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Bubbles for Fama[☆]

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ABSTRACT

We evaluate Eugene F. Fama's claim that stock prices do not exhibit price bubbles. Based on US industry returns (1926–2014) and international sector returns (1985–2014), 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 predict a substantially heightened probability of a crash but not of a further price boom; (3) attributes of the price run-up, including volatility, turnover, issuance, and the price path of the run-up, help forecast an eventual crash; and (4) these attributes also help forecast future returns. Results hold similarly in US and international samples.

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]

1. 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 substantially 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, 1954; Kindleberger, 1978; Shiller, 2000), as well as many modern theoretical, empirical, and experimental investigations. But is it correct?

In this paper, 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 40 such episodes. We examine the characteristics of these portfolios and their performance going forward, just as Fama recommends. We then repeat the exercise for international sector portfolios

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

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between 1985 and 2014 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. Average returns following a price run-up approximately match those of the broader market in the following two years, and they are unremarkable in raw terms as well. The historical accounts are typically based on burst bubbles and do not consider the fact that many industries that have gone up notably in price just keep going up. The famed technology bubble of the late 1990s is one that has burst. 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 two years to 100%, the probability of a crash rises from 20% to 53%. For episodes with a 150% industry net of market return, the probability of a crash rises to 80%. 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. At the same time, the probability of a further 40% price increase falls after very high past returns. In our data, following a sharp price run-up, investors can expect a substantial left-shift in the distribution of future returns. The predictability of a future crash from past industry returns suggests that Fama's conclusion should be interpreted carefully, as it implicitly draws a distinction between future returns and the likelihood of a crash.

The reasons for the difference in results between returns and crash probabilities are twofold. First, some industries just keep going up and do not crash at all. Second, bubble peaks are notoriously hard to tell, and prices often keep going up 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 first drew attention to high US stock prices in December 1996, and prices proceeded to double after that, eventually falling much later. In our data, even of the 21 episodes in which a crash does occur ex post, on average prices peak six 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 30%, confirming the adage that it is difficult to bet against the bubble, even if one 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 looks only at the weak form in his assessment of bubbles. Investors looking at industries with large price increases have a good deal of other information, such as turnover, issuance, patterns of volatility, and fundamentals. This raises the semi-strong form market efficiency question: In conjunction with an observation of a rapid price increase, can any additional information be helpful for predicting future performance?

To answer this question, we again distinguish between forecasting crashes and forecasting future returns. We examine characteristics of industry portfolio growth episodes, most of which have been recognized to some extent in earlier work. These include volatility (in levels and changes), turnover (in levels and changes), 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 (P/E) ratio. We also propose a new variable, *Acceleration*, based on the abruptness of the price run-up.

We find that many of these characteristics vary systematically between episodes in which prices keep rising and those in which they ultimately crash. Run-ups that end in a crash are more likely to have increases in volatility, stock issuance, acceleration, associated increases in the market P/E ratio, and disproportionate price rises among newer firms.

We then investigate whether these characteristics can help predict future returns. 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 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. Share turnover tends to be high not only 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 (although it has some forecasting power in the international sample). At the same time, several variables do help predict which bubbles both crash and earn low returns. Increases in 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. However, returns are predictable.

A significant concern with our analysis is statistical power. Large price run-ups, by nature, are rare. We identify only 40 of them in all of US stock market history since 1928.[2] With the benefit of hindsight, we can point to some common elements in these events, with potentially dubious predictive value going forward. We have two responses to this concern. First, we examine international industry data between 1985 and 2014 as an out-of-sample test. We confirm that, in the international data as well, price run-ups do not forecast average returns, but they are associated with a substantially elevated probability of a crash. More important, several of the features of price run-ups that predict crashes in the US (high volatility and

[2] For this reason, bubbles are not a particularly fertile field for testing market efficiency. Market efficiency is much more effectively tested by looking at the violations of the law of one price [e.g., Lee et al. (1991) for closed-end funds, Froot and Dabora (1999) for dual-listed stocks, or Lamont and Thaler (2003) for spinoffs].

share issuance) also have predictive value in the international data. Second, in the spirit of Bonferroni (1936) and Dunn (1959), we conduct statistical tests to adjust for the multiple comparison problem, which holds that some of the characteristics predicting returns we uncover do so by chance because we are studying many at the same time. We address this problem by controlling for the false discovery rate, which is the percentage of characteristics that are expected to be Type I errors. Even with these adjustments, and despite the limited number of observations, at least five characteristics emerge as predictive of future returns.

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 no predictability exists, because sharp price increases do predict a heightened likelihood of a crash. More important, other attributes of well-performing portfolios help distinguish portfolios that earn low and high returns going forward. Based on this information, there is some statistically significant predictability of returns.

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: 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. And because one can measure it, one can also identify, imperfectly, but well enough to predict returns, asset price bubbles in advance.

Our paper is related to several lines of research. First, a large literature uses characteristics to forecast industry returns, especially industry momentum, although we differ from most of these papers by focusing on episodes subsequent to a large price run-up.[3] More recently, Daniel et al., (2017) show that some high momentum stocks subsequently experience crashes. Second, many empirical studies examine individual bubbles, and especially the most recent .com episode of the late 1990 s.[4] Our paper asks whether some of their findings (such as patterns of high issuance and trading volume) generalize. A few papers also suggest that some apparent bubble episodes can be reconciled with rational asset pricing, either because of cash flow forecasts or changes in discount rates (Garber, 1990; Pastor and Veronesi, 2006; Pastor and Veronesi, 2009). Others suggest that high prices during bubble episodes could be driven by a combination of risk premia and learning (Pastor and Veronesi, 2006; Pastor and Veronesi, 2009). Third, some research has tried to forecast market crashes using characteristics such as past skewness, returns, or trading volume (Chen et al., 2001). Fourth, Goetzmann (2016) studies rapid price increases of national stock markets and their subsequent returns, but not characteristics of these markets beyond the price run-up. Finally, our paper connects to a vast theoretical literature on bubbles, including De Long et al. (1990), Abreu and Brunnermeier (2003), Scheinkman and Xiong (2003), and Barberis et al. (2018). Some of this research deals with so-called rational bubbles (e.g., Blanchard and Watson, 1982; Tirole, 1985), but recent evidence has not been kind to these theories (Giglio et al., 2016).

2. 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 two- and five-year horizon to avoid picking up recoveries from periods of poor performance. Our database contains returns from January 1926 to March 2014. This allows us to identify every price run-up episode between January 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.[5]

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 definition of price run-up based on past returns suggests that we would identify many overlapping two-year intervals in consecutive months. For example, if we identify a price run-up in Computer Software in March 1999, the two-year interval ending in September 1999 would also qualify as a run-up. For this reason, we choose the first instance for which a run-up is observed and do not allow for a new run-up to be identified until two years later.

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).[6] We use the first 48 of their industries, excluding the residual industry "other," and restrict attention to industries with ten

[3] See Grinblatt and Moskowitz (1999), Asness, Porter, and Stevens (2000), Hou and Robinson (2006), Hong et al. (2007), among others.

[4] See Ofek and Richardson (2003), Brunnermeier and Nagel (2004), Pastor and Veronesi (2006), and Griffin et al. (2011).

[5] We do not impose the five-year return requirement until 1931, because stock returns in the Center for Research in Security Prices database begin in 1926.

[6] 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 Computer 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 two-digit Standard Industrial Classification code and broader Fama-French industry aggregates, as well as Global Industry Classification Standard definitions popular among investment professionals.

or more firms, to ensure that the price run-up is experienced by enough firms. Following standard procedure, returns are measured monthly and based on all stocks with share codes of 10 or 11 in the Center for Research in Security Prices (CRSP) database. Stocks are matched to industries each month using the most recent Standard Industrial Classification code on Compustat, or CRSP if not available.[7] Returns are value weighted across stocks.

Fama does not specify whether the term "bubble" applies at the individual stock, industry, or market level, and the industry or sector perhaps is not his ideal unit of analysis. However, the two examples cited in his Nobel Lecture include the .com bubble of the 1990s and the real estate boom of the 2000s. We study industries for three reasons. First, most historical accounts of bubbles have a strong industry component. The White (1990) descriptions of the 1929 stock market boom and subsequent bust, for example, emphasize utilities and telecommunications stocks and suggest that old-economy railroad stocks languished. The stock market boom of the late 1990s was concentrated in .com stocks, which far outperformed the value-weighted index (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. For example, in only three episodes since 1925 has the aggregate US stock market returned more than 100% in a two-year period.[8] Third, we can compare potential bubble industries with other stocks trading at the same time. This matters 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 rare. We observe only 40 since 1928. This is not surprising, given that the average price run-up represents a 5.5 standard deviation event[9]. These 40 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 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, categorizing 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 Utilities, could seem reasonable. Such ex post consolidation 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.[10] For the international data, we cluster standard errors by country-calendar year.

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 40 episodes into 21 that crash in the subsequent two years and 19 that do not. We define a crash as a 40% 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). 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.

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. This conservative approach exposes us to Type II errors, that is, concluding that an episode is not a bubble, even if, for example, an industry with a price run-up in year t experiences returns of -20% per year in each year from $t+1$ through $t+4$. Because our threshold for a crash is high, some of the industries we classify as not having crashed nevertheless experience mediocre subsequent returns. For example, airlines 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 criterion of a 40% drawdown does not require the crash to be sudden, in most cases it is. In 17 of the 21 episodes with a crash, the industry experiences a single-month return of -20% or worse during the drawdown period.

Fig. 1 summarizes the average returns for the 40 price run-ups. It 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, indus-

[7] We do not match exactly the industry returns reported by Ken French on his website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), 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%.

[8] See tabulation in the Online Appendix. The international data have slightly more episodes with high past returns also associated with elevated probability of a crash. See Goetzmann (2016) for additional historical analysis at the market level.

[9] 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.

