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Version May 3, 2012

ERIM REPORT SERIES *RESEARCH IN MANAGEMENT*	
ERIM Report Series reference number	ERS-2009-058-F&A
Publication	May 2012
Number of pages	61
Persistent paper URL	http://hdl.handle.net/1765/17525
Email address corresponding author	kole@ese.eur.nl
Address	Erasmus Research Institute of Management (ERIM) RSM Erasmus University / Erasmus School of Economics Erasmus Universiteit Rotterdam P.O.Box 1738 3000 DR Rotterdam, The Netherlands Phone: + 31 10 408 1182 Fax: + 31 10 408 9640 Email: info@erim.eur.nl Internet: www.erim.eur.nl

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REPORT SERIES
RESEARCH IN MANAGEMENT

ABSTRACT AND KEYWORDS	
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Free Keywords	bubbles, limits to arbitrage, market efficiency, structural breaks
Availability	The ERIM Report Series is distributed through the following platforms: Academic Repository at Erasmus University (DEAR), DEAR ERIM Series Portal Social Science Research Network (SSRN), SSRN ERIM Series Webpage Research Papers in Economics (REPEC), REPEC ERIM Series Webpage
Classifications	The electronic versions of the papers in the ERIM report Series contain bibliographic metadata by the following classification systems: Library of Congress Classification, (LCC) LCC Webpage Journal of Economic Literature, (JEL), JEL Webpage ACM Computing Classification System CCS Webpage Inspec Classification scheme (ICS), ICS Webpage

Riding Bubbles*

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May 3, 2012

*We thank Guillermo Baquero, Martin Bohl, Markus Brunnermeier, Phil Davies, Jeroen Derwall, Dick van Dijk, Mathijs van Dijk, Ingolf Dittmann, Alex Edmans, Piet Eichholtz, Rüdiger Fahlenbrach, Robert Flood, Mark Grinblatt, Campbell Harvey, Kewei Hou, Marcin Jakowski, Raymond Kan, Andrew Karolyi, Kees Koedijk, Philipp Koziol, Marcel Marekwica, Alex Michaelides, Stefan Nagel, Ľuboš Pástor, Thomas Post, Sebastien Pouget, Terrance Odean, Adriano Rampini, Lev Ratnovski, Mark Rubinstein, Erwan Le Saout, Peter Schotman, Sophie Shive, Marta Szymanowska, Rene Stulz, Jerome Taillard, Marno Verbeek, and (seminar) participants at the Haas School of Business, PanAgora Asset Management, the European School of Management and Technology (ESMT), the 2010 CRSP Forum at the University of Chicago, Manchester Business School, the 2010 Annual Meeting of the Academy of Behavioral Finance and Economics, the 2010 Annual Meeting of the European Economic Association, the 2010 Midwest Macro Meeting, the 2010 European Winter Finance Summit, the 2009 European Finance Association (EFA) Annual Meeting, 2009 McGill Global Asset Management Conference, the 2009 European Winter Finance Conference, the 2008 Society for Financial Econometrics Conference, the 2008 Washington Area Finance Association Meeting, the 2008 Norges Bank workshop in Venastul (Norway), WHU's Campus for Finance 2008 conference, the 2007 French Finance Association Meeting, the 2007 CEPR-Banque de France conference, Erasmus University, Maastricht University and at the PhD Seminar Series at Ohio State University for helpful comments and discussions. We thank Sandra Sizer for editing. Kole gratefully acknowledges financial support from the Vereniging Trustfonds Erasmus Universiteit Rotterdam and NWO. We thank the Quantitative Research Group at PanAgora Asset Management for awarding the Crowell Memorial Second Prize for this paper. E-mail addresses: `nk.guenster@maastrichtuniversity.nl`, `kole@ese.eur.nl`, `b.jacobsen@massey.ac.nz`.

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Abstract

Bubbles can persist because investors are better off riding bubbles. We define bubbles in a natural way as significant, prolonged deviations from fundamental values measured by the well-known asset pricing models. Our real-time bubble detection system shows that–using US industry returns–periods of both higher volatility and higher abnormal returns follow noisy positive bubble signals. However, for the typical investor the risk-return trade-off improves. Riding bubbles generates annual abnormal returns of three to nine percent. These conclusions are robust to different assumptions and our system allows for alternative multifactor models as proxies for fundamental value.

Key words: bubbles, limits to arbitrage, market efficiency, structural breaks

JEL classification: G10, G14, C14

Introduction

An unanswered question in finance is whether asset price bubbles can persist or even inflate in the presence of rational investors. The answer to this question directly depends on whether investors benefit from bubbles. Our results suggest they do. We define a bubble in a straightforward way that is in line with the literature; for instance, Abreu and Brunnermeier (2003) or the Minsky model as described by Kindleberger (2000). Firstly, a bubble requires a prolonged period of price growth that is higher than the growth rate of the asset's fundamental value. Secondly, the growth rate of the price should experience a sudden, significant acceleration. These two conditions capture the main characteristics of asset price bubbles. For proxies of the growth rates of fundamental values, we use the traditional asset pricing models: the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), the three-factor model developed by Fama and French (1993), and the four-factor model introduced by Carhart (1997). However, our approach can easily be used with other multifactor models. Based on these conditions and models, we develop a new real-time bubble detection system. As a result, our bubble signals are not perfect in real time, but in line with the uncertainty an investor faces when deciding whether or not a bubble might be growing.

Most of the famous historical bubbles started in industries. Examples are the recent housing bubble (1998-2009), the internet bubble (1995-2000), the tronics boom (1959-1962) or the railway mania (1840s). Therefore, industries seem a natural candidate for our analysis. We apply our bubble detection system to the 48 Fama and French (1997) US industry returns from 1926 to 2009.

While we formally introduce our bubble detection system in Section 1, an example might help to shape the reasoning underlying our approach. An investor might use the CAPM as a proxy for fundamental value and run regressions of the industry returns on market returns over the past ten years. In these regressions the investor looks for the largest positive and statistically significant structural break in the intercept (i.e., Jensen's alpha) in the most recent five to one years based on the test statistic of Andrews (1993). The minimum of one year excludes short-term deviations. If there is a significantly positive break, then a bubble might be forming and the investor needs to check (1) whether the intercept following the break point is significantly positive and (2) whether there has not been a crash in the last six months that might have ended the bubble. If both conditions are met, the investor assumes that there is a bubble and the signal is positive for the next month. As the signal is updated every month, the investor captures bubbles with life spans of at least one year and a maximum of five years. Our system works well in the sense that the bubbles are in line with the general perception. In our base scenario, bubbles tend to be rare: they only occur between three and five percent of the time. Bubble growth is economically significant: the bubbles grow (in deviation from fundamental value) by about two percent a month. And they are here for the long run: the average bubble lasts around thirty months. The average bubble can therefore have a total price deviation of about sixty percent, which conforms well with the general concept of bubbles. Just like investors, we face a large number of choices in the development and implementation of a real-time system. We test a large number of realistic choices and our results are robust. Simulations show that our method is–not surprisingly–noisy. Nevertheless, the system clearly detects famous bubbles over the last ninety years like the tronics boom, the internet bubble and the bubble in concept stocks in 1967 and 1968. Our bubbles correlate well with the sentiment indicators of Baker and Wurgler (2006, 2007) and Lemmon and Portniaguina (2006).

When we analyze the return distributions in months immediately following the positive bubble signals, we find that investors benefit from bubbles. Firstly, abnormal returns are significantly higher following the positive bubble signals. Secondly, we find significant increases for various risk measures. Evaluating both effects together, we find that the overall risk-return trade-off improves. The difference in monthly abnormal returns is about 0.43% for both the Fama-French and the Carhart models. Bubble signals in a CAPM framework generate monthly abnormal returns of 0.80% per month. Volatility increases by 14% for the CAPM and 19% for the other two models. Downside risk measures like value-at-risk (VaR) and expected shortfall (ES) show comparable increases. This analysis errs on the side of caution: the returns include crashes when the bubble bursts, which explains the increase in risk measures following positive bubble signals. In that case the bubble signal is positive but the industry crashes in the next month.

To find out whether an investor should ride, sideline, or short an industry experiencing a bubble, we investigate the asset allocation implications of the bubble signals for typical investors. Power-utility investors substantially increase their optimal weight if they receive a positive bubble signal. This increase is statistically and economically significant. Portfolio weights as a fraction of wealth go up by 0.79 (Fama-French model), 0.93 (Carhart model), and 1.62 (CAPM) for an investor with a coefficient of relative risk aversion equal to two.

We also compute the risk-free return required as compensation for not increasing the weight after a positive signal. On a yearly basis, these certainty equivalents are 1.76% (Fama-French model), 2.43% (Carhart model) and 7.38% (CAPM). A simple dynamic riding bubble strategy earns annual abnormal returns of three to four percent based on the Fama-French and Carhart models, and nine percent for the CAPM. These conclusions are robust to different preferences. Investors who are particularly averse to skewness, kurtosis, or downside risk also ride bubbles.

Assumptions are inherent to developing a bubble detection system but our main results are insensitive to many variations in these assumptions. For instance, we test for robustness against different estimation windows, different significance levels, different risk measures, different investor preferences, and different asset pricing models. Robustness checks and tables displaying the results for each of the 48 industries are in an online appendix.[1] We also examine several alternative explanations for our findings. One alternative is a misspecification of the asset pricing model. We show that an omitted structural break in any of the risk factors, an omitted risk factor, or a structural break in an omitted risk factor are not likely to explain our results. We compare the industry bubbles to industry momentum, as described by Moskowitz and Grinblatt (1999), but find that bubbles are distinct phenomena. Also underreaction to good news does not explain our results because bubbles are followed by negative returns over the following two years.

