%	0%	0%	0%	0%	0%	0%
Price Run-up Only	41 (All)	55%	3%	0%	18%	5%	10%	21%	-5% [-1.12]	0% [0.03]	8% [0.69]	-4% [-0.55]	10% [0.94]	11% [0.78]
Price Run-up +														
Volatility	20	65%	8%	4%	19%	10%	10%	23%	0% [-0.09]	4% [0.80]	9% [1.35]	1% [0.32]	10% [1.44]	**13%** **[1.79]**
Volatility 1yr-Δ	13	77%	11%	4%	17%	14%	8%	23%	2% [1.45]	4% [1.13]	6% [1.44]	**5%** **[1.76]**	8% [1.65]	**13%** **[1.84]**
Turnover	21	43%	4%	-4%	10%	3%	-3%	6%	-5% [-1.55]	-4% [-0.62]	-1% [-0.05]	-6% [-1.45]	-3% [-0.33]	-4% [-0.35]
Turnover 1yr-Δ	20	55%	7%	2%	19%	9%	8%	22%	-1% [-0.53]	3% [0.70]	9% [1.49]	0% [0.09]	8% [1.49]	12% [1.57]
Age	17	76%	10%	6%	20%	13%	13%	26%	1% [0.69]	6% [1.58]	**10%** **[2.13]**	5% [1.26]	**13%** **[2.36]**	**16%** **[2.29]**
Age Tilt	9	78%	9%	4%	16%	10%	7%	20%	0% [0.01]	4% [1.31]	**6%** **[1.82]**	1% [0.34]	**7%** **[1.89]**	**10%** **[2.17]**

Strategy	# Price Run-ups Identified as potential bubbles	% Identified run-ups with a subsequent crash	Raw Returns						Net of Benchmark Returns					
			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified		
			1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
%Issuer	14	64%	10%	4%	20%	10%	8%	21%	1% [0.62]	4% [1.07]	**10% [2.49]**	2% [0.61]	8% [1.30]	11% [1.43]
Book-to-Market	20	70%	10%	6%	19%	13%	15%	27%	2% [0.41]	6% [1.23]	9% [1.56]	4% [0.80]	**15% [2.00]**	**16% [1.70]**
Sales Growth	21	52%	2%	-2%	10%	0%	2%	5%	-7% [-2.02]	-1% [-0.22]	-1% [-0.06]	-8% [-1.97]	2% [0.30]	-5% [-0.46]
CAPE	11	82%	6%	1%	15%	8%	8%	24%	-2% [-0.73]	2% [0.41]	4% [1.45]	0% [-0.03]	8% [1.25]	**14% [1.87]**
Acceleration	15	53%	9%	4%	20%	10%	11%	6%	1% [0.30]	5% [1.25]	9% [1.67]	2% [0.48]	**11% [1.88]**	**17% [2.15]**

[Table 6 Continued]

Panel B: International Sectors

Strategy	# Price Run-ups Identified as potential bubbles	% Identified run-ups with a subsequent crash	Raw Returns						Net of Benchmark Returns					
			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified			Switch to Market when "Bubble" Identified			Switch to Risk-free when "Bubble" Identified		
			1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret	1-yr ret	2-yr ret	4-yr ret
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Hold = Benchmark	0	0	0%	6%	40%	0%	6%	40%	0%	0%	0%	0%	0%	0%
Price Run-up Only	104 (All)	49%	-2%	6%	30%	3%	5%	9%	-2% [-0.73]	0% [-0.03]	-10% [-0.82]	3% [0.44]	-1% [-0.16]	-31% [-1.66]
Price Run-up +														
Volatility	30	83%	3%	11%	38%	10%	18%	39%	2% [1.39]	**4% [2.07]**	-2% [-0.30]	**9% [2.40]**	**11% [2.51]**	-1% [-0.07]
Volatility 1yr-**Δ**	40	63%	4%	13%	40%	5%	12%	26%	**3% [1.79]**	**6% [2.42]**	-2% [-0.27]	5% [1.47]	6% [1.21]	-12% [-0.98]
Turnover	51	47%	2%	11%	45%	5%	10%	36%	1% [0.42]	4% [1.23]	5% [0.53]	4% [1.13]	2% [0.39]	-4% [-0.26]
Turnover 1yr-**Δ**	43	53%	1%	9%	39%	3%	9%	38%	0% [0.24]	2% [0.52]	-3% [-0.35]	3% [0.83]	2% [0.47]	-1% [-0.12]
Age	44	59%	-2%	2%	31%	-1%	-3%	13%	2% [0.76]	**5% [2.22]**	0% [0.03]	5% [1.52]	7% [1.47]	-5% [-0.46]
Age Tilt	30	60%	-1%	8%	36%	2%	9%	32%	-2% [-0.94]	1% [0.58]	-4% [-0.58]	0% [0.15]	1% [0.34]	-9% [-0.80]
%Issuer	29	59%	3%	10%	44%	7%	13%	43%	2% [1.33]	2% [1.05]	4% [1.32]	**6% [2.40]**	5% [1.14]	3% [0.59]
Book-to-Market	46	67%	3%	12%	40%	6%	14%	35%	-2% [-0.66]	-1% [-0.19]	5% [1.21]	4% [1.09]	**9% [1.75]**	**12% [2.04]**
Sales Growth	46	59%	0%	6%	36%	4%	6%	29%	-1% [-0.40]	-1% [-0.30]	-6% [-0.74]	3% [0.81]	0% [0.01]	-10% [-0.86]
CAPE	19	79%	4%	10%	45%	8%	16%	50%	**3% [2.33]**	**3% [2.15]**	**5% [2.24]**	**7% [3.09]**	**8% [2.62]**	**9% [3.06]**
Acceleration	22	82%	0%	9%	37%	3%	14%	35%	-1% [-0.54]	2% [1.41]	-3% [0.06]	2% [0.67]	**6% [1.89]**	-6% [-0.53]