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

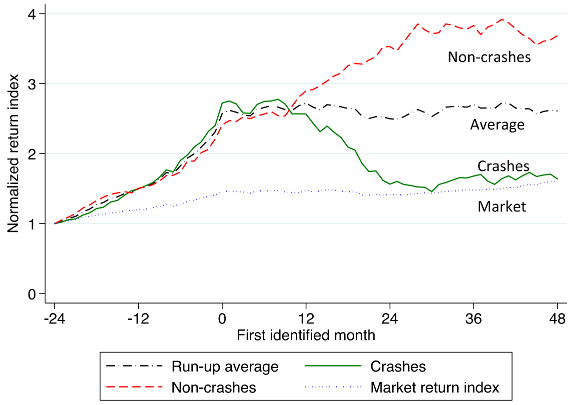


Fig. 1. Cumulative returns to all US industries that experienced a large price run-up between month t-24 and t. The sample includes all industries between 1928 and 2012 and is based on Fama and French (1997) 49-industry classifications. We identify 40 episodes in which an industry experiences both a 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. Twenty one of these 40 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.

tries that experienced a price run-up continue to go up by 7% over the next year (5% net of market) and 0% over the next two years (0% net of market). Neither raw nor market adjusted returns are statistically distinguishable from zero.

Fig. 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, they are associated with poor average subsequent market returns. Across all episodes, the value-weighted market earns only 2% in the first year post–run-up and 0% over two years. After netting out the risk-free return, market excess returns are −2% in the first year and −10% over two years. The market performs particularly poorly during the episodes that we record as experiencing industry crashes. The average two-year market return in these 21 cases is −13% and the average two-year excess market return is −24%. Overall, the substantial correlation between large industry crashes and market under-performance supports our approach of studying industry portfolios.

Table 1 summarizes returns for each episode, grouping episodes by whether or not a crash ultimately occurred. For the 21 industries that do crash, average returns are −5% (−3% net of market) in the next year and −42% in the next two years (−29% net of market). The two-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 Fig. 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 30% (and is as much as 107% in the case of precious metal stocks in the late 1970 s). This confirms the adage that it is difficult to bet against the bubble, even if one has correctly identified it as such ex ante.

Panel B of Table 1 shows 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 21% in the subsequent year (13% net of market) and 46% in the next two years (31% net of market).

2.1. International sectors

We repeat our analysis using a sample of all international firms with complete volume and returns in the Compustat Xpressfeed database. The international data do not constitute a fully independent test, as 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 Global Industry Classification Standard (GICS) code. The GICS sector is a broader definition of industry than that of Fama and French (11 GICS sectors versus 49 Fama-French industries), which helps ensure that for smaller stock markets such as Sweden, an industry includes a sufficient number of firms to be meaningful. As for the US data, we restrict our attention to sectors with ten or more firms. Returns are measured in US dollars (the return in US dollar is 99.9% correlated with the return computed in local currency) 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. [11] The data begin in October 1985, with 88% of the observations in 1996 or later. Overall, the starting point is 85,226 sector-months of returns, compared with 49,541 industry-months in our US analysis.

Following an otherwise identical methodology, we identify 107 price run-ups in 31 countries between October 1987 and December 2012, summarized in Table 2. Of these price run-ups, 53 crash and 54 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. Fig. 2 shows that Fama's central claim holds up in the international data. That is, 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% (2% net of market) in the next year and 7% (0% net of market) in the next two years. In short, our conclusion about average returns drawn from US industries also holds in the international data.

Because international episodes are too numerous to list individually, Table 2 summarizes price run-up episodes by

[11] We use dollar returns instead of 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 use only securities that are traded on exchanges in their home country, i.e., we exclude American Depositary Receipts and equivalents.

Table 1
Returns after industry price run-ups, US industries 1928–2012.
We list all price run-ups of Fama and French 49 industries, defined as any incident with 100% raw and value-weighted return over the past two years, 100% net of market returns over the past two years, and 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 show 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). N/A: Not applicable.

Panel A: Run-ups that subsequently experienced a crash (21 episodes)

			Subsequent performance & maximal drawdown over next two years								
Industry name	Number of firms	Price run-up first observed	12-month raw return (percent)	24-month raw return (percent)	12-month net of risk-free return (percent)	24-month net of risk-free return (percent)	12-month net of market return (percent)	24-month net of market return (percent)	24-month maximal drawdown (percent)	Months to price peak	Return to peak (percent)
Automobiles and trucks	42	3/1928	29	−22	25	−30	−6	−58	−53	11	30
Chemicals	13	1/1929	−5	−47	−9	−54	4	−15	−67	7	54
Electrical equipment	18	1/1929	−11	−41	−16	−48	−3	−8	−55	7	31
Utilities	23	7/1929	−24	−45	−28	−51	0	4	−53	2	11
Machinery	37	5/1936	32	−34	32	−34	15	−3	−55	14	41
Steel works	61	2/1937	−44	−35	−44	−36	−9	−11	−63	1	6
Tobacco products	13	11/1961	−42	−42	−45	−48	−32	−52	−44	0	0
Real estate	24	5/1968	76	−16	70	−29	68	1	−52	12	76
Personal services	12	5/1968	−21	−63	−27	−76	−29	−46	−69	5	20
Entertainment	24	5/1972	−25	−54	−30	−67	−24	−39	−60	7	11
Restaurants and hotels	40	6/1972	−39	−53	−44	−67	−39	−39	−55	6	4
Precious metals	14	12/1979	65	9	54	−19	33	−17	−48	9	108
Petroleum and natural gas	272	10/1980	−13	−25	−28	−53	−13	−43	−49	1	24
Construction	51	10/1980	−40	−40	−55	−68	−41	−57	−64	1	11
Computer hardware	190	3/1999	103	−32	99	−43	85	−25	−68	17	113
Computer software	551	3/1999	54	−36	49	−47	36	−29	−60	11	59
Electronic equipment	347	12/1999	−37	−56	−43	−66	−28	−37	−75	3	31
Steel works	77	8/2000	−53	−70	−58	−77	−29	−33	−66	0	0
Measuring and control equipment	127	2/2000	−46	−65	−51	−72	−21	−27	−61	0	0
Steel works	48	5/2007	7	−59	4	−63	14	−22	−75	12	7
Coal	13	6/2008	−72	−64	−73	−65	−46	−49	−74	0	0
Crash mean	95	N/A	−5	−42	−10	−53	−3	−29	−60	6.0	30
All run-up mean	68	N/A	7	0	3	−10	5	0	−41	N/A	N/A

(*continued on next page*)

Table 1
(*continued*)

Panel B: Run-ups without a crash in the next two years (19 episodes)

			Subsequent performance & maximal drawdown over next two years						
Industry name	Number of firms	Price run-up first observed	12-month raw return (percent)	24-month raw return (percent)	12-month net of risk-free return (percent)	24-month net of risk-free return (percent)	12-month net of market return (percent)	24-month net of market return (percent)	24-month maximal drawdown (percent)
Aircraft	12	10/1939	−11	−8	−11	−8	−2	8	−27
Textile	21	5/1946	−35	−4	−36	−5	−13	1	−32
Aircraft	21	12/1954	27	50	26	46	−4	11	−17
Pharma. Products	17	11/1958	35	31	32	25	20	18	−14
Aircraft	31	11/1965	3	48	−2	39	13	37	−26
Industrial Mining	31	1/1966	3	32	−2	23	7	26	−28
Meas. and Control Equipment	28	4/1967	6	14	2	4	−1	−3	−21
Construction	19	6/1967	43	21	38	11	29	7	−26
Entertainment	27	6/1967	56	40	51	30	42	26	−17
Restaurants &Hotels	23	11/1967	45	34	41	23	32	19	−29
Aircraft	33	9/1976	62	56	57	44	44	50	−19
Healthcare	36	4/1978	4	70	−1	58	8	63	−12
Computer Software	14	8/1978	23	128	15	106	16	100	−25
Healthcare	35	4/1980	15	124	5	102	3	92	−28
Computer Software	205	10/1992	16	42	13	36	1	23	−8
Textile	49	10/1992	16	−3	13	−10	2	−23	−21
Recreation	44	10/1992	29	22	26	15	14	3	−14
Construction	51	10/2003	21	68	20	64	11	49	−13
Industrial Mining	14	2/2005	41	110	37	101	32	88	−12
Non-crash mean	38	N/A	21	46	17	37	13	31	−20
All run-up mean	68	N/A	7	0	3	−10	5	0	−41

Table 2

Returns after Industry Price Run-ups, International Country Sectors 1987–2012.

We list all price run-ups of international sectors, 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. International data cover 38 countries with more than eight years of data available in Compustat. We identify 107 country-sector price run-ups in 31 countries. N/A: not available.