Although investors might see our real-time bubble detection system as practically useful or even as a stock-market prediction system, we feel that the main contribution of our

[1] Available at `http://people.few.eur.nl/kole/RidingBubbles_webappendix.pdf`.

paper is that it helps answer the important question of why bubbles persist. We show empirically that exerting a correcting force on prices during bubbles, as Fama (1965) suggests, is not optimal. Our empirical evidence also does not indicate that shorting the overvalued asset is too risky as De Long et al. (1990a) and Shleifer and Vishny (1997) propose. Consistent with the theoretical predictions made by Abreu and Brunnermeier (2003) and De Long et al. (1990b), short-term expected returns after positive bubble signals are positive. Riding bubbles is a risky though highly profitable strategy. While the arbitrageurs in the theoretical work of Abreu and Brunnermeier (2003) are risk-neutral, our empirical results indicate that riding bubbles is even optimal for risk-averse investors.

Our results also add to the empirical literature that explains why bubbles continue by focusing on specific well-known historical bubble episodes. The papers most closely related to our work are Brunnermeier and Nagel (2004) and Temin and Voth (2004). Brunnermeier and Nagel (2004) show that hedge-fund managers were profitably riding the technology bubble in the late 90s. Temin and Voth (2004) provide similar evidence for a London-based bank during the South Sea bubble in 1720. We generalize the findings of Brunnermeier and Nagel (2004) and Temin and Voth (2004) to a large population of bubbles and investors. Riding bubbles is not only optimal for highly sophisticated institutional investors but also for a prototype risk-averse investor with a very basic information set. Even these investors have been able to profit from bubbles because the run-ups last for sufficiently long periods. This finding is not limited to a specific bubble, but applies to a large sample of bubble periods. We further complement previous work by focusing on the optimal strategy in real time. Our setup mimics the situation of a real-world investor who needs to make a choice at every point in time, without knowing whether a positive bubble signal is correct. Extracting bubble signals at every point in time is a noisy process. Because positive signals that are "truly" just noise are not followed by positive abnormal returns, our approach is realistic and conservative by comparison to focusing on famous historical bubbles.

1 Bubbles and Bubble Signals

1.1 A Basic Bubble Model

We summarize our bubble model in Table 1. Before time s_0, everything is normal. Both the price, p_s, and the asset's fundamental or intrinsic value, $p_{\mathrm{i},s}$, grow at the equilibrium rate in an asset pricing model. The equilibrium growth rate of intrinsic value follows a factor model, $r_{\mathrm{f},s} + \boldsymbol{\beta}'\boldsymbol{f}_s$, where $r_{\mathrm{f},s}$ is the risk-free rate and $\boldsymbol{f}_s$ is a vector of factors. The growth rate of the price $r_{\mathrm{f},s} + \boldsymbol{\beta}'\boldsymbol{f}_s + e_s$ is stochastic because we add the zero-mean error term e_s.

[Table 1 about here.]

Between s_0 and s_1, due to some good news, the growth rates of the asset's price and its intrinsic value accelerate. Both rates increase by an amount a, for example, on some news that productivity in an industry structurally improves. Kindleberger (2000, p. 14) describes this sudden acceleration as a displacement in a Minsky model. At a certain point in time, as described by Shiller (2000), "irrationally exuberant" investors who believe in a "new economy" overestimate the impact of the new technology and prices rise above their intrinsic values. In our model, this exuberant extrapolation occurs between s_1 and s_2 as the intrinsic value grows again at the equilibrium rate, but the price continues to grow at the higher rate. A bubble, $p_{\mathrm{b},s}$, starts growing at rate a as illustrated in Figure 1. Between s_2 and s_3 the bubble bursts and the prices decline at rate d_s. After the correction has taken place, the prices and their intrinsic values grow again at the equilibrium rate.

[Figure 1 about here.]

In line with Abreu and Brunnermeier (2003), our model does not put any restrictions on a and differs from the rational bubble models where the (expected) growth rate of the bubble a has to satisfy the Euler equation in an asset pricing model (see Campbell et al., 1997, Ch. 7 or Cochrane, 2005, Ch. 20). The rational bubble models (e.g., Blanchard and Watson, 1982) impose this condition because they assume that investors are indifferent between selling or investing in the asset. Inherently, our research question does not apply to this specific type of bubble. Therefore, we also do not use existing tests for rational bubbles such as Campbell and Shiller (1987), Diba and Grossman (1988), Phillips et al. (2010), or Jarrow et al. (2011). Instead, we develop our own method to derive bubble signals.[2]

[2]Rational bubbles cannot be negative (see Blanchard and Watson, 1982)). For "irrational" bubbles it is not obvious whether they can be negative and one could potentially consider applying our method to negative bubbles. We focus on positive bubbles in this paper.

1.2 Bubble Signals

At the end of each month t, we try to infer whether there is a bubble, as defined in the previous section, to make an investment decision for the immediately following month $t+1$. If we find evidence of a potential bubble by using prices up to and including month t, then the signal is positive for month $t+1$. If there is no evidence of a bubble, then the signal is negative. We denote $B_{i,t} = 1$ ($B_{i,t} = 0$) as a positive (negative) bubble signal for industry i.

To derive signals, we follow a three-step procedure. First, we estimate in every month t for each industry an asset pricing model and test for a structural break in the intercept $\alpha_{i,t,\tau}$:

$$r_{i,t-\tau} = \alpha_{i,t,\tau} + \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t-\tau} + \varepsilon_{i,t,\tau},\ \mathrm{E}[\varepsilon_{i,t,\tau}] = 0,\ \mathrm{E}[\varepsilon^2_{i,t,\tau}] = \sigma^2_{i,t}, \quad \tau = 0, 1, \ldots, T-1 \quad (1)$$

where $r_{i,t-\tau}$ is the return on an industry i, $\boldsymbol{f}_{t-\tau}$ is a vector of factors, and T is the length of the estimation window.[3] The null hypothesis occurs when $\alpha_{i,t,\tau}$ experiences no break. The alternative is a structural break for some unknown point ζ:

$$H_{1T}(\zeta) : \alpha_{i,t,\tau} = \begin{cases} \alpha^{\mathrm{a}}_{i,t}(\zeta) & \text{for } \tau = \zeta+1, \zeta+2, \ldots, T-1 \\ \alpha^{\mathrm{p}}_{i,t}(\zeta) & \text{for } \tau = 0, 1, \ldots, \zeta \end{cases} \quad (2)$$

$$\text{with } \zeta_L \leq \zeta \leq \zeta_U,\ \alpha^{\mathrm{p}}_{i,t}(\zeta) > \alpha^{\mathrm{a}}_{i,t}(\zeta),$$

[3] We use two time subscripts because our bubble detection system uses a moving window. The subscript t indicates the point in time where the investor makes his decision, and where his information set ends. The first t for which we can conduct an estimation equals T. The subscript τ runs back in time to the point where the estimation window starts, that is, T months ago.

where $\alpha^{\mathrm{a}}_{i,t}(\zeta)$ refers to the part of our test period before the structural break, and $\alpha^{\mathrm{p}}_{i,t}(\zeta)$ to the part after the structural break. For each value of ζ, we calculate the t-statistic for the hypothesis $\alpha^{\mathrm{a}}_{i,t}(\zeta) = \alpha^{\mathrm{p}}_{i,t}(\zeta)$. We select the breakpoint ζ^* with the largest t-statistic and determine its critical value based on the tables in Andrews (1993).[4] In case there is no break, the bubble signal is negative. We end the three-step procedure, move one month forward and start again with step one. If a positive structural break occurs, then we proceed to step two.

In the second step, we test whether the intercept after the breakpoint $\alpha^{\mathrm{p}}_{i,t}(\zeta^*)$ is significantly positive using a standard t-test (see Bai, 1994; Bai and Perron, 1998). A positive structural break can also occur if $\alpha^{\mathrm{a}}_{i,t}(\zeta^*)$ is negative, and $\alpha^{\mathrm{p}}_{i,t}(\zeta^*)$ is close to zero. This pattern resembles underperformance and its subsequent correction. Within reason, we do not want to interpret this type of break as a positive bubble signal. Therefore, if $\alpha^{\mathrm{p}}_{i,t}(\zeta^*)$ is not significantly positive, then the bubble signal is negative and we start with step one of our procedure for the next month. If $\alpha^{\mathrm{p}}_{i,t}(\zeta^*)$ is significantly positive, then we continue with step three.

In the third and final step of the signal detection procedure, we test whether a crash has happened during the last κ months. A crash is defined as a value of $\varepsilon_{i,t,\tau}$ in Equation (1) below a cut-off point. We choose the cut-off point as a multiple k of the standard deviation

[4] Andrews (1993) discusses two-sided tests for the detection of a structural break, whereas our alternative hypothesis is one-sided. Estrella and Rodriguez (2005) derive the corresponding asymptotic distribution of the t-statistic. They show that halving the p-value for a given critical value when moving from a two-sided to a one-sided alternative gives a good approximation.

$\sigma_{i,t}$ of $\varepsilon_{i,t,\tau}$. The end of a bubble is often associated with one or more crashes. If we find crashes, then the bubble has ended, that is, the bubble signal is negative. If we find no crashes, then the bubble signal is positive for month t for a specific industry. Because this is the last step of our procedure, in either case, we continue with the next month for this industry. Once we have a positive or negative signal for every month in an industry, we move to the next industry. Ultimately, we end up with a positive or negative bubble signal for every month in every industry.