Panel A. Run-ups that subsequently experienced a crash (53 episodes)

		Country means: subsequent performance and maximal drawdown over next two years across all episodes									
Country	Number of episodes	Average number of firms	12-month raw return (percent)	24-month raw return (percent)	12-month net of risk-free return (percent)	24-month net of risk-free return (percent)	12-month net of market return (percent)	24-month net of market return (percent)	24-month maximal drawdown (percent)	Months to price peak	Return to peak (percent)
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
Canada	2	638	−27	−36	−29	−40	−10	−20	−48	2	7
China	5	175	−34	−31	−37	−34	−2	−4	−62	2	14
France	2	51	−41	−55	−45	−61	−12	−25	−69	4	5
Germany	1	15	−14	81	−19	71	−15	45	−48	23	107
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
South 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
Switzerland	2	14	−41	−51	−45	−56	−25	−42	−63	1	9
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	85	−23	−38	−27	−44	−5	−13	−65	4.1	38
All run-up mean	2.3	74	1	7	−2	2	2	0	−43	N/A	N/A

(*continued on next page*)

Table 2
(*continued*)

Panel B. Run-ups without a crash in the next 2 years (54 episodes)

		Country means: subsequent performance and maximal drawdown over next two years across all episodes							
Country	Number of episodes	Average number of firms	12-month raw return (percent)	24-month raw return (percent)	12-month net of risk-free return (percent)	24-month net of risk-free return (percent)	12-month net of market return (percent)	24-month net of market return (percent)	24-month maximal drawdown (percent)
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
Canada	1	30	13	48	11	46	20	32	−4
China	2	228	−8	−24	−8	−24	−3	−3	−36
Denmark	2	18	10	23	6	17	0	−26	−22
Finland	5	26	30	66	29	62	28	43	−15
France	1	19	14	68	8	58	2	14	−12
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
South Korea	2	177	24	77	19	67	3	12	−31
Malaysia	2	64	15	−29	12	−35	−10	−21	−11
Mexico	1	12	−7	21	−7	21	−2	4	−26
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
South Africa	2	62	46	95	45	92	15	−4	−17
Spain	1	12	−19	−18	−24	−28	−14	−16	−38
Switzerland	2	24	19	42	18	40	11	11	−20
Thailand	9	37	64	105	63	103	19	43	−20
UK	2	85	5	9	3	4	3	−3	−31
Non-crash mean	2.4	63	24	51	23	46	10	13	−22
All run-up mean	2.3	74	1	7	−2	2	2	0	−43

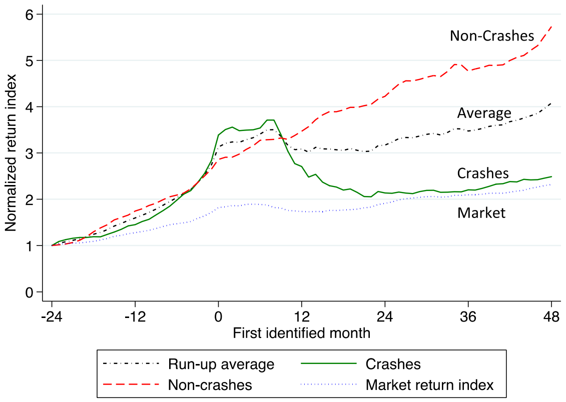


Fig. 2. Cumulative returns to all country-sectors that experienced a large price run-up between month t-24 and t. The sample includes all Global Industry Classification Standard (GICS) sectors in 38 countries between 1987 and 2012 and is based on two-digit GICS sector classifications. We identify 107 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. Fifty four episodes experienced a subsequent crash, and fifty three 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.

country. As before, we start with the episodes with a subsequent crash. For these episodes, average one-year returns following the price run-up are −23% (−5% net of market) and average two-year returns are −38% (−13% net of market). These sectors experience an average maximal drawdown of −65% in the two-year period following the price run-up. As in 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 Australia, France, Germany, Hong Kong, India, Japan, Malaysia, Sweden, Switzerland, and the United Kingdom. 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 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 38% subsequent return until the price peak, similar to that in the US sample.

Turning to the international episodes with no crash in the two years post–price run-up, average one-year returns are 24% (10% net of market) and average two-year returns are 51% (13% net of market), and these industries experience an average maximal drawdown of only 22%. The best performing industries include information technology in India, which experienced a first price run-up of 100% between June 1997 and June 1999 and subsequent returns of 436% until the price peaked, 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 years after the initial price run-up.

2.2. 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 present raw, excess (of the risk-free rate) and net of market returns for the 12-and 24-month periods subsequent to the price run-up. Average post–run-up returns for both US industries and international sectors are based on different return thresholds. 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 this threshold in a two-year period. In the Online 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.

For return cutoffs under 100%, Fama remains correct about average returns. 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 15 incidents of a 150% price run-up in US data, average net of market returns were −9% and −10% and average excess returns were −17% and −28%. The general pattern is that subsequent returns fall as the ex ante threshold rises, although the statistical significance is marginal.

Panel B of 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 excess returns of −18% and −23%, with both statistically below zero at the 10% significance level.

Our earlier conclusion that Fama is correct about average returns must be tempered for high past return thresholds, although the statistical significance is marginal.

3. Probability of crashes or booms 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 1926 and 2014, 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 24%.

In this section, we show that the probability of a crash is strongly associated with high past returns. For very high past returns (such as 150% in a two-year period), a crash is nearly certain, although its timing is not. We also show that the increased probability of a crash is not matched by an increased probability of a further boom. The distribution of returns post–run-up shifts to the left.

Fig. 3 presents the 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 A shows the probability of a crash as a function of the industry return net of market; Panel B, the probability as a function of the past raw return. As before, a crash event takes on a value of one if the industry experiences a 40% or greater drawdown at any point in the

Table 3
Price run-ups and crashes.
We identify episodes based on different thresholds of price run-up (50%, 75%, 100%, 125%, and 150%) experienced by US industries and international sectors. 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 during a five-year period, where X is noted in the table. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. A boom is defined as a 40% net of risk-free return over the subsequent two years. Panel A presents summary statistics on the subsequent returns for each sample of run-ups. Panel B describes the percentage of episodes that experience crashes and the average drawdown experienced during these crashes. Panel C describes the percentage of episodes that experience a subsequent price boom. *t*-statistics are shown in brackets. Standard errors are clustered by calendar year in Panel A and by sector - calendar year in Panel B. N/A: Not applicable.

		Return statistics							Subsequent crashes		Subsequent booms	
Pick-up threshold	Number of run-ups identified	12-month net of risk-free return (percent)	24-month net of risk-free return (percent)	12-month net of market return (percent)	24-month net of market return (percent)	Standard deviation of 24-month net of risk-Free return	Skewness of 24-mont net of risk-Free return	Kurtosis of 24-mont net of risk-free return	Crashes (percent)	Drawdown of crashes (percent)	Booms (percent)	24-month net of risk-free return (percent)
Panel A: US industries 1926–2012												
Unconditional	N/A	10	21	2	4	0.25	2.0	17.9	N/A	N/A	N/A	N/A
50%	168	7	11	2	3	0.21	1.1	5.5	20	−53	20	83
		[1.79]	[1.89]	[0.83]	[0.63]					[−28.40]		[12.22]
75%	77	5	0	3	1	0.19	0.6	3.0	36	−54	14	78
		[1.10]	[0.04]	[0.95]	[0.32]					[−32.87]		[10.28]
100%	40	3	−10	5	0	0.28	0.6	2.4	53	−60	18	75
		[0.53]	[−0.89]	[0.90]	[−0.03]					[−31.08]		[7.14]
125%	21	−11	−30	−6	−14	0.29	1.7	5.2	76	−60	10	112
		[−1.32]	[−1.72]	[−1.02]	[−1.04]					[−17.64]		[11.97]
150%	15	−17	−28	−9	−10	0.40	1.6	4.0	80	−62	13	112
		[−2.23]	[−1.22]	[−1.45]	[−0.57]					[−17.39]		[11.97]
Panel B: International sectors 1987–2012												
Unconditional	N/A	11	24	2	5	0.68	5.9	93.5	N/A	N/A	N/A	N/A
50%	237	9	15	5	5	0.37	1.0	5.0	36	−62	29	90
		[2.58]	[2.45]	[2.67]	[1.70]					[−25.16]		[15.20]
75%	153	4	9	4	4	0.42	1.2	5.4	42	−62	26	95
		[0.90]	[1.34]	[1.55]	[1.21]					[−25.20]		[10.88]
100%	107	−2	2	2	0%	0.49	1.3	5.5	50	−65	26	96
		[−0.31]	[0.20]	[0.82]	[−0.00]					[−22.95]		[8.52]
125%	74	−6	−6	−1	−6	0.50	1.3	4.9	53	−68	23	97
		[−0.99]	[−0.64]	[−0.44]	[−1.33]					[−23.39]		[6.50]
150%	51	−18	−23	−6	−14	0.48	1.5	5.2	67	−70	16	103
		[−2.55]	[−1.94]	[−1.48]	[−2.27]					[−23.31]		[4.40]

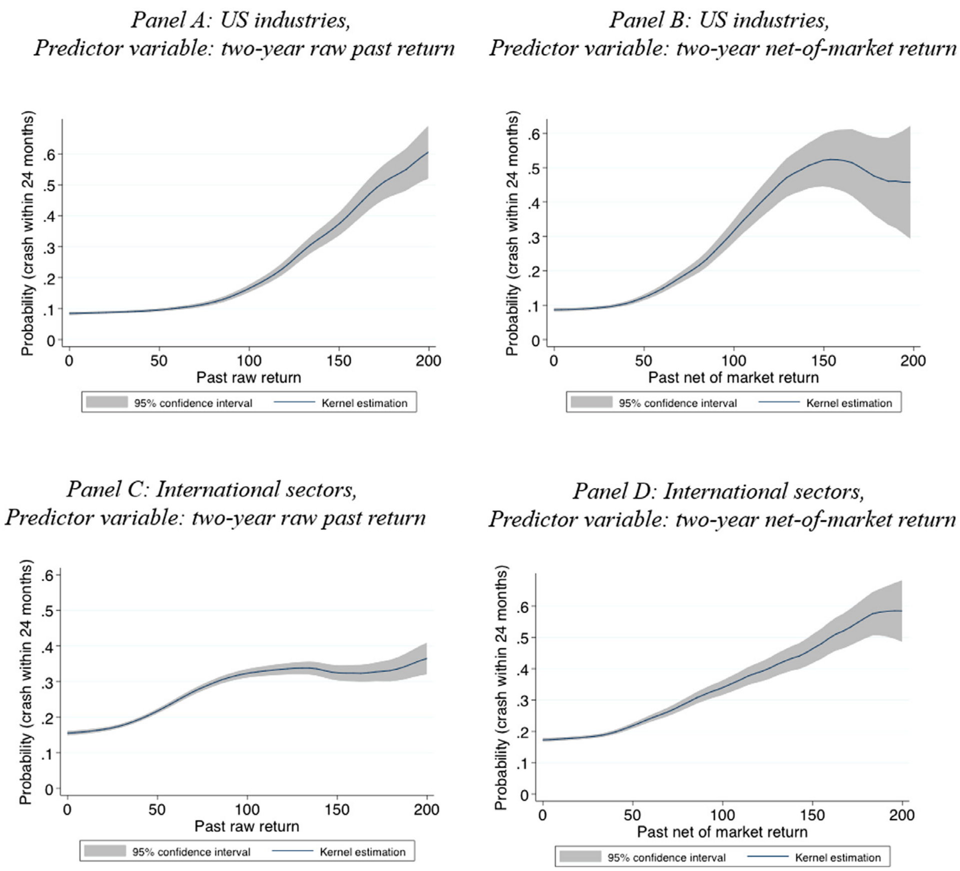


Fig. 3. Probability of crash as a function of past two-year raw and net of market returns in US industries and international country-sectors. Panels A and B are based on a monthly Fama and French 48 US industry panel data 1926–2014 with no fewer than ten firms and positive past 24-month raw or net of market return. Panels C and D are based on monthly country-sector panel data 1985–2014 with no fewer than ten 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 subsequent two years. The shaded area represents the 95% confidence interval.

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. Panel C and D repeat the analysis using international sector returns, with nearly identical results.

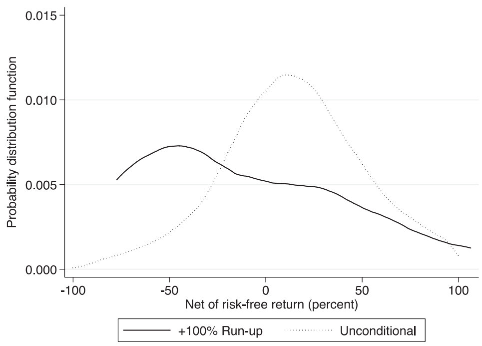
Table 3 summarizes the crash probability as a function of past industry return. As in Tables 1 and 2, for a given return threshold, we require both value-weighted raw and net of market industry returns to exceed the return threshold in a two-year period.[12] At a past return threshold of 50%, only 20% of episodes crash in US industries and 36% in international country-sectors, only slightly above the unconditional crash probabilities. However, the probability of a crash increases substantially with past returns, from 20% to 53% in US industries and from 36% to 50% in international sectors. As the threshold increases further to 150%, we identify fewer price run-ups of this magnitude, but a higher percentage of them crash. Of the 15 episodes with a 150% price run-up observed in US data, 80% crashed in the subsequent two years. Among international sectors, 67% of the 51 episodes with 150% price run-ups subsequently experienced a crash. Our findings of elevated crash probabilities following price run-ups are similar to those in Goetzmann (2016), 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 modest.[13]

Is the elevated likelihood of a crash following a price run-up matched by an increased probability of a continued price boom, perhaps because of higher volatility? To investigate this possibility, we define a price boom symmetrically to a crash as a 40% excess return in the two-year

[12] Because we require both net of market returns and raw returns to exceed the threshold, the crash probabilities do not match those shown in the kernel density plots in Fig. 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.

[13] Apart from the differences in sample, 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 can be modest (even positive) despite the presence of a crash.

Panel A: US industries: distribution of excess returns after a price run-up



Panel B: International sectors: distribution of excess returns after a price run-up

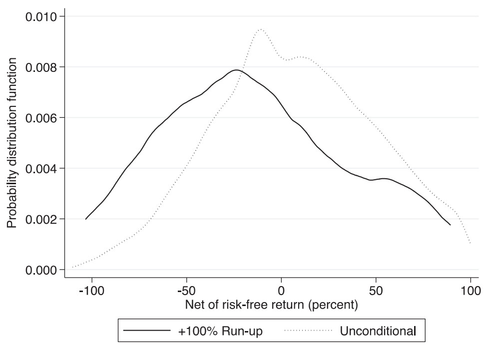
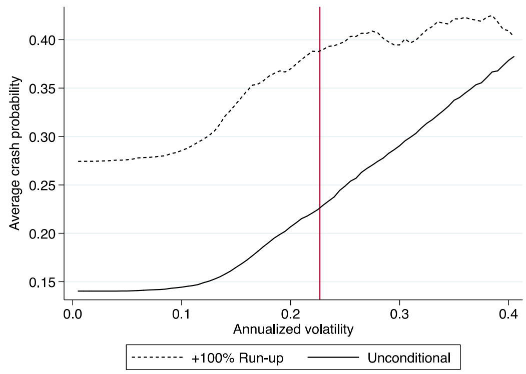


Fig. 4. Non-parametric kernel density of 24-month net of risk-free rate returns. The sample contains 40 large industry price run-ups in the US and 107 sector price run-ups internationally. Panel A shows the distribution for the US sample; Panel B, the distribution for the international sample.

Panel A. US Industries: Crash probability conditional on volatility



Panel B. International sectors: Crash probability conditional on volatility

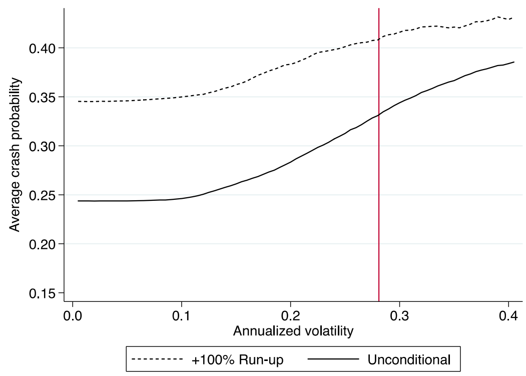


Fig. 5. Crash probability conditional on volatility. Using the full industry panel, we plot the unconditional (solid line) and conditional (dashed line) crash probability as a function of the annualized volatility computed from return in the past 12 months. Panel A shows the function for the US sample; Panel B, the function for the international sample. The vertical lines denote the mean of annualized volatility for US and international industry data.

period post–run-up. Table 3 shows that the probability of a boom is only 18% following a 100% price run-up and 26% in international data. As we increase the past return threshold, the probability of a boom falls somewhat.

Fig. 4 combines our findings about post–price run-up crash and boom probabilities by plotting the kernel density of the 24-month excess return. For comparison, we also plot the unconditional distribution of 24-month excess returns for the entire industry panel. Large price run-ups are followed by a dramatic leftward shift in the distribution of returns.[14] Formally, Table 3 shows that, compared with the unconditional distribution of 24-month returns, after a 100% price run-up, the conditional return distribution has lower skewness (i.e, higher crash risk) and lower kurtosis.

To further evaluate the role of volatility predicting crashes, we examine the probability of a crash as a function of both past volatility and a price run-up. Fig. 5 shows the probability of a crash as a function of past volatility using the full panel of industry returns. This relation is upward-sloping. The dashed line presents the same relation of the subset of industries that have experienced a 100% price run-up. The figure reveals that, even conditional on the level of volatility, a price run-up predicts a dramatically higher probability of a crash. Similar results can be seen in Panel B, which uses the international data.[15]

The data thus show that crashes are much more predictable than returns. What explains this? Some industries just keep going up and do not crash at all, although true

[14] Compared with unconditional log-return distribution, the log-return distribution conditional on price run-up is more left-skewed and fatter-tailed. See Online Appendix Table OA3.

[15] We can investigate this more formally by estimating regressions of the form

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

where *Crash* takes a value of one if the industry experiences a 40% drawdown at any point between month t and month t+24. $[R_{it\text{-}1} > X\%]$ denotes a dummy variable that takes a value of one if the industry's return (or net-of-market return) is greater than a threshold X, and σ denotes volatility of returns prior to the price run-up. We estimate this specification 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. The results for all return thresholds are presented in the Online Appendix.

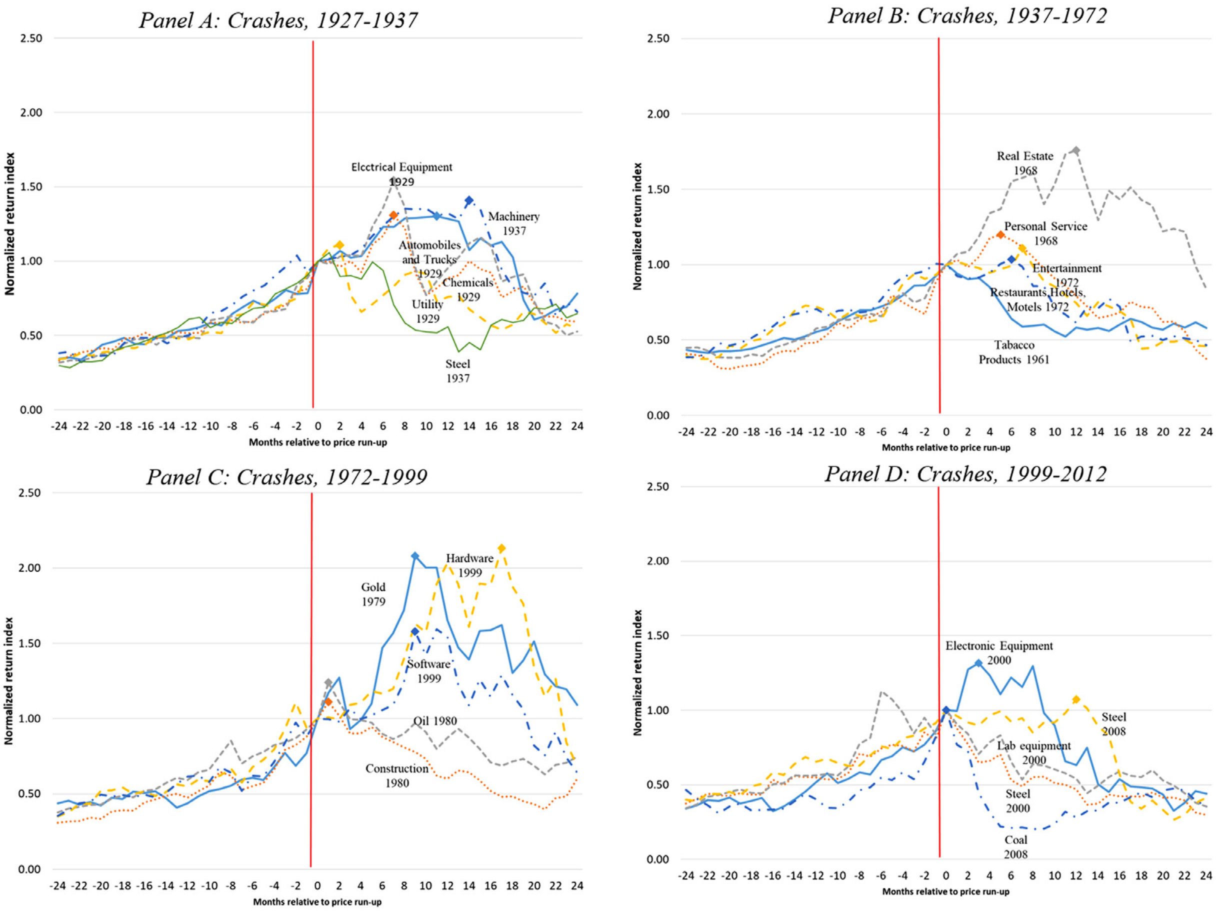


Fig. 6. Price path for crash episodes. The figure shows cumulative returns for the 21 episodes with a subsequent crash following price run-up. Event time 0 denotes the month when price run-up is first identified. The vertical axis denotes a cumulative return index. All price run-ups have been normalized to have a total return index of one at the time 0. We separate the episodes into four figures for visibility.