As noted in the introduction, bubbles often occur in industries; therefore, it seems reasonable to apply our bubble detection system to the 48 industry portfolios of Fama and French (1997). This data set contains value-weighted returns from July 1926 to December 2009. We consider three commonly applied asset pricing models, the CAPM, the Fama and French three-factor model and the Carhart four-factor model. The CAPM of Sharpe (1964) and Lintner (1965) contains only the market factor. The Fama-French model has three factors: the market factor, the size factor (SMB), and the value versus growth factor (HML) (Fama and French, 1993). The Carhart four-factor model adds the momentum factor (MOM) to the Fama-French model based on the findings of Jegadeesh and Titman (1993) and Carhart (1997).[5]

Our procedure to obtain bubble signals can depend on parameter choices. However,

[5]Because data on momentum are only available as of January 1927, our analysis for the Carhart model has six months less observations than the analysis for the Fama-French model and the CAPM. All factor portfolios and the risk-free rate are taken from French's Data Library at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Appendix A shows that results are robust for a wide variety of choices. For our main analysis, we choose a confidence level of 97.5% for the structural break test in Equation (2) and the subsequent t-test on $\alpha^{\mathrm{p}}_{i,t}(\zeta^{*})$, if applicable. This level is in between two common choices, 95% and 99%, for which we report results in the Appendix. We choose an estimation window of ten years, that is, $T = 120$, and allow ζ to range from $\zeta_L = 12$ to $\zeta_U = 60$. The minimum of $\zeta_{\mathrm{L}} = 12$ corresponds to the maximum lag of twelve months for news to be incorporated into prices. This lag refers to the time between s_0 and s_1 in our model. Because bubbles are associated with an overreaction to salient news, one year is a conservative choice. According to Chan (2003), a market reaction to positive headline news only lasts a couple of months. We set ζ_U equal to 60 months and thus bubbles can last a maximum of five years. In our model, that is the time between s_1 and s_3. Looking at famous historical bubbles, these choices are reasonable. For example, the run-up in prices in the railway boom lasted from 1841 to 1845 (Gayer et al., 1940), the "Roaring Twenties" were from about 1925 to October 1929 (White, 1990, and Donaldson and Kamstra, 1996), the "tronics boom" lasted from about 1957 to December 1961 (Malkiel, 1996, and Brown, 1991), and the internet bubble lasted roughly from 1995 to 2000. Our robustness checks in Appendix A, consider a T of five years with a ζ_U of 36 months. Additionally, we also decrease ζ_U to 36 months and increase it to 84 months for a T of 120 months. Here, we classify a return below two standard deviations as a crash and thus choose $k = 2$. Appendix A considers the cases of $k = 2.25$ or $k = 1.75$. We take crashes into account that are up to six months prior to t ($\kappa = 6$). To examine the robustness of our results to this choice, we increase κ to 12 months or decrease it to zero, implying that the crash criterion is removed. The results are similar.

1.3 Descriptive Statistics for Bubble Signals

Table 2 presents the descriptive statistics for the bubble signals. Panel A shows the frequency of the positive versus negative bubble signals. We derive signals for the complete sample of 48 industries from 1926 to 2009 that yields 39,696 signals for the CAPM and the Fama-French model, and 39,456 for the Carhart model. For the CAPM, 5% (1,966 of 39,696) of the signals are positive. We find less signals if we use the three- or four-factor model. For these models, about 3.4% of the bubble signals are positive. In line with the idea that bubbles are rare events, 96.6% of the signals are negative.

Panel B of Table 2 focuses on the positive signals. The first two rows show the intercepts before and after the breakpoint. The average of the intercept before the break, $\alpha^{\text{a}}_{i,t}$, is slightly negative, but economically small and statistically indistinguishable from zero. The average of the intercept after the break, $\alpha^{\text{p}}_{i,t}$, is economically large and, by construction, significantly positive. Closely related, we report the "strength" of the bubble signal and define it as the t-statistic of $\alpha^{\text{p}}_{i,t}$ in row four. Both the average and median strength are close to three and indicate that most bubble signals pass the second condition (i.e., $\alpha^{\text{p}}_{i,t} > 0$) easily. We define the "length" of the bubble signal, shown in row five, as the time between the breakpoint ζ^* and t. On average, the time since the breakpoint is much longer than the minimum length of 12 months. For the CAPM-based bubble signals, the average (median) length is 33.9 (31) months. The mean (median) length of the bubble signals for the three-and four-factor models are slightly shorter at around 30 (26) months.

[Table 2 about here.]

Bubbles derived from the signals are discussed in Section 4. Their characteristics are in line with the general perception of bubbles, and the system detects famous bubbles over the last ninety years like the tronics boom, the internet bubble, and the bubble in concept stocks. Although simulations show our method is noisy, the resulting bubbles correlate well with other proxies for mispricing.

2 Risk and Return After Bubble Signals

To find out whether an investor should short, stay away, or ride a bubble, we compare the returns that follow positive and negative bubble signals. We construct two portfolios based on the bubble signals at the end of month t and compare their risk-return characteristics for the immediately following month $t+1$. The first portfolio is named the "bubble portfolio" and contains the industries for which we have a positive bubble signal $B_{i,t} = 1$. If we do not have a positive signal for any industry, then we do not invest this portfolio. Note that this portfolio has large negative returns if after a bubble, the industry crashes and our bubble detection system has not picked up that the bubble ended. The second portfolio, the "no-bubble portfolio," contains the industries for which we have a negative signal $B_{i,t} = 0$. Similar to Moskowitz and Grinblatt (1999), the portfolios are equally weighted at the industry level, but value weighted within industries. As a robustness check, we devise a strategy that is value weighted at the industry level in Appendix A.4 and get similar results. The first rows of Table 3 provide descriptive statistics for the two portfolios. The no-bubble portfolio is continuously invested, well-diversified with an average of more than 40 industries, and has a turnover of less than 20%. Because most of the industries are in the no-bubble portfolio, this portfolio closely resembles a market portfolio. Very differently, the bubble portfolio is invested in only 69% (CAPM) or 64% (Fama-French and Carhart models) of the months. It contains on average 3.2 industries for the CAPM and 2.4 for the Fama-French and Carhart models. The number of industries in the portfolio varies strongly: the standard deviation of the number of industries is 2.64 for the CAPM, 1.49 for the Fama-French model, and 1.51 for the Carhart model. The bubble portfolio also has a very high turnover. Monthly turnover for the CAPM is 179%, which comes close to the possible maximum of 200% (if all industries leave the portfolio and new ones enter). For the Fama-French and Carhart models, turnover is 145% per month.

The bubble portfolio earns much higher returns in excess of the risk-free rate than the no-bubble portfolio. If we derive the signals using the CAPM, then the excess return on the bubble portfolio is 1.7% per month compared to an excess return of only 1.01% on the no-bubble portfolio. Similarly, if we get bubble signals from the four-factor model, the monthly excess return on the bubble portfolio is 56 basis points higher than the excess return on the no-bubble portfolio. It seems that the higher return comes to some extent at the expense of a higher portfolio risk. Across all specifications, the volatility of the bubble portfolio is higher than the volatility of the no-bubble portfolio. Still, the bubble portfolio has substantially higher Sharpe ratios than the no-bubble portfolio, ranging between 22%

higher for the Fama and French model to 50% higher for the CAPM.

We now consider whether these results hold for risk-return measures based on abnormal returns. Because the composition of the bubble portfolio is highly unstable, estimates based on a single performance-attribution regression that imposes constant factor exposures over time are likely to be biased. We allow for time-varying factor exposures by using a rolling-window approach as in Carhart (1997), and compute abnormal returns for $t+1$ as:

$$\eta_{i,t+1} = r_{i,t+1} - \hat{\boldsymbol{\beta}}'_{i,t} \boldsymbol{f}_{t+1}, \tag{3}$$

where the $r_{i,t+1}$ is the excess return at $t+1$ for industry i, and $\hat{\boldsymbol{\beta}}_{i,t}$ is a vector of estimates based on Equation (1) under the null hypothesis. We always use the same factor model to compute abnormal returns as for the bubble signals. For example, if we derive bubble signals with the Carhart model, we also use that model to compute the abnormal returns.

The abnormal returns on the bubble portfolio are significantly larger both economically and statistically than the abnormal returns on the no-bubble portfolio. For the CAPM, Jensen's alpha is 76 basis points per month for the bubble portfolio and only six basis points for the no-bubble portfolio. For the three-factor and four-factor models, the differences are smaller but still sizable. For the four-factor model, the difference in abnormal returns is 30 basis points per month, which amounts to 3.6% per year. The test results in Table 3(b) show that we reject the hypothesis of equality of the average abnormal returns of the bubble and the no-bubble portfolios with p-values below 1%. We conduct these tests in weighted least-squares (WLS) and generalized least-squares (GLS) settings. Because of its highly unstable composition, returns on the bubble portfolio are strongly heteroscedastic.

Tests based on ordinary least squares do not suffice in this case. Unlike the often-used White standard errors, the GLS and WLS tests allow us to take into account the form of heteroscedasticity, thus leading to more efficient estimates (see e.g., Verbeek, 2004). Consistent with the construction of the abnormal returns in Equation (3), we use the variances and covariances of the residuals in Equation (1) under the null hypothesis to construct the variances of the portfolios (see Appendix A.4 for details). The WLS tests assume that the returns of the bubble and the no-bubble portfolios are independent, while the GLS test allows for dependence. The test results for the GLS are weaker than for the WLS, but still significant at the 1% level. Our tests for the value-weighted portfolio in Appendix A.4 also show significant differences with p-values below 5%.

[Table 3 about here.]

Figure 2 confirms that the bubble portfolio earns consistently higher returns than the no-bubble portfolio. The graphs also suggest that a bubble riding strategy is very risky. The results based on the Fama-French and Carhart models especially show that investors holding the bubble portfolio sometimes face very steep losses.

[Figure 2 about here.]

In line with this observation, Table 3(a) shows that the variances and downside risk measures are much higher for the bubble portfolio than for the no-bubble portfolio. There are two potential explanations for this finding. First, a strategy of riding bubbles might be very risky as investors are likely to experience the negative returns of bursting or deflating bubbles. Second, however, the bubble portfolio might just seem more risky than the no-bubble portfolio because it is less diversified. Further, although the differences in risk are large in magnitude, it is not obvious in this setting whether they are statistically significant. Because the portfolio returns are strongly heteroscedastic, we cannot use standard tests for differences in variances and other risk measures.