booms are not likely. 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. Fig. 6 shows this result more formally across all 21 of our crash episodes (the Online Appendix plots returns for the remaining 19 non-crash episodes). We plot event-time normalized price paths for the 21 episodes with an eventual crash (the Online Appendix shows price paths for the remaining episodes). 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 nine episodes in which the crash begins within three months, average one-year raw returns are −41% and, for the remaining episodes, average one-year raw returns are 22%, 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 nine episodes in which the crash begins within three months, average two-year returns are −49%, compared with −37% for the remaining episodes.

The evidence that larger industry stock price increases are associated with sharply higher probabilities of a crash is not, by itself, dispositive on the question of market efficiency. After all, investors can update their valuations of new industries in response to positive news until and unless they learn something that disappoints them. Still, the crash evidence is consistent with models of bubbles such as Barberis et al. (2018), in which larger run-ups are associated with larger deviations of prices from fundamental values and, thus, a higher probability of a crash.

4. 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 (1841), Kindleberger (1978), and others, as well as studies of the .com bubbles of the late 1990s, to systematically construct nonprice features of the price run-ups identified in Section 3. 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 5, we ask whether these additional characteristics also help forecast future average returns.

We consider characteristics of six types, all but one motivated by prior accounts of bubbles and partially driven by data availability (because we require the characteristics to be available as far back 1926 in the US data). First are trading volume and volatility which some studies find to be elevated during recent bubbles (Hong and Stein, 2007). Second, bubbles can arise from new industries and paradigm shifts (Kindleberger, 1978; Garber, 1989; Garber, 1990; Pastor and Veronesi, 2006; Greenwood and Nagel, 2009; Frehen et al., 2013). We construct a variable *age tilt*, 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 to take advantage of such mispricing and to fund investment opportunities (Loughran and 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; Fama and French, 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 become available from Compustat. Sixth, 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 three 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. 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 et al., 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 volatility, turnover, and age.

We have experimented with two ways to deal with this challenge. The first is to compute the percentage change of that characteristic (say, volatility or turnover) compared with 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 with other industries at the same time. The former emphasizes time series changes in industry attributes, and 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. In practice, both ways of measuring industry characteristics lead to similar conclusions. For example, as shown by Hong and Stein (2007), .com stocks not only experienced an increase in trading volume between 1997 and 1999, but also had high trading volume compared with other industries in 1999. We present results based on cross-sectional comparisons, and the Online Appendix reports 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 average turnover of the industry was higher than 86% of all listed stocks.

Age: Firm age is measured as the number of months since the firm first appeared on either Compustat or CRSP. 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: This variable represents the 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 5% 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 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 omits information on newly listed firms for which we do not have two years of data.

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 are value-weighted volatility and its one-year change, value-weighted percentile ranked turnover and its one-year change, value-weighted percentile ranked firm age, age tilt (equal-weight one-year gross return minus age-weighted one-year gross return), percentage of issuers and its one-year change. An issuer is defined as a company that issued 5% or more shares or initial public offering within one year, value-weighted book to market ratio, value-weighted percentile ranked sales growth, market cyclically adjusted price-earnings ratio, and acceleration (two-year gross return minus first half one-year gross return). *t*-statistics are based on standard errors clustered by calendar year. Seemly unrelated regression (SUR) tests the joint significance of all bubble features. We report the joint F-statistic and its corresponding *p*-value. N/A: Not applicable.

	All industry-months		Run-ups		Run-ups with crash		Run-ups with no crash		Crash minus no crash	
Features	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Difference	*t*-statistic
Past two-year return	0.272	(0.42)	1.574	(0.33)	1.722	(0.34)	1.411	(0.22)	0.311	[3.14]
Excess past two-year return	0.023	(0.32)	1.123	(0.15)	1.138	(0.17)	1.108	(0.13)	0.030	[0.64]
Turnover and volatility										
Volatility (VW)	0.328	(0.14)	0.498	(0.12)	0.508	(0.12)	0.487	(0.12)	0.021	[0.46]
Volatility (VW)−1yr-Δ	−0.002	(0.10)	0.039	(0.14)	0.093	(0.16)	−0.028	(0.07)	0.113	[2.61]
Turnover (VW)	0.545	(0.19)	0.684	(0.16)	0.667	(0.17)	0.703	(0.14)	−0.036	[−0.67]
Turnover (VW)−1yr-Δ	0.002	(0.09)	0.032	(0.10)	0.029	(0.10)	0.034	(0.10)	−0.005	[−0.15]
Age										
Firm age (VW)	0.740	(0.17)	0.652	(0.21)	0.724	(0.21)	0.574	(0.17)	0.150	[2.30]
Age tilt	−0.002	(0.06)	0.017	(0.12)	0.053	(0.14)	−0.022	(0.08)	0.075	[2.46]
Issuance										
Percentage of issuers	0.245	(0.18)	0.285	(0.17)	0.343	(0.18)	0.221	(0.14)	0.122	[2.17]
Fundamentals versus price										
Book to market (VW)	0.603	(0.65)	0.367	(0.21)	0.291	(0.19)	0.439	(0.20)	−0.148	[−1.75]
Sales growth	0.197	(0.41)	0.257	(0.15)	0.289	(0.18)	0.229	(0.12)	0.061	[1.04]
CAPE	18.272	(7.56)	22.438	(9.34)	25.454	(11.32)	19.104	(4.90)	6.350	[1.87]
Acceleration	N/A	N/A	1.074	(0.34)	1.228	(0.26)	0.905	(0.33)	0.323	[2.99]
Joint F-statistic										[3.62]
p-value (Probability > F)										0.000

CAPE: This variable is the cyclically adjusted price-earnings ratio in the month in which the price run-up is identified, available on Robert Shiller's website (http://www.econ.yale.edu/~shiller/). International CAPE series are available through Global Financial Data, covering 30 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 times. The remaining variables have a construction that is more time invariant, and so we use these variables in their natural units.

Fig. 7 plots these characteristics for the 40 industry price run-ups that we identify in US data. For each characteristic, we plot means for the industries that crash and compare them with the industries that do not. All plots are done in event time, with the event time of zero corresponding to the end of the month in which we first noticed a 100% price run-up. The most stunning patterns in the data occur for volatility, age tilt, issuance, book-to-market ratio, and market-level CAPE ratio. For example, Panel A shows that run-ups that are followed by a crash tend to experience increases in volatility in the last year of the run-up. Panel F shows that crash episodes have much lower book-to-market ratios.

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 Columns 3 and 4, we summarize the characteristic for all price run-ups and then separately show means for the price run-ups that crashed (Columns 5 and 6) and those that did not (Columns 7 and 8). Finally, in the last two columns, we show the difference in characteristics between price run-ups with and without a crash, as well as the *t*-statistics on this difference. As before, standard errors account for the clustering of events in a calendar year. Significant values in Column 10 suggest that, conditional on a price run-up, these characteristics help forecast a crash. The table summarizes average pre–and post–run-up returns for these subsamples, mirroring the results in Table 1.

Table 4 shows that, in general, price run-ups are associated with highly volatile firms. Industry volatility for price run-ups is 0.50, 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 experienced rapid increases in volatility relative to other industries in the year prior (1-year $\Delta = 0.09$), and industries that do not subsequently crash experience no such increase (1-year $\Delta = -0.03$), with the difference of 0.11 significant at the 5% level.

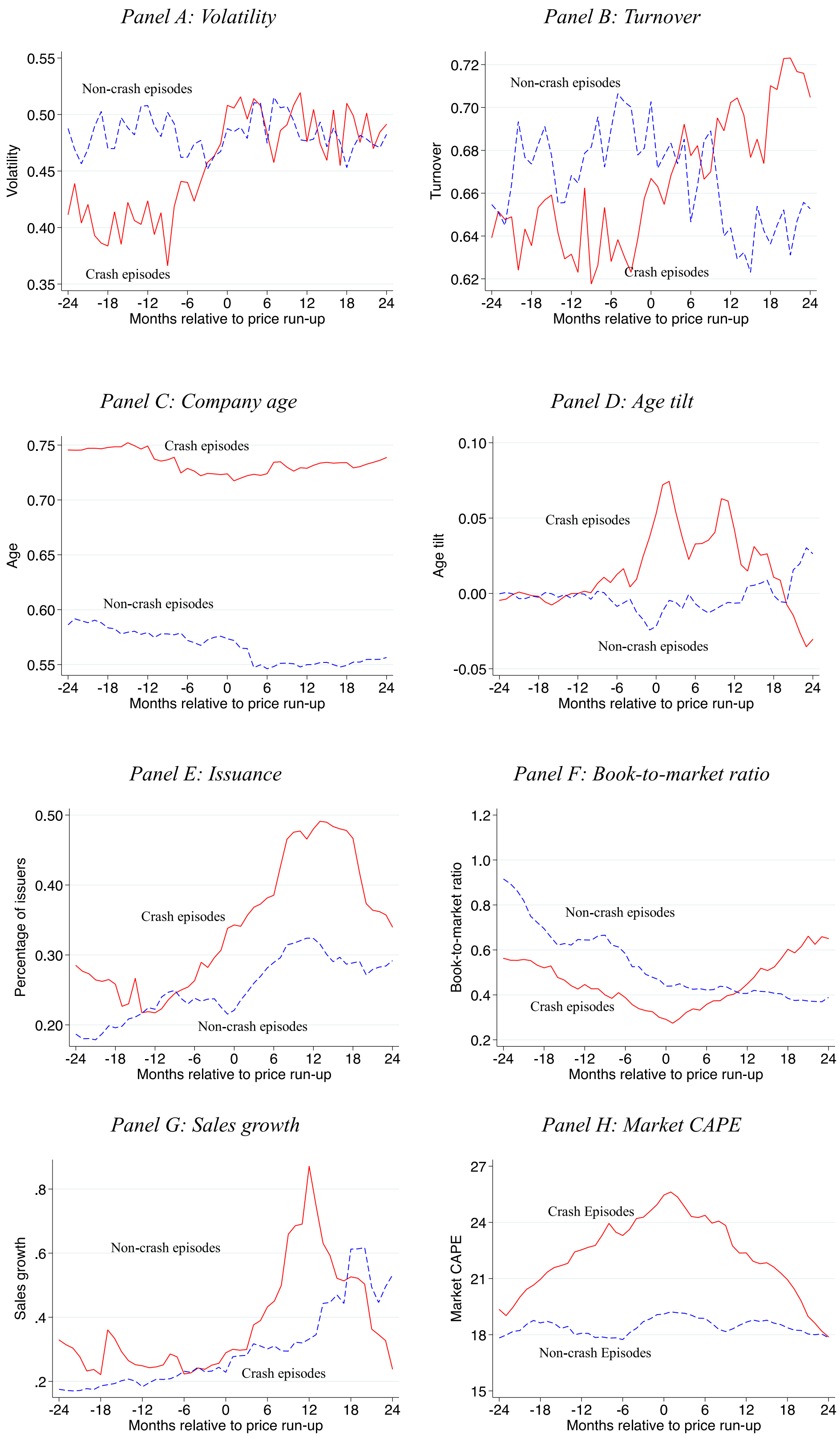


Fig. 7. Characteristics for 40 US industry price run-ups. The figure shows the characteristics separated by those that crash (solid line) and those that do not (dashed). The graphs show event-time plots for volatility, turnover, age, age tilt, issuance, the book-to-market ratio, sales growth, and market cyclically adjusted price-earning ratio (http://www.econ.yale.edu/~shiller/data.htm).

Proceeding in this way down Column 9 in Table 4 shows 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 industry book-to-market ratio also appear predictive, although the results are significant only at the 10% level. In short, price run-ups experiencing increases in volatility, involving younger firms, having higher relative 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, turnover does not seem to be a characteristic that meaningfully distinguishes the price run-ups that ultimately crash. On average, turnover is extremely elevated among the 40 run-ups (an average of 0.68, compared with an unconditional average of 0.55), but it 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 4 also presents F-statistics on the joint hypothesis that no difference exists between the characteristics of crashes and non-crashes, for all of the characteristics we have considered, from volatility to acceleration. In conducting this test, we account for the fact that regressors are correlated across episodes using a seemingly unrelated regressions (SUR) methodology. One limitation of the standard F-test is that characteristics predicting crashes with the wrong economic sign also contribute to the joint significance. To address this concern, we prespecify the sign for all characteristics.[16] If a predictor emerges with the wrong sign, we replace the characteristic with noise, computed by taking the residual from a regression of the crash dummy on the characteristic. This adjustment eliminates the statistical contribution from the wrong sign characteristics and punishes the F-test by introducing more noise.

The F-statistic of 3.62 means that we can reject with a high level of confidence the joint hypothesis that no difference exists between the characteristics of crashes and non-crashes. In other words, while some of the characteristics we have studied, such as turnover, do not have much predictive power for crashes, overall we can easily reject the hypothesis that crashes and non-crashes are identical ex ante.

Table 5 repeats this analysis for the 107 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 because of 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 0.060, t-statistic of 1.68). 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 15.4 percentile points, with a t-statistic of 5.50.

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 US. And, as in the US, turnover is elevated during price run-ups but does not help distinguish between the price run-ups that do and do not crash. The F-statistic of 5.74 on the joint test across all characteristics confirms that, much like in the US data, we can easily reject the hypothesis that crashes and non-crashes have identical characteristics ex ante.

5. Predicting returns

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.

We begin by presenting simple forecasting regressions of future returns on characteristics of the price run-up. These regressions have the form

$$R_{it\to t+24} = a + b \cdot Char_{it} + u_i, \tag{1}$$

for each price run-up episode i. The dependent variable R denotes either the 24-month raw return to the industry, the 24-month excess (net of risk-free) return, or the 24-month net of market return. $Char_{it}$ denotes a characteristic of the price run-up episode, such as the change in volatility or issuance, measured using data through the end of month t. We use the same set of characteristics as in Tables 4 and 5.

Table 6 presents these results. Panel A presents regressions using the 40 US run-up episodes. The change in *Volatility, Age tilt, Issuance, Book-to-market, CAPE*, and *Acceleration* significantly predict both raw returns and excess returns. Only the change in *Volatility* and *Age tilt* successfully predict net of market returns, suggesting that the concept of an industry bubble is closely intertwined with that of overall market valuation. Table 6 also presents the one-sided F-statistic[17] on the joint test that all coefficients predicting returns are zero, a hypothesis we can reject with a high degree of confidence, even at 10% statistical significance for net of market returns in the last three columns.

Panel B of Table 6 shows that our forecasting results using US data hold similarly, if not stronger, in the international data. *Volatility, Age, Age tilt, Issuance, Book-to-market ratio, CAPE*, and *Acceleration* all predict excess and

[16] To pre-sign the predictor variables, we assume that bubbles tend to have higher volatility, higher volatility one year changes, higher turnover, higher turnover one-year changes, lower firm age, larger age tilt, more issuance, lower book-to-market ratios, higher CAPE, and higher acceleration.

[17] We pre-sign the variables in accordance with footnote 16.

Table 5
Characteristics of price and crashes: international sectors.
The table summarizes features of price run-ups of international sectors. We compare means across crashes and non-crash episodes. A crash is defined as a 40% drawdown from any point in the two years after the initial price run-up. The features are value-weighted volatility and its one-year change, value-weighted percentile ranked turnover and its one-year change, value-weighted percentile ranked firm age, age tilt (equal-weight one-year gross return minus age-weighted one-year gross return), percentage of issuers (an issuer is defined as a company with more than 5% share issuance within one year), value-weighted book to market ratio, value-weighted percentile ranked sales growth, market cyclically adjusted price-earnings ratio, and acceleration (two-year gross return minus first half one-year gross return). *t*-statistics are based on standard errors clustered by sector and calendar year. The seemingly unrelated regression (SUR) tests the joint significance of all bubble features. We report the F-statistic and its corresponding *p*-value. N/A: Not applicable.

	All industry-months		Run-ups		Run-ups with crash		Run-ups with no Crash		Crash minus no Crash	
Feature	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Difference	t-statistic
Past two-year return	0.264	(0.65)	2.119	(0.94)	2.388	(1.16)	1.856	(0.54)	0.532	[2.98]
Excess past two-year return	0.040	(0.44)	1.297	(0.54)	1.439	(0.74)	1.157	(0.13)	0.282	[2.80]
Turnover and volatility										
Volatility (VW)	0.367	(0.16)	0.500	(0.16)	0.577	(0.15)	0.423	(0.13)	0.154	[5.50]
Volatility (VW)−1yr-Δ	−0.003	(0.16)	0.059	(0.17)	0.089	(0.17)	0.029	(0.16)	0.060	[1.77]
Turnover (VW)	0.609	(0.16)	0.580	(0.16)	0.587	(0.17)	0.572	(0.15)	0.015	[0.44]
Turnover (VW)−1yr-Δ	0.004	(0.10)	0.029	(0.12)	0.040	(0.12)	0.019	(0.11)	0.021	[1.03]
Age										
Firm age (VW)	0.585	(0.18)	0.588	(0.20)	0.544	(0.21)	0.630	(0.17)	−0.087	[−2.25]
Age tilt	−0.009	(0.45)	0.486	(1.95)	0.906	(2.22)	0.058	(1.55)	0.848	[2.25]
Issuance										
Percentage of issuers	0.459	(0.41)	0.500	(0.50)	0.575	(0.59)	0.427	(0.39)	0.147	[1.57]
Fundamentals versus price										
Book to market (VW)	0.659	(1.19)	0.346	(0.24)	0.258	(0.16)	0.432	(0.27)	−0.174	[−4.02]
Sales growth	0.537	(0.15)	0.582	(0.15)	0.598	(0.14)	0.566	(0.16)	0.032	[1.10]
CAPE	20.185	(8.79)	25.366	(12.49)	30.863	(14.10)	19.981	(7.59)	10.882	[4.63]
Acceleration	N/A	N/A	1.529	(0.91)	1.936	(1.07)	1.130	(0.45)	0.806	[5.18]
Joint F-statistic										[5.74]
p-value (Probability > F)										0.000

Table 6
Return predictability and bubble characteristics.
Univariate regressions predict future 24-month returns using characteristics of the price run-ups. We predict 24-month raw return, net of risk-free return, and net of market return:

$$R_{it\to t+24} = a + b \bullet Char_{it} + u_i$$

Panel A shows results for US industry price run-ups. Panel B show results for international data. To evaluate joint significance, the stacked ordinary least square regressions test the joint significance of all bubble characteristics and output the F-statistics and the corresponding p-values. t-statistics and one-sided F-statistics are based on robust standard errors clustered by calendar year in Panel A and standard errors clustered by sector - calendar year in Panel B. VW: value-weighted; CAPE: cyclically adjusted price-earnings ratio.