We complement our results at the portfolio level by analyzing the returns following positive and negative bubble signals at the asset level. We pool the complete sample of abnormal returns across all industries and for all months. Then, we split it into two sets. The first (second) set contains all abnormal returns at $t + 1$ for which we have a positive (negative) bubble signal at t. This approach has three main advantages. First, it allows us to abstract from differences imposed by portfolio construction, notably, differences in diversification. Second, this setup makes it possible to conduct statistical tests using bootstraps, which are based on less stringent assumptions than the WLS or the GLS. This approach thus ensures the robustness of our findings for the portfolios. Third, using bootstraps, we can formally test for differences in variances, skewness, kurtosis, and downside risk.

We standardize the abnormal returns by dividing them by the residual standard deviation to accommodate time-varying volatilities and different volatilities across industries ($\tilde{\eta}_{i,t+1} \equiv \eta_{i,t+1}/\sigma_{i,t}$). Then, we compute means, medians, higher moments, and downside risk measures. Table 4 shows the results for both sets of returns. The standard errors reported in parentheses are based on a temporal bootstrap as in Kapetanios (2008) and Lahiri (2003) to accommodate cross-sectional correlations in abnormal returns. Although we report standard errors for convenience, our real interest is in testing for differences between both distributions. We conduct a second bootstrap under the null hypothesis that the two distributions are equal and compute quantiles. If the p-value is 5% or smaller (95% or larger), we reject the null hypothesis and conclude that the characteristic is significantly larger (smaller) following a positive signal rather than following a negative signal.

The p-values for the tests on the mean and median abnormal returns are well below 1% for all three asset pricing models. Abnormal returns are economically and statistically significantly larger following positive bubble signals than following negative signals. The results also show that variances and downside risks are higher following positive signals than following negative signals, even when diversification effects do not play a role. For the CAPM-based results, only volatility is significantly higher following positive bubble signals. However, for the Fama-French and Carhart models the volatility, VaR, and ES are significantly higher following positive rather than negative signals. For example, for the Carhart model, abnormal return volatility is 1.08 after a negative signal and rises to 1.28 after a positive signal. The p-value is well below 1%. Skewness and kurtosis are not significantly different.

[Table 4 about here.]

Overall, the results suggest that investors face a trade-off. Riding bubbles is a profitable though highly risky strategy. At this point, we can already conclude that it is the optimal strategy for risk-neutral investors as proposed by Abreu and Brunnermeier (2003).

2.1 Sequences of Positive Bubble Signals and Profitability of Strategy

To gain more insights on why a strategy of riding bubbles is profitable, we investigate how the returns following positive signals depend on the length of a (uninterrupted) sequence of positive signals. Table 5 shows the duration, number of sequences per duration, and their average abnormal returns. Most sequences last only a few months. Thus, the bubble signals are associated with rather short investment opportunities. However, the short sequences are not the profitable ones. Instead, only longer sequences are associated with positive abnormal returns. We also look at the last return of each sequence and how many sequences end with crashes. Only about 19% end with a crash. This finding supports Brunnermeier (2008) who suggests that although bubbles end with crashes in theoretical models, they deflate in reality.

We look at the average last return in relation to the length of the sequence. The average standardized abnormal return in the last month of a series is about -1.15, which amounts to an abnormal return of approximately -4.6%. There is little relation between the length of the sequence and the magnitude of the last return. This finding helps to explain why riding short bubbles is not profitable. Investors earn less on the ride up, but given that they cannot time the crash or deflation, they still face substantial losses before they get out. For bubbles that grow over a long time, and then deflate slowly, investors can profit from riding the bubble without having to suffer the full extent of the deflation.

Brunnermeier and Nagel (2004) show that hedge-fund managers as sophisticated investors were able to profit from the internet bubble and get out in time. Our analysis shows that there is not much skill or superior information needed to make riding bubbles a profitable strategy. Even an investor with basic information that consists only of returns is able to profit from a run-up if the bubble lasts long enough.

[Table 5 about here.]

3 Optimal Response

Following a positive bubble signal, abnormal returns and risk are significantly higher than after negative signals. To evaluate this trade-off and determine an optimal strategy, we take the perspective of a utility maximizing risk-averse investor. Here in the main paper, we focus on a power-utility investor. But Appendix A.5 shows the results for downside risk-averse investors, mean-variance investors, and investors who are particularly averse to skewness and kurtosis. The results are robust.

If investors significantly increases the weight of the asset when they receive a positive bubble signal, then we conclude that the optimal strategy is to ride bubbles. To the contrary, if investors significantly decrease their position, then we conclude that investors are trading against the bubble or shorting. Of course, a strict interpretation of shorting requires that investor hold a negative position. We choose a somewhat more conservative interpretation because investors might hold a certain amount of the asset for diversification purposes. The third alternative is that the change in risk after positive bubble signals outweighs the change in the expected return. In this case, risk-averse investors might refrain from changing their allocation, and we then conclude that investors are sidelining.

3.1 Derivation of the Optimal Portfolio

We consider an investor who can allocate her wealth W at the end of month t between a single risky asset, which is the typical industry, and a risk-free asset. The investor can hedge systematic risk factors in industry returns. This approach allows us to isolate the impact of the bubble signal on the optimal asset allocation from the impact of systematic determinants of industry returns. The portfolio return $r_{\mathrm{p},t+1}$ in month $t+1$ obeys:

$$r_{\mathrm{p},t+1} = w r_{t+1} - w\boldsymbol{\beta}'\boldsymbol{f}_{t+1} + (1-w) r_{\mathrm{f},t+1} = r_{\mathrm{f},t+1} + w\eta_{t+1} \tag{4}$$

where w is the fraction of wealth invested in the industry, and η_{t+1} is its abnormal return. We set the risk-free rate equal to its long-run average of 30.5 basis points per month (3.67% per year).

The investor's preferences over wealth are described by a power-utility function:

$$U(W) = \frac{W^{1-\gamma} - 1}{1-\gamma} \quad \gamma \neq 1, W > 0 \tag{5}$$

where γ is the coefficient of risk aversion. For $W \leq 0$, the investor is bankrupt, and we set the utility to $-\infty$. Based on Equation (4), the next period's wealth is given by $W_{t+1} = W_t(1 + r_{\mathrm{f},t+1} + w\eta_{t+1})$. The investor infers the bubble signal B_t at the end of month t as in Subsection 1.2 and solves for the optimal weight:

$$\max_{w} \mathrm{E}\left[\left. \frac{\left(W_t\left(1 + r_{\mathrm{f},t+1} + w\eta_{t+1}\right)\right)^{(1-\gamma)}}{1-\gamma} \right| B_t \right] \tag{6}$$

that results in the first-order condition:

$$\mathrm{E}\left[(1 + r_{\mathrm{f},t+1} + w^{*}\eta_{t+1})^{-\gamma}\eta_{t+1}\middle| B_t\right] = 0. \tag{7}$$

Because the optimal weight can differ depending on the bubble signal, we use w_{B} to denote the optimal weight for positive bubble signals and w_{NB} for negative bubble signals. Similarly, we define the value functions $V_{\mathrm{B}} \equiv \mathrm{E}[U(1 + r_{\mathrm{f},t+1} + w_{\mathrm{B}}\eta_{t+1}|B_t = 1]$ and $V_{\mathrm{NB}} \equiv \mathrm{E}[U(1 + r_{\mathrm{f},t+1} + w_{\mathrm{NB}}\eta_{t+1}|B_t = 0]$.

To determine the economic significance of trading on bubble information, we compute the certainty equivalent return. We calculate the risk-free return that the investor requires as compensation for not changing her portfolio when she receives a positive bubble signal. The certainty equivalent return λ satisfies the condition:

$$\mathrm{E}[U(1 + r_{\mathrm{f},t+1} + w_{\mathrm{B}}\eta_{t+1}|B_t = 1] = \mathrm{E}[U(1 + r_{\mathrm{f},t+1} + w_{\mathrm{NB}}\eta_{t+1} + \lambda|B_t = 1]. \tag{8}$$

Table 6 shows that the optimal weight increases substantially when an investor receives a positive bubble signal. For an investor with a moderate risk-aversion level of two, the weight rises from 0.08 to 1.70 for abnormal returns based on the CAPM. For the Fama-French and Carhart models the optimal weight rises from zero to 0.93, and from 0.12 to 0.91 respectively.[6] The standard errors in the parentheses indicate that the weight allocated to the risky asset in the absence of a positive bubble signal is indistinguishable from zero.

[6] In the case of the CAPM, the investor takes a levered position that can theoretically lead to negative wealth with a non-zero probability. We find a levered position to be optimal, because the optimization is based on the empirical distribution. Including the possibility of extreme negative returns would lead to a maximum investment of one. For higher degrees of risk aversion, allocations do not change.

When the investor gets a positive bubble signal, it becomes significantly positive. The p-values in the last column show that the difference in weight is statistically significant at the 5% level for all specifications. As in Table 4, we derive the p-values from a bootstrap under the null hypothesis that the weights are equal for positive and negative bubble signals.

[Table 6 about here.]

We investigate how the change in optimal weight is affected by different risk-aversion levels. Even for rather high levels of risk aversion, the difference in portfolio weights is economically significant. For the most conservative estimate, which we base on the Carhart model with a risk-aversion level of ten, the optimal weight increases ninefold. The approximation $\mathrm{E}[(1+r_{\mathrm{f}}+w^{*}\eta_i)^{-\gamma}\eta_i] \approx \mathrm{E}[\exp\left(-\gamma(r_{\mathrm{f}}+w^{*}\eta_i)\right)\eta_i]$ for the first-order condition in Equation (7) shows that a multiplication of γ with a constant requires a division of w^{*} by the same factor to maintain optimality. Therefore, the p-values depend very little on the level of risk aversion. To test $w_{\mathrm{B}} = w_{\mathrm{NB}}$, we construct a series of portfolio differences based on a bootstrap. Because both weights are approximately inversely related to risk aversion, the same holds for the difference, and the test is only marginally affected.