	24-month raw return			24-month net of risk-free return			24-month net of market return		
Characteristic	b	[t-statistic]	R-squared	b	[t-statistic]	R-squared	b	[t-statistic]	R-squared
Panel A: US industries 1926–2012									
Volatility (VW)	0.012	[0.02]	0.000	−0.140	[−0.18]	0.001	−0.167	[−0.29]	0.002
Volatility (VW)−1yr-Δ	−1.288	[−3.67]	0.106	−1.346	[−3.87]	0.120	−0.832	[−2.13]	0.078
Turnover (VW)	0.764	[1.12]	0.049	0.777	[1.20]	0.052	0.580	[1.15]	0.050
Turnover (VW)−1yr-Δ	0.824	[0.64]	0.022	0.743	[0.62]	0.019	1.007	[1.40]	0.058
Firm age (VW)	−0.758	[−1.37]	0.084	−0.748	[−1.43]	0.084	−0.541	[−1.31]	0.076
Age tilt	−1.651	[−2.26]	0.129	−1.765	[−2.70]	0.152	−1.336	[−2.55]	0.150
Percentage of issuers	−1.058	[−2.42]	0.110	−0.994	[−2.37]	0.101	−0.585	[−1.77]	0.060
Book-to-market (VW)	1.151	[2.37]	0.165	1.017	[1.90]	0.131	0.696	[1.49]	0.104
Sales growth	0.642	[0.83]	0.027	0.429	[0.56]	0.012	0.283	[0.47]	0.009
CAPE	−0.025	[−2.54]	0.192	−0.022	[−2.19]	0.156	−0.011	[−1.29]	0.068
Acceleration	−0.434	[−1.71]	0.074	−0.463	[−1.85]	0.087	−0.259	[−1.37]	0.047
Joint F-statistic		[3.43]			[4.00]			[1.84]	
p-value (Probability > F)		0.006			0.002			0.103	
Panel B: International sectors 1987–2012									
Volatility (VW)	−1.677	[−5.36]	0.146	−1.722	[−5.43]	0.152	−0.746	[−3.98]	0.085
Volatility (VW)−1yr-Δ	−0.646	[−1.39]	0.025	−0.641	[−1.34]	0.024	−0.757	[−3.20]	0.100
Turnover (VW)	−0.651	[−1.58]	0.023	−0.698	[−1.67]	0.026	−0.547	[−2.23]	0.048
Turnover (VW)−1yr-Δ	0.113	[0.16]	0.000	0.080	[0.11]	0.000	−0.054	[−0.13]	0.000
Firm age (VW)	0.994	[2.47]	0.080	1.026	[2.50]	0.084	0.525	[2.13]	0.061
Age tilt	−0.055	[−1.72]	0.024	−0.059	[−1.84]	0.028	−0.035	[−1.46]	0.028
Percentage of issuers	−0.261	[−2.81]	0.035	−0.261	[−2.76]	0.035	−0.135	[−2.31]	0.028
Book-to-market (VW)	1.176	[3.071	0.163	1.220	[3.16]	0.173	0.311	[1.31]	0.034
Sales growth	0.321	[0.71]	0.005	0.307	[0.67]	0.004	0.397	[1.64]	0.021
CAPE	−0.026	[−4.92]	0.206	−0.027	[−5.04]	0.219	−0.007	[−2.38]	0.052
Acceleration	−0.201	[−4.65]	0.068	−0.210	[−4.79]	0.073	−0.068	[−2.67]	0.023
Joint F-statistic		[6.17]			[6.75]			[2.05]	
p-value (Probability > F)		0.000			0.000			0.039	

raw returns. Most of these characteristics also predict net of market returns as well. In contrast with the results using the US sample, *Turnover* and *Firm age* are more helpful for predicting returns. Price run-ups experiencing either high turnover or high sales growth are more likely to experience low subsequent returns.

5.1. Assessing statistical significance

We have assessed the statistical significance of our findings using conventional t-statistics clustered by calendar year. For example, for each characteristic such as turnover or age, the t-statistics in Table 6 test a null hypothesis of no predictability. We have also presented the joint F-tests, which reject the null hypothesis that none of the characteristics has any predictive value for crashes (Tables 4 and 5) or returns (Table 6).

A separate concern is the potential for data snooping. The multiple comparison problem described by Bonferroni (1936) and Dunn (1959) suggests that some of the characteristics we uncover as being predictive could arise by chance because we are studying many at the same time. For example, at a 5% significance level, 5% of the characteristics that we study would be significant merely by chance. This problem is mitigated by the fact that we have shown results for all variables that we have examined, including those that turn out not to be especially predictive (such as turnover). Data snooping is also limited by our long historical sample, limiting how many variables we can study. Nevertheless, we must be cautious in over-attributing statistical significance to any individual characteristic.

To address the multiple comparison problem, we apply the Bonferroni adjustment to each of our individual findings. Let H_1, ...H_k be the family of t-tests in Table 4 and $p_1 \ldots p_k$ be their corresponding p-values. The Bonferroni inequality states that individual hypotheses must be significant at the α/k level, where α is a pre-determined significance level and k ($k = 11$ here) is the number of characteristics we study. With 11 characteristics and a desired significance level of 5%, this means requiring a p-value of 0.45%, or a t-statistic of approximately 3.01. With a desired significance level of 10%, this means requiring a t-statistic of 2.75.

Only a few of the characteristics we have studied here clear the Bonferroni adjustment. With only 40 observations in the US sample, only *Acceleration* can pass the 10% level test after Bonferroni adjustment. In the international sample, having more run-up observations increases the power of our tests: *Volatility, Acceleration, CAPE* and *Book-to-market ratio* are significant at the 10% level.

The Bonferroni adjustment controls for the probability of making a single Type I error across all the variables we test, setting a very high bar for statistical significance, which perhaps explains why it is so seldom used in empirical work. For our purposes, the Bonferroni adjustment is useful for accepting or rejecting the null hypothesis of zero predictability for each characteristic individually. For example, a *p*-value of 0.9% for each characteristic implies that only a 10% probability exists of incorrectly rejecting a single null hypothesis across all 11 *t*-tests that we run, a very high bar. Applying the Bonferroni criteria, we are far more likely to make a Type II error.

An alternative approach is to control for the fraction of rejections that are expected to be Type I errors or false discoveries in the sense that they incorrectly reject the null hypothesis of zero predictability. In essence, such an approach ensures that of all the rejections we make, only a very limited number, say 10%, can be expected to be Type I errors. For a researcher interested in the question of whether returns can be predicted at all, or whether any characteristics forecast the end of a bubble, but is less concerned with the statistical significance of any individual characteristic, this is a more appropriate approach.

We control for the false discovery rate using the Benjamini and Hochberg (1995) procedure. The essence of this procedure is to impose a tolerance for false discovery across all of the characteristics we study and to ask, given this tolerance, how many characteristics can we admit as being predictive. To implement it, we rank all 11 characteristic variables from lowest to highest by their *p*-value and then compare the *p*-value with the adjusted *p*-value, given by ($\alpha \times$ rank) / 11. This stepwise procedure starts with the variable with the highest *p*-value. If the *p*-value is higher than the adjusted *p*-value, the variable is taken to be insignificant. As soon as a variable is reached for which the *p*-value is lower than the adjusted *p*-value, the procedure concludes that this variable and all variables with lower *p*-values are significant. For the lowest *p*-value characteristic, this is the same as the Bonferroni adjustment. We apply the false discovery tests to all of the characteristic-related findings shown previously in Tables 4–6.

Panel A of Table 7 shows the false discovery tests that correspond to our prior results in Tables 4 and 5, in which

Table 7
False discovery tests.
The table tests the joint significance of the bubble features in Table 4, Table 5, and Table 6 allowing for a maximal false discovery rate of 10%. In the spirit of Bonferroni correction (Dunn, 1959), we adopt the maximal false discovery rate procedure from Soric (1989) and Benjamini and Hochberg (1995) to compute the probability of false discovery. We rank all variables by their *p*-values. Panel A tabulates bubble features sorted ascending in order by *p*-values. Columns (1) and (2) present the t-statistics and corresponding *p*-values for the last column in Tables 4 and 5. Column (3) displays the *p*-value thresholds for 10%, and Column (4) reports whether the bubble features can pass the false discovery test. Panel A shows the results of false discovery tests for Tables 4 and 5. The variables with * show the opposite sign with prespecified directions and are assigned with 0.5 *p*-value in the one-sided test. In Panel B and Panel C, we report the joint false discovery tests for all regressions in Table 6. "True" in the "10% significance" column represents that the bubble characteristic jointly passes the false discovery test at 10% significance. Numbers in bold represent that the bubble characteristic individually passes the Bonferroni test at 10% significance. CAPE: cyclically adjusted price-earnings ratio.