In line with our results for the optimal weight, we find that riding bubbles is associated with significant increases in expected utility. We report the ratio of utilities $V_{\mathrm{B}}/V_{\mathrm{NB}}$. For an investor with a risk aversion of $\gamma = 2$, the ratios of expected utility values are 1.63 for the Carhart model and 9.25 for the CAPM.

Investors require a sizable compensation for not updating their portfolio when they obtain a positive bubble signal. For the CAPM, the investor requires a risk-free return of 7.38% annually. The certainty equivalent returns for the Fama-French and Carhart models are 2.43% and 1.76% respectively for an investor with a risk-aversion level of two. As risk aversion decreases, the certainty equivalent increases. The certainty equivalent is significantly positive across all the different specifications, as the p-values in the last column show.

Our results show strong support for the riding bubbles hypothesis. Increases in portfolio weights are statistically and economically significant and the certainty equivalent returns for a bubble riding strategy are non-trivial.

4 Bubble Episodes: Scrutinizing our Bubble Detection Method

Based on the positive bubble signals we derive in Subsection 1.2, we construct historical bubble episodes to see whether they look reasonable and match anecdotal evidence. If the investor receives a positive signal at t ($B_{i,t} = 1$) and the observation is between t and the breakpoint $t - \zeta^*$, then we classify an observation as belonging to a bubble. As long as the sequence of bubble observations is not interrupted, we count these observations as belonging to the same bubble. Table 7 presents descriptive statistics for these bubbles. The mean and median number of bubbles per industry is close to three. The raw and abnormal returns during bubbles are economically large. The standardized abnormal returns during bubbles are 0.49, 0.51, and 0.52 per month for the CAPM, the Fama-French, and Carhart model, respectively. The average idiosyncratic volatility ranges from 4.17% for the CAPM to 3.86% for the Fama-French model and 3.81% for the Carhart model. If we assume an average idiosyncratic return volatility of 4%, then these returns translate into annual abnormal returns of about 23%. We also find that the residual volatility of the standardized abnormal returns is substantially larger than one. Although our method of deriving signals is based on abnormal returns, for illustrative purposes we compute the raw returns during the bubbles. The raw return of the average industry during a bubble ranges from 30.2% for the CAPM to 31.4% for the Fama-French model and 31.0% for the Carhart model.

[Table 7 about here.]

Figure 3 displays the number of bubbles over time. For all three asset pricing models, we find that the three highest spikes coincide with the famous historical bubbles over the last century. The largest increase in the number of industries that experience a bubble is during the well-known internet bubble in the mid- to late 90s that started deflating in 2000. We also observe a large increase in the number of bubble industries during the "Bubble in Concept Stocks" as termed by Malkiel (1996). According to Baker and Wurgler (2006) this "major bubble" developed in 1967 to 1968. Malkiel (1996) notes that during this time period people believed the best strategy was to buy "stocks with an exciting concept or compelling story" that had either recently experienced strong earnings growth or were expected to do so in the near future. Because this bubble ended with the bear market of 1969 to 1971 (see, Malkiel, 1996, p. 76), the graph documents a sharp decrease in the number of industries experiencing the bubble. The graph shows a third major spike in the number of bubble industries during the first bubble period report by Baker and Wurgler (2006). Malkiel (1996) calls it the "tronics boom" and dates it to 1959 to 1961. Besides these famous historical bubbles, we observe many less pronounced bubble periods in the graph. To investigate more systematically the nature of these bubbles, we proceed along two lines. First, using simulations, we formally investigate how many bubbles can potentially be attributed to noise or a general misspecification of an asset pricing model. Second, in Subsection 4.2, we investigate whether the bubbles we find correlate well with other proxies for mispricing.

[Figure 3 about here.]

4.1 Bubbles, Signals, Noise, and Misspecification

How many bubbles and bubble signals can potentially be attributed to noise or a misspecification of the asset pricing models?[7] Because our method is a real-time detection system, and spotting bubbles in real time is not easy, we expect that the method is rather noisy. In our case, a noisy method makes us err on the side of caution: signals that can be attributed to noise or a misspecification are not followed by the risk-return trade-off documented in previous sections. Instead, there is–by definition–no difference between the return distributions following the positive or negative signals that are attributable to noise or a misspecification (see Appendix C).

[7] We investigate the effect of more closely defined misspecifications such as an omitted risk factor and an omitted structural break in Sections 5.3 and 5.4.

We set up two simulation studies for which we construct pseudo samples by a bootstrap based on the original data as in Kosowski et al. (2006). In the first study, we focus on the effect of noise. The pseudo industry returns consist of factor realizations and an idiosyncratic part that has by construction a zero mean. For the idiosyncratic part, we bootstrap from the industry returns where both the factor exposure and the mean have been removed. In the second study, we do not impose that the idiosyncratic part has a zero mean, and we bootstrap directly from the industry returns after removing their risk-factor exposures. In both cases, we apply a temporal bootstrap. More formal mathematical explanations and detailed results of the simulation studies are in Appendix C.

We compare the percentage of our sample classified as bubbles or positive bubble signals for the two types of simulations and the real data. In the simulations, the fraction of the sample classified as positive bubble signals is between 1.73% and 1.81%. Comparing the fraction of positive signals in the simulations to the fraction of positive signals in the real data shows that we find about twice as many positive bubble signals in the real data for the Fama-French and Carhart models, and three times as many for the CAPM. Similarly, we find about 1.8 to 1.9 bubbles in the simulated data. So, around half to two-thirds of the bubbles in the real data can potentially be attributed to noise or misspecifications.

This evidence shows that our method of extracting signals is very noisy. Many of the less pronounced bubble periods in Figure 3 might be at least partially attributable to noise. It is striking that despite the fact that our method is relatively noisy, our results on the returns following positive versus negative bubble signals are economically and statistically very strong. If such a basic and noisy method leads to the strong conclusion that riding bubbles is optimal, then it comes at no surprise that Brunnermeier and Nagel (2004) show that hedge-fund managers were able to profit from riding the internet bubble. Arguably, hedge-fund managers have a much better information set and thus more precise signals.

4.2 Bubbles and Sentiment

Based on Baker and Wurgler (2007), we hypothesize that the number of industries experiencing a bubble should be positively correlated with investor sentiment. Further, based on the cross-sectional findings of Baker and Wurgler (2006, 2007), we propose that more speculative growth industries such as telecommunications or biotech are more likely to experience a bubble when sentiment is high. In turn, safe, more traditional, and asset intensive industries have a higher probability of experiencing bubbles if sentiment is low, for example, in periods such as the "Nifty-Fifties." Representative industries that belong to this category are raw materials, for example, gold, steel, or coal; or industries like utilities and transportation.

We use the sentiment index $SENTIMENT^{\perp}$ from Jeffrey Wurgler's homepage for 1964 to 2007.[8] For robustness we also use the Consumer Confidence Indicator (CCI) of the University of Michigan (see Lemmon and Portniaguina, 2006, for more information). As a crude, though for all industries readily available measure for speculative versus safety, we use the book-to-market ratio (BE/ME). If sentiment is high, then industries with low BE/ME ratios are more likely to experience bubbles. To the contrary, if sentiment is low, then high BE/ME ratios have a higher probability of experiencing a bubble. To

[8] http://pages.stern.nyu.edu/~jwurgler/

test this hypothesis, we first compute the difference in the BE/ME ratio of the portfolio of industries that experiences a bubble versus the portfolio of industries that does not experience a bubble. Second, we compute the correlation with $SENTIMENT^{\perp}$. We do not repeat this analysis for the CCI because Lemmon and Portniaguina (2006) point out that the CCI does not relate to the value premium.

Table 8 shows the correlation coefficient between the monthly Baker and Wurgler (2007) sentiment index and the number of bubbles we identify for a given month. For the CAPM-based bubbles, the correlation is 0.17 and not statistically significant. However, for the bubbles identified using the Fama-French and Carhart models, the correlation is much larger at 0.46 and highly significant. The same pattern emerges if we use the CCI as a proxy for investor sentiment. In line with our expectations, we also observe a significantly negative correlation between the sentiment indicator and the difference in the BE/ME ratios. Indeed, in times of high sentiment, industries with low BE/ME ratios are more likely to experience a bubble; but in times of low sentiment, industries with high BE/ME ratios are more likely to be in a bubble. These findings confirm that the bubbles we find are not specific to our analysis. On an aggregate level as well as in the cross-section, we find that these bubbles are related to investor sentiment.

[Table 8 about here.]

5 Alternative Explanations

Our results are consistent with the riding bubbles hypothesis put forward by De Long et al. (1990b) and Abreu and Brunnermeier (2003). In this section, we investigate whether alternative explanations can also explain our findings.

5.1 Industry Momentum

One alternative explanation is buy-side industry momentum (i.e., the "winner" portfolio) as identified by Moskowitz and Grinblatt (1999). Just like a bubble, buy-side industry momentum is associated with an upward trend in prices. When comparing buy-side industry momentum with the positive bubble signals, one difference that becomes apparent is the timing of both phenomena. Table 2 shows that the average length of a positive bubble signal is about 30 months. Over this time interval, buy-side industry momentum actually reverses and profits become negative. This finding accords with Fama and French (1988), who report a negative autocorrelation for industry returns at similar horizons. This negative correlation contrasts with our finding of positive abnormal returns following positive bubble signals.

We examine the relation between positive bubble signals and industry momentum more formally along two lines. First, we investigate whether using an industry momentum factor instead of MOM affects our results. Using the Carhart (1997) factor might not be sufficient to explain return momentum in an industry portfolio because stock momentum does not subsume industry momentum (Moskowitz and Grinblatt, 1999). Second, we double-sort the sample of industries on the buy-side momentum and the positive bubble signals. If buy-side industry momentum can explain the effect of a positive bubble signal on the distribution of abnormal returns, then the effect should be less strong or absent if we find a positive bubble signal but the industry does not experience buy-side momentum.

We construct industry momentum portfolios based on our sample of 48 industry portfolios. Moskowitz and Grinblatt (1999) use 20 industry portfolios in their study. They allocate the top (bottom) three industries to the winner (loser) portfolio, which corresponds to 15% of their sample. For our sample, 15% translates into including the top (bottom) seven ($48 \times 0.15 \approx 7$) industries in the winner (loser) portfolio. Following Moskowitz and Grinblatt (1999), we construct a six-month, six-month momentum factor with a one-month lag. Since we require a minimum length of 12 months for the positive bubble signals, we additionally build a momentum portfolio based on a 12-month ranking period, a one-month lag, and an investment during the following month.

We replace the Carhart (1997) momentum factor in Equations (1) and (3) with one of the two industry momentum factors. Table 9 shows that our findings for the risk-return trade-off do not change substantially. They are similar to the results for the conventional Carhart model presented throughout this paper. The mean and median abnormal returns after a positive bubble are significantly larger than after a negative signal. Volatility and downside risk are also higher after a positive signal.

[Table 9 about here.]

To provide further corroborating evidence, we double-sort the industries on positive bubble signals and buy-side momentum. We focus again on two strategies. First, in line with our approach above, we use a 12-month ranking period, an one-month lag, and an one-month holding period. Second, we again use a six-month ranking period and an one-month lag. However, we deviate slightly from our previous setting and Moskowitz and Grinblatt (1999) by using a one-month holding period to be consistent with the returns we report for the positive bubble signals. This modification should not affect our results as the buy-side momentum effect is even larger in magnitude for a one-month holding period than for a six-month holding period (see Moskowitz and Grinblatt, 1999, Table 3, p. 1270).

In Table 10 we compare distributional characteristics of the abnormal returns of the two different buy-side momentum strategies to the positive bubble signal. As usual, we display the results for the three different asset pricing models in panels. In the first column of each panel, we show the abnormal returns of the industries that experience buy-side momentum and for which we have a positive bubble signal at the same time. In most instances, the risk-return pattern is relatively similar to the one in Table 4 for the complete sample of positive bubble signals. In one case, Panel C, the abnormal return is small and not statistically significant. However, column two shows that the abnormal return becomes significantly positive if we look at industries with a positive bubble signal that do not experience momentum.

[Table 10 about here.]

To formally analyze whether buy-side momentum causes the positive abnormal returns and higher risk of the bubble strategy, we conduct a one-sided test on whether the abnormal returns and risk measures in column one are larger than in column two. If we cannot reject the hypothesis that the distributional characteristics of the abnormal returns following a positive bubble signal are identical in the absence or presence of buy-side momentum, then we can conclude that buy-side momentum is not driving our findings. For the average and median abnormal returns none of the p-values are close to conventional levels of significance. Thus, we can safely conclude that momentum is not driving the positive returns of the bubble strategy. For the risk measures, we can also generally conclude that our findings are not driven by industry momentum. Only in one instance do we find that the volatility is larger if there is also momentum (Panel C). However, that instance is before we account for stock-return momentum. The results for the Carhart model show that the p-value goes up to 0.50. We also display the distributional characteristics of the abnormal returns of the momentum strategy in the absence of a positive bubble signal (column 3). Although not the main point of this paper, an interesting observation is that a momentum strategy is more profitable if there is a positive bubble signal (though the difference is not statistically significant). A bubble strategy tends to be more profitable than a momentum strategy.

5.2 Good News Reported in the Media

Another potential explanation for our findings is good news reported in the media. Chan (2003) analyzes the stock-market reaction to news releases and finds that it is limited to a couple of months. Thus, the reaction to a single positive news item is much shorter than the minimum length of the positive bubble signals. However, perhaps there is a stream of good news that, especially if the market underreacts to the new information, might cause a prolonged period of positive abnormal returns. We call this phenomenon a "rally."

Although it is not possible to distinguish between bubbles and rallies ex ante, we can expect a different pattern ex post. During a rally, the asset is initially undervalued and the price rises to become equal to its fundamental value. Once the asset is no longer substantially undervalued, abnormal returns should, on average, be close to zero. For bubbles, the opposite should hold. The asset is overvalued and the price will ultimately return to its fundamental value.

To examine whether rallies are a feasible explanation for our findings, we investigate the returns following bubbles constructed from positive signals as in Section 4. Figure 4 presents the monthly abnormal returns for two years after a bubble. For all three asset pricing models, we observe a large negative return in the first month after the bubble. Because bubbles end with crashes, this finding is not surprising. After the initial very negative return we see a continuous price deflation over the next one to two years. Twelve months after the end of a bubble, the cumulative abnormal returns are -11.9% for the CAPM, -10.14% for the Fama-French model, and -9.06% for the Carhart model. During the second year, the decline slows down. Two years after a bubble, the cumulative abnormal returns are -14.77% for the CAPM, -13.45% for the Fama-French model, and -10.82% for the Carhart model. Overall, we conclude that on average, returns following bubbles are very negative. We cannot rule out that not a single one of the bubbles we identify is truly a rally, but this finding indicates that the bubbles are generally distinct from rallies.

[Figure 4 about here.]

5.3 Structural Breaks in Risk Factors

Another explanation for our results could be that the asset pricing model is misspecified because we do not account for structural breaks in the risk factors. An omitted structural break in any of the risk-factor exposures could translate into an estimated structural break in the intercept. We might wrongly classify these structural breaks as positive bubble signals. In such a scenario, one could attribute the positive abnormal returns after positive signals to the higher systematic risk not captured by the asset pricing model.

We investigate whether such a scenario is a plausible alternative explanation for our findings. We formally derive the effect of latent structural breaks in the risk-factor coefficients on our method to derive bubble signals and estimate the relevant parameters from our sample. We conclude that a structural break in any of the risk-factor exposures must be implausibly large to lead to a misspecification as a positive bubble signal. During our sample period, we do not observe any changes in exposures of the size needed for misspecification.

First, we derive the effect of a structural break in any of the risk-factor coefficients on our method to detect bubble signals. We assume that the following expected return model is the true model at time t:

$$r_{i,t-\tau} = \alpha_{i,t} + \beta_{i,t,\tau} f_{1,t-\tau} + \boldsymbol{\gamma}'_{i,t} \tilde{\boldsymbol{f}}_{t-\tau} + \varepsilon_{i,t,\tau},\ \mathrm{E}[\varepsilon_{i,t,\tau}] = 0,\ \mathrm{E}[\varepsilon^2_{i,t,\tau}] = \sigma^2_{i,t},\ \tau = 0, 1, \ldots, T-1, \quad (9)$$

over the past T months. The vector $\tilde{\boldsymbol{f}}_t$ contains the other risk factors. We assume that a structural break in the coefficient for the first risk factor is present:

$$\beta_{i,t,\tau} = \begin{cases} \beta^{\mathrm{a}}_{i,t} & \text{for } \tau = \zeta+1, \zeta+2, T-1 \\ \beta^{\mathrm{p}}_{i,t} & \text{for } \tau = 0, 1, \ldots, \zeta, \end{cases} \tag{10}$$

where $\zeta_L \leq \zeta \leq \zeta_U$. This model can be extended to any number of risk factors (see Appendix D).

To derive bubble signals, we carry out the steps of Subsection 1.2 and estimate the misspecified model:

$$r_{i,t-\tau} = a_{i,t,\tau} + b_{i,t} f_{1,t-\tau} + \boldsymbol{c}'_{i,t} \tilde{\boldsymbol{f}}_{t-\tau} + e_{i,t,\tau},\ \mathrm{E}[e_{i,t,\tau}] = 0,\ \mathrm{E}[e_{i,t,\tau}] = \sigma^2_{e,i,t},\ \tau = 0, 1, \ldots, T-1,$$

$$a_{i,t,\tau} = \begin{cases} a^{\mathrm{a}}_{i,t} & \text{for } \tau = \zeta+1, \zeta+2, \ldots, T-1 \\ a^{\mathrm{p}}_{i,t} & \text{for } \tau = 0, 1, \ldots, \zeta \end{cases} \tag{11}$$

and test for a break in $a_{i,t,\tau}$. To distinguish the estimated misspecified model from the true model, we use Latin letters for the estimated model. In Appendix D.1 we analyze the consequences of misspecification in the asymptotic framework of Andrews (1993) in which the number of observations goes to infinity, but the fraction of observations before and after the break stays constant. We show that this misspecification leads to a bias in the difference between the estimates $\hat{a}^{\mathrm{a}}_{i,t}$ and $\hat{a}^{\mathrm{p}}_{i,t}$ with the asymptotic value:

$$\mathrm{plim}_{T\to\infty}(\hat{a}^{\mathrm{p}}_{i,t} - \hat{a}^{\mathrm{a}}_{i,t}) = (\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})\,\mathrm{E}[f_1]. \tag{12}$$

Assuming a positive structural break in the risk-factor exposure, $\beta^{\mathrm{p}}_{i,t} > \beta^{\mathrm{a}}_{i,t}$, and $\mathrm{E}[f_1] > 0$, the asymptotic bias is positive.

An omitted structural break not only affects the asymptotic value of the difference in intercepts, but also the variance:

$$T\mathrm{Var}[\hat{a}^{\mathrm{p}}_{i,t} - \hat{a}^{\mathrm{a}}_{i,t}] \to (\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})^2 \mathrm{Var}[f_1] + \frac{1}{\xi(1-\xi)}\sigma^2_{i,t}, \tag{13}$$

where $\xi = (T - \zeta - 1)/T$ is the fraction of observations before the structural break. An omitted structural break in the risk-factor coefficients biases the variance upwards.