Panel A: Tests for Tables 4 and 5

Feature	[*t*-statistic] (1)	*p*-value (2)	10% threshold (3)	10% significance (4)
US industries 1926 – 2012				
Acceleration	[2.99]	0.002	0.009	True
Volatility (VW)- 1yr-Δ	[2.61]	0.005	0.018	True
Age tilt	[2.46]	0.008	0.027	True
Percentage of issuers	[2.17]	0.016	0.036	True
CAPE	[1.87]	0.032	0.045	True
Book-to-market (VW)	[−1.75]	0.042	0.055	True
Volatility (VW)	[0.46]	0.323	0.064	False
Turnover (VW)−1yr-Δ*	[−0.67]	0.500	0.073	False
Turnover (VW) *	[−0.15]	0.500	0.082	False
Sales growth*	[2.30]	0.500	0.091	False
Firm age (VW)*	[1.04]	0.500	0.100	False
International sectors 1987 – 2012				
Volatility (VW)	[5.50]	0.000	0.009	True
Acceleration	[5.18]	0.000	0.018	True
CAPE	[4.63]	0.000	0.027	True
Book-to-market (VW)	[−4.02]	0.000	0.036	True
Firm age (VW)	[−2.25]	0.013	0.045	True
Age tilt	[2.25]	0.013	0.055	True
Volatility (VW)−1yr-Δ	[1.77]	0.040	0.064	True
Percentage of issuers	[1.57]	0.060	0.073	True
Turnover (VW)−1yr-Δ	[1.03]	0.153	0.082	False
Turnover (VW)	[0.44]	0.330	0.091	False
Sales growth*	[1.10]	0.500	0.100	False

(*continued on next page*)

Table 7
(continued)

Panel B: Tests for Table 6 US industries

Features	24-month raw return			24-month net of risk-free return			24-month net of market return		
	[*t*-statistic]	*p*-value	10% significance	[*t*-statistic]	*p*-value	10% significance	[*t*-statistic]	*p*-value	10% significance
Volatility (VW)	[0.02]	0.984	False	[−0.18]	0.858	False	[−0.29]	0.773	False
Volatility (VW)−1yr-Δ	[−3.67]	0.001	True	[−3.87]	0.000	True	[−2.13]	0.040	False
Turnover (VW)	[1.12]	0.270	False	[1.20]	0.237	False	[1.15]	0.257	False
Turnover (VW)−1yr-Δ	[0.64]	0.526	False	[0.62]	0.539	False	[1.40]	0.169	False
Firm age (VW)	[−1.37]	0.179	False	[−1.43]	0.161	False	[−1.31]	0.198	False
Age tilt	[−2.26]	0.029	True	[−2.70]	0.010	True	[−2.55]	0.015	False
Percentage of issuers	[−2.42]	0.020	True	[−2.37]	0.023	True	[−1.77]	0.085	False
Book-to-market (VW)	[2.37]	0.023	True	[1.90]	0.065	False	[1.49]	0.144	False
Sales growth	[0.83]	0.412	False	[0.56]	0.500	False	[0.47]	0.641	False
CAPE	[−2.54]	0.015	True	[−2.19]	0.035	True	[−1.29]	0.205	False
Acceleration	[−1.71]	0.095	False	[−1.85]	0.072	False	[−1.37]	0.179	False

Panel C: Tests for Table 6 International Sectors

Features	24-month raw return			24-month net of risk-free return			24-month net of market return		
	[*t*-statistic]	*p*-value	10% significance	[*t*-statistic]	*p*-value	10% significance	[*t*-statistic]	*p*-value	10% significance
Volatility (VW)	[−5.36]	0.000	True	[−5.43]	0.000	True	[−3.98]	0.000	True
Volatility (VW)−1yr-Δ	[−1.39]	0.167	False	[−1.34]	0.183	False	[−3.20]	0.002	True
Turnover (VW)	[−1.58]	0.117	False	[−1.67]	0.098	False	[−2.23]	0.028	True
Turnover (VW)−1yr-Δ	[0.16]	0.873	False	[0.11]	0.913	False	[−0.13]	0.897	False
Firm age (VW)	[2.47]	0.015	True	[2.50]	0.014	True	[2.13]	0.035	True
Age tilt	[−1.72]	0.088	False	[−1.84]	0.069	False	[−1.46]	0.147	False
Percentage of issuers	[−2.81]	0.006	True	[−2.76]	0.007	True	[−2.31]	0.023	True
Book-to-market (VW)	[3.07]	0.003	True	[3.16]	0.002	True	[1.31]	0.193	False
Sales growth	[0.71]	0.479	False	[0.67]	0.504	False	[1.64]	0.104	False
CAPE	[−4.92]	0.000	True	[−5.04]	0.000	True	[−2.38]	0.019	True
Acceleration	[−4.65]	0.000	True	[−4.79]	0.000	True	[−2.67]	0.009	True

we compared characteristics between price run-ups that did and did not crash. With a 10% false discovery rate, six characteristics (*Acceleration*, the change in *Volatility, Age tilt, Issuance, CAPE* and *Book-to-market ratio)* are admitted as jointly predictive. Among the six characteristics, *Acceleration*, the change in *Volatility,* and *Age tilt* are individually predictive even after Bonferroni correction. In the international data, eight characteristics (*Volatility, Acceleration, CAPE, Book-to-market, Age, Age tilt*, the change in *Volatility* and *Issuance*) are admitted as jointly predictive. Among the eight characteristics, *Volatility, Acceleration, CAPE,* and *Book-to-market ratio* are individually predictive even after Bonferroni correction. For comparison, the table also shows in boldface the characteristics that pass the stricter Bonferroni test.

Panel B of Table 7 shows the false discovery tests applied to our regressions from Table 6. We use characteristics at the time of price run-up to predict future 24-month returns. With a false discovery rate of 10%, five characteristics (the change in *Volatility, Age tilt, Issuance, Book-to-market ratio,* and *CAPE*) predict raw returns, and four characteristics (change in *Volatility, Age tilt, Issuance*, and *CAPE*) predict excess returns in US data. In the international data, six characteristics (*Volatility, Age, Issuance, Book-to-market ratio, Sales growth, CAPE* and *Acceleration*) predict raw returns, six characteristics (*Volatility, Age, Issuance, Book-to-market ratio, CAPE,* and *Acceleration*) predict excess returns, and seven characteristics (*Volatility,* the change in *Volatility, Turnover, Age, Issuance, CAPE,* and *Acceleration*) predict net of market returns.

5.2. From forecasting regressions to trading strategies

The fact that many characteristics predict returns following a price run-up directly implies that an investor with this information could form a trading strategy to time his exit from the bubble industry. More formally, in Table 6 we present time series forecasting relations of the form

$$R_{t+1} = \alpha + \beta \cdot x_t + \varepsilon_{t+1}, \tag{2}$$

where R is the excess industry return and x is the forecasting variable. Consider a trading strategy that switches between the risk-free asset and the industry according to x. The excess returns on this market timing portfolio are given by

$$R^{MktTime}_{t+1} = R_{t+1} \cdot (x_t - \bar{x}) \tag{3}$$

The Sharpe ratio of this portfolio is proportional to the population t-statistic of the ordinary least squares estimator of β from Eq. (2). Put simply, higher t-statistics in Table 6 correspond to higher Sharpe ratios for market timers exploiting the predictability. One must exercise some caution in assessing such trading strategies, because implementing them involves look-ahead bias as to which characteristics turn out to be predictive of returns.

As a robustness exercise, we have also analyzed simpler trading strategies that exit an industry entirely following a price run-up, provided that a characterstic such as *Acceleration* or *Volatility* reaches a threshold value. An investor could monitor a price run-up and, conditional on the run-up as well as, for example, acceleration, volatility, and a high CAPE, exit the industry and shift funds into the market or the risk-free asset. As a practical matter, implementing such strategies trades off false positives and false negatives. For example, one can set high threshold values for calling a bubble, but doing so would identify only a limited number of episodes, even if such episodes crash with a high probability.

In the Online Appendix, we summarize the performance of such trading strategies. Beyond the predictability of returns that we have already discussed, we reach two additional conclusions from this analysis. First, the ability to time a bubble depends on the horizon. At a horizon of one year, it is virtually impossible to generate outperformance, reflecting our earlier observation that even a correct call of a bubble misses the peak by an average of six months. However, at a horizon of two years or more, conditioning on the price run-up together with volatility, issuance, age, age tilt, book-to-market ratio, and acceleration generates statistically significant outperformance, even with our small sample of bubble events. Second, outperformance tends to be larger, in terms of both economic and statistical significance, for trading strategies that switch out of the industry with a price run-up into the risk-free asset, instead of the broader stock market. This is because industry price run-ups tend to occur during broader market rallies. When an industry bubble is called correctly, it is best to avoid the stock market altogether.

6. Conclusion

In this paper, we address Fama's challenge of whether stock market bubbles can be identified ex ante. We use industry-level data for both the US and internationally, and we ask whether we can predict what happens after a 100% industry return. We present four findings. First, Fama is correct 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. The probability of a price boom does not rise, meaning that price run-ups are associated with leftward shifts in the distribution of future returns. 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. Fourth, using these attributes helps to forecast returns, through avoidance of some of the crashes.

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 used only variables that the literature has already talked about and we have used them one at a time. We have not sought to identify dynamic strategies of optimal exit from the industry but focus on simply exiting after a run-up. Most important, we start with industries that have a very large price increase of 100% above market, which has limited our sample to 40 episodes in US data and 107 in international data. All of this can perhaps be changed to use more sophisticated algorithms, and some of these algorithms could increase the reliability and size of abnormal returns. However, considering more complex trading strategies would raise concerns about the lookback bias and data mining that we have tried to avoid.

Even so, this evidence needs to be taken with a grain of salt. By the nature of the question, observations are scarce, very few are in the US, and these are far from independent observations. Choices of two-year run-up window, 100% threshold, and so forth are somewhat arbitrary. We consider a number of potential predictors that, when combined with limited observations, make spurious correlation a concern. We take reasonable steps to mitigate these concerns and, after doing so, continue to find significant predictability, but one would not have to look far to find more conservative corrections.

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

To put these points somewhat differently, Fama has set a bar for identifying bubbles. He says that one needs to find evidence that crashes and returns can be predicted. This is a relatively high bar. If assets are overvalued relative to fundamentals but adjust to efficient valuations slowly over time and with some volatility, Fama would not call it a bubble. Nonetheless, we believe that the evidence clears Fama's bar. Several variables predict both crashes and returns at high levels of statistical significance even once we correct for the multiple comparison problem. We have few observations, and history never repeats itself exactly, but we can still identify bubbles in Fama's sense.

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