The test statistic for the structural break in the intercept is the ratio of the difference between $\hat{a}^{\mathrm{a}}_{i,t}$ and $\hat{a}^{\mathrm{p}}_{i,t}$ to the variance of this difference. Using Equations (12) and (13), its bias is:

$$\chi_{\text{SBF}} = \frac{\sqrt{T}(\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})\,\mathrm{E}[f_1]}{\sqrt{(\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})^2 \mathrm{Var}[f_1] + \frac{1}{\xi(1-\xi)}\sigma^2_{i,t}}}. \tag{14}$$

Equation (14) shows that both the numerator and the denominator of this t-statistic increase because of the misspecification. Because the increases in the numerator and the denominator depend on the expected value $\mathrm{E}[f_1]$ and the variance $\mathrm{Var}[f_1]$ of the risk factor, the combined effect is an empirical question.

We compute the long-run average and variance of each risk factor. To determine the range of interest, we determine the largest increases in the factor exposures over a period of ten years for all industries based on the Carhart model. We find maximal increases of 1.16 in the exposure to the market return, 2.7 for SMB, 2.16 for HML, and 1.31 for MOM. Then we compute the resulting test statistic for structural breaks of a varying size. We assume that the structural break is located exactly in the middle of the test period (i.e., $\xi = 1/2$) because the bias is maximized for this setting (see Appendix D.1). We set the residual variance equal to the overall average of 4%.

Figure 5(a) shows the bias in the χ statistic as a function of the true structural break size in $\beta_{i,t}$. The solid line corresponds to the case in which the structural break is in the exposure to the market factor. We observe that the bias in χ increases if the true structural break becomes larger. For a break in the CAPM-β of 0.5, the bias equals 0.40. If the break becomes larger, for example one, then the bias rises to 0.69. For a confidence level of 97.5%, the critical value given by Andrews (1993) is 2.82. Even for improbably large structural breaks exceeding two, the bias in χ is well below this value. We also display the bias for the other factors. The bias due to breaks in the exposure to the size factor SMB or value factor HML are well below those for the market return. A break in the exposure to MOM can have a larger effect, but this bias is also well below the critical value of 2.82.

[Figure 5 about here.]

The long-run average might understate the potential bias. We repeat the analysis using the largest ten-year average of each risk factor in our sample. Figure 5(b) shows the relation between bias and the true structural break size for this subset. A break in the exposure to the market return produces the largest bias. Over the period of July 1949 to June 1959, the average market return equals 1.46% per month with a volatility of only 3.21%. If the structural break in the CAPM-β is 0.5, then the bias is 0.98. For a break of one, the bias is 1.87. Only for implausibly large breaks exceeding 1.75 does the bias exceed the critical value of 2.82.

Based on this analysis, we conclude that our method is very unlikely to identify a positive bubble signal when an industry is actually exhibiting a structural change in its exposure to a risk factor. Even when we choose the parameter values such that the effect of misspecification is the worst case, we need an unrealistically large structural break in the factor exposure to surpass the critical values. We conclude that structural breaks in factor exposures do not qualify as an alternative explanation for our findings.

5.4 Omitted Risk Factors

We investigate whether the positive bubble signals could be an omitted risk factor. In such a scenario, the positive abnormal returns following the positive signals might truly be a compensation for the omitted risk factor. We derive the effect of an omitted risk factor in Appendix D.2. In this subsection we discuss the main results.

The true underlying model is similar to Equation (9):

$$r_{i,t-\tau} = \alpha_{i,t} + \beta_{i,t,\tau} f_{1,t-\tau} + \gamma_{i,t} f_{2,t-\tau} + \varepsilon_{i,t,\tau},\ \mathrm{E}[\varepsilon_{i,t\tau}] = 0,\ \mathrm{E}[\varepsilon_{i,t\tau}^2] = \sigma_{i,t}^2 \quad \tau = 0, 1, \ldots, T-1. \tag{15}$$

We assume without loss of generality that the model contains two factors and that the first factor is omitted in the estimation. The exposure to this factor might be constant, that is, $\beta_{i,t,\tau} = \beta_{i,t}$; or show a structural break as in Equation (10). Instead of the true model, we omit the first factor and estimate the following model:

$$\begin{aligned} r_{i,t-\tau} &= a_{i,t\tau} + c_{i,t} f_{2,\tau} + e_{i,t,\tau},\ \mathrm{E}[e_{i,t,\tau}] = 0\ \ \mathrm{E}[e_{i,t,\tau}] = \sigma_{e,i,t}^2,\ \tau = 0, 1, \ldots, T-1, \\ a_{i,t,\tau} &= \begin{cases} a_{i,t}^{\mathrm{a}} & \text{for } \tau = \zeta+1, \zeta+2, \ldots, T-1 \\ a_{i,t}^{\mathrm{p}} & \text{for } \tau = 0, 1, \ldots, \zeta. \end{cases}. \end{aligned} \tag{16}$$

Again, we look at the bias of the test statistic for structural break in the intercept. In Appendix D.2 we derive the asymptotic difference between the estimates $\tilde{a}^{\mathrm{a}}_{i,t}$ and $\tilde{a}^{\mathrm{p}}_{i,t}$:

$$\mathrm{plim}_{T\to\infty}\, \tilde{a}^{\mathrm{p}}_{i,t} - \tilde{a}^{\mathrm{a}}_{i,t} = (\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})\, \mathrm{E}[f_1]. \tag{17}$$

This expression is equal to our result in the previous subsection that shows that the asymptotic bias in the difference is the product of the size of the structural break and the average of the omitted factor. This expression shows that an omitted factor influences the structural break test only if the asset exhibits a structural break in its exposure towards this factor. If an omitted factor does not show a structural break, then the effect on the constant is the same for $\tilde{a}^{\mathrm{a}}_{i,t}$ and $\tilde{a}^{\mathrm{p}}_{i,t}$; and the effects cancel out when we take the difference. Therefore, a constant exposure to an omitted risk factor cannot be mistaken as a positive bubble signal.

If the omitted risk factor exhibits a structural break, then its effect on our method to obtain bubble signals is similar to the effect of a risk factor for which we omit only the break. The only difference is that because we need to add the error of missing out on the factor completely, the increase in the residual variance is even larger. A larger residual variance leads to a larger variance of the estimated difference between $\tilde{a}^{\mathrm{a}}_{i,t}$ and $\tilde{a}^{\mathrm{p}}_{i,t}$. In Appendix D.2 we prove that:

$$\chi_{\mathrm{OBF}} = \frac{(\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})\, \mathrm{E}[f_1]}{\mathrm{Var}[\tilde{a}^{\mathrm{p}}_{i,t} - \tilde{a}^{\mathrm{a}}_{i,t}]} \leq \frac{(\beta^{\mathrm{p}}_{i,t} - \beta^{\mathrm{a}}_{i,t})\, \mathrm{E}[f_1]}{\mathrm{Var}[\hat{a}^{\mathrm{p}}_{i,t} - \hat{a}^{\mathrm{a}}_{i,t}]} = \chi_{\mathrm{SBF}}. \tag{18}$$

Equation (18) shows that the effect of a structural break in a factor exposure on the test statistic is actually smaller when the factor is omitted than when it is added to the asset pricing model. Hence, as long as the omitted factors have characteristics (i.e., means and variances) similar to the typical factors used in asset pricing, they cannot explain our results.

6 Conclusion

The findings of this study contribute to explaining why bubbles persist. Because riding bubbles is optimal, investors will not cause a bubble to burst. Instead, investors have strong incentives to fuel bubbles and thus increase their size. From a practical perspective, our study helps to explain the existence of sizable bubbles since the inception of financial markets hundreds of years ago.

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Table 1: Structure of the Bubble Model

Period	Δp_s	$\Delta p_{\mathrm{i},s}$	$\Delta p_{\mathrm{b},s}$
$s \leq s_0$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + e_s$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s$	
$s_0 < s \leq s_1$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + a + e_s$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + a$	
$s_1 < s \leq s_2$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + a + e_s$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s$	a
$s_2 < s \leq s_3$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + d_s + e_s$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s$	d_s
$s > s_3$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s + e_s$	$r_{\mathrm{f},s} + \boldsymbol{\beta}' \boldsymbol{f}_s$	

This table provides an overview of the change in the logarithm of the asset price p_s, its intrinsic value $p_{\mathrm{i},s}$, and the bubble component $p_{\mathrm{b},s}$ for each time period. The risk-free rate is $r_{\mathrm{f},s}$, $\boldsymbol{f}_s$ is a vector of risk factors given by an asset pricing model, and $\boldsymbol{\beta}$ is the corresponding vector of coefficients. The unexplained part of the price process is represented by the error term e_s and the constant a.

Table 2: Descriptive Statistics for Bubble Signals

(a) Number of Signals

	CAPM	Fama-French model	Carhart model
Total	39,696	39,696	39,456
Positive	1,966	1,344	1,337
	5.0%	3.4%	3.4%
Negative	37,730	38,352	38,119
	95.0%	96.6%	96.6%

(b) Positive Bubble Signals

	CAPM			Fama-French model			Carhart model		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
$\alpha^{\mathrm{a}}_{i,t}$	-0.0061	-0.0057	0.0053	-0.0050	-0.0045	0.0052	-0.0049	-0.0044	0.0050
$\alpha^{\mathrm{p}}_{i,t}$	0.023	0.020	0.012	0.022	0.019	0.012	0.021	0.019	0.012
Strength	3.21	3.14	0.780	3.15	3.04	0.779	3.11	2.99	0.707
Length	33.9	31.0	15.4	30.2	26.0	14.9	30.4	26.0	15.0

This table reports the number and fraction of bubble signals in panel A and the mean, median, and standard deviation (SD) of several properties of the positive bubble signals in Panel B. To construct the signals, we regress the industry returns on a constant and the market return (column titled CAPM), Fama and French (1993)'s three-factor model (column titled Fama-French model), or Carhart (1997)'s four-factor model (column titled Carhart model). If a ten-year series of industry returns shows evidence of an upward structural break in the intercept, the intercept is significantly positive after the break, and there was no crash during the past six months, then we derive a positive bubble signal. Critical values for the structural break test correspond with a 97.5% confidence level and are obtained from Andrews (1993). We denote the constant before the structural break by $\alpha^{\mathrm{a}}_{i,t}$ and the one after it by $\alpha^{\mathrm{p}}_{i,t}$. The strength is the t-statistic of $\alpha^{\mathrm{p}}_{i,t}$. The length is the number of months since the structural break.

Table 3: Portfolios based on Bubble Signals

(a) Portfolio descriptives, excess and abnormal returns

	CAPM		Fama-French model		Carhart model	
	Bubble	No-bubble	Bubble	No-bubble	Bubble	No-bubble
Portfolio descriptives						
Months with signals	69%	100%	64%	100%	64%	100%
Average No. of Industries	3.25	42.78	2.40	43.48	2.40	43.52
Std. Dev. of No. of Industries	2.64	3.69	1.49	3.26	1.51	3.25
Average Portfolio Turnover	1.79	0.16	1.45	0.13	1.45	0.13
Raw return						
Average return	1.70%	1.01%	1.44%	1.02%	1.57%	1.00%
Volatility	6.40%	4.92%	6.27%	4.93%	6.25%	4.93%
Abnormal return						
Average abnormal return	0.76%	0.06%	0.27%	0.02%	0.34%	0.04%
Abnormal return volatility	4.26%	1.24%	3.96%	0.91%	3.77%	0.88%
Information Ratio	0.178	0.044	0.067	0.017	0.090	0.043
VaR(0.95)	-5.12%	-1.70%	-5.85%	-1.25%	-5.29%	-1.20%
ES(0.95)	-6.87%	-2.61%	-8.15%	-2.11%	-7.59%	-1.96%

(b) Tests on equality of average abnormal returns

	CAPM		Fama-French model		Carhart model	
	Bubble	No-bubble	Bubble	No-bubble	Bubble	No-bubble
Average, WLS	0.58%	-0.01%	0.39%	0.00%	0.39%	0.01%
	(0.12)	(0.04)	(0.12)	(0.03)	(0.12)	(0.03)
Test, WLS	4.67		3.23		3.13	
	[< 0.001]		[0.001]		[0.002]	
Average, GLS	0.44%	-0.01%	0.32%	-0.01%	0.34%	0.01%
	(0.12)	(0.04)	(0.12)	(0.04)	(0.12)	(0.03)
Test, GLS	3.92		2.69		2.70	
	[< 0.001]		[0.007]		[0.007]	

This table reports the descriptive statistics for the bubble portfolio (Bubble) and the no-bubble portfolio (No-bubble) in Panel A. For every month $t+1$, we form two portfolios based on the signal we receive at the end of month t. The no-bubble portfolio (bubble portfolio) comprises the industries for which we receive a negative (positive) bubble signal. If there is no positive signal, then the bubble portfolio is not invested. The table shows the average number of industries in each portfolio per month and its standard deviation, and the percentage of months for which each portfolio is invested. We calculate the average turnover of the portfolios as the average absolute change in portfolio weights. We report the average excess return and its volatility per month. The Sharpe ratio is annualized. The average monthly abnormal returns are corrected for the risk-factor exposures of the industries as in Equation (3). The information ratio is calculated as the ratio of the average abnormal returns and their standard deviation. The realized value-at-risk (VaR) and expected shortfall (ES) are for a confidence level of 95% and based on the abnormal returns. Panel B reports the results of testing for the equality of the average abnormal returns of the bubble and no-bubble portfolios. We address heteroscedasticity in the portfolio returns by estimating the averages by WLS and (feasible) GLS regressions. We use the variance and covariance of the residuals of Equation (1) to estimate the variance of the portfolios' abnormal returns. Standard errors are in parentheses. The rows labeled test report the t-statistic for the equality of abnormal returns with p-values below in brackets.

Table 4: Standardized Abnormal Returns Following Positive and Negative Bubble Signals

(a) CAPM

Signal	Negative		Positive		p-value
mean	0.007	(0.010)	0.19	(0.038)	< 0.0001
median	-0.012	(0.008)	0.15	(0.043)	< 0.0001
volatility	1.04	(0.016)	1.18	(0.032)	< 0.0001
skewness	0.19	(0.073)	0.49	(0.20)	0.077
kurtosis	5.75	(0.35)	5.38	(1.30)	0.53
VaR(0.95)	1.61	(0.027)	1.69	(0.066)	0.10
ES(0.95)	2.25	(0.052)	2.18	(0.083)	0.77
VaR(0.975)	2.04	(0.043)	2.07	(0.091)	0.34
ES(0.975)	2.70	(0.074)	2.52	(0.10)	0.90

(b) Fama-French model

Signal	Negative		Positive		p-value
mean	0.002	(0.008)	0.11	(0.043)	< 0.0001
median	-0.022	(0.008)	0.068	(0.036)	0.0017
volatility	1.07	(0.015)	1.26	(0.031)	< 0.0001
skewness	0.21	(0.069)	0.11	(0.097)	0.66
kurtosis	5.87	(0.37)	3.83	(0.19)	0.98
VaR(0.95)	1.66	(0.026)	1.86	(0.085)	0.0033
ES(0.95)	2.29	(0.048)	2.57	(0.12)	0.0098
VaR(0.975)	2.06	(0.036)	2.34	(0.17)	0.010
ES(0.975)	2.74	(0.070)	3.08	(0.16)	0.026

(c) Carhart model

Signal	Negative		Positive		p-value
mean	0.011	(0.008)	0.11	(0.043)	< 0.0001
median	-0.015	(0.008)	0.083	(0.039)	0.0008
volatility	1.08	(0.014)	1.28	(0.032)	< 0.0001
skewness	0.21	(0.058)	0.095	(0.10)	0.69
kurtosis	5.69	(0.33)	3.76	(0.19)	0.99
VaR(0.95)	1.67	(0.027)	1.90	(0.086)	0.0019
ES(0.95)	2.30	(0.044)	2.59	(0.13)	0.0070
VaR(0.975)	2.08	(0.037)	2.34	(0.12)	0.016
ES(0.975)	2.75	(0.064)	3.07	(0.19)	0.028

This table reports the summary statistics and downside risk measures for the pooled set of standardized abnormal returns at time $t+1$, conditional on the bubble signal at time t being negative or positive. The abnormal returns are based on rolling regressions of the CAPM (Panel A), the Fama-French model (Panel B), or the Carhart model (Panel C) in Equation (1) with a 120-month estimation window. For each regression, we construct an abnormal return for the period after the estimation window as in Equation (3). To correct for time-varying volatility, we divide the abnormal return by the residual volatility of the regression model. For each statistic, we compute standard errors and p-values based on 10,000 temporal bootstraps. The column titled p-value reports the results of tests for the equality of the statistics for the cases positive and negative bubble signal under the null hypothesis of no distributional difference.

Table 5: Sequences of Positive Bubble Signals

Series	CAPM				Fama-French model				Carhart model			
duration	# series	average	last	crash	# series	average	last	crash	# series	average	last	crash
1	94	−0.86	−0.86	11	109	−1.12	−1.12	18	116	−1.10	−1.10	20
2	42	−0.22	−0.87	5	42	−0.25	−0.93	5	57	−0.36	−1.18	8
3	35	−0.07	−1.26	8	33	−0.10	−1.36	8	26	−0.02	−1.02	3
4	28	0.25	−1.07	4	20	0.04	−1.24	3	13	0.06	−1.30	2
5	18	0.20	−1.36	2	26	0.14	−1.34	6	17	0.24	−1.21	2
6	20	0.24	−1.55	7	11	0.21	−1.01	2	14	0.45	−1.30	5
7	18	0.27	−1.26	3	6	0.42	−1.26	2	9	0.12	−0.96	2
8	9	0.22	−1.64	3	3	0.05	−1.67	1	11	0.06	−1.08	1
9	6	0.33	−1.54	1	9	0.32	−1.17	0	6	0.33	−1.31	1
10	13	0.31	−1.49	3	5	0.32	−2.17	3	9	0.34	−1.72	3
11	3	0.26	−1.97	2	8	0.27	−1.03	3	5	0.27	−1.34	3
12	6	0.16	−1.36	2	6	0.30	−0.93	1	4	0.38	−1.72	1
13-18	13	0.49	−1.21	2	10	0.38	−1.29	2	11	0.38	−1.31	3
19-24	6	0.20	−1.44	2	9	0.30	−1.53	3	6	0.51	−1.63	2
> 24	15	0.29	−0.66	1	3	0.60	0.28	0	4	0.33	−1.55	1
total	326	0.19	−1.11	56	300	0.11	−1.17	57	308	0.11	−1.18	57

This table shows the number of series of different durations, their length, their monthly average standardized abnormal returns, their average standardized abnormal returns of the last month of the series, and the number of crashes during the last month of the series (standardized abnormal return below -2).

Table 6: Optimal Portfolio Choice and Expected Utility

(a) CAPM

γ	w_{NB}		w_B		p-value	V_B/V_{NB}	p-value	λ	p-value
0.5	0.32	(0.46)	6.05	(0.77)	< 0.0001	9.35	< 0.0001	28.36	< 0.0001
1	0.16	(0.23)	3.35	(0.65)	< 0.0001	5.35	< 0.0001	14.73	< 0.0001
2	0.08	(0.12)	1.70	(0.35)	< 0.0001	3.18	< 0.0001	7.38	< 0.0001
3	0.05	(0.08)	1.14	(0.23)	< 0.0001	2.45	< 0.0001	4.91	< 0.0001
5	0.03	(0.05)	0.68	(0.14)	< 0.0001	1.87	< 0.0001	2.94	< 0.0001
10	0.02	(0.02)	0.34	(0.07)	< 0.0001	1.43	< 0.0001	1.47	< 0.0001

(b) Fama-French model

γ	w_{NB}		w_B		p-value	V_B/V_{NB}	p-value	λ	p-value
0.5	0.00	(0.39)	3.56	(1.19)	0.0034	3.60	0.0014	9.56	0.0008
1	0.00	(0.19)	1.84	(0.68)	0.0029	2.32	0.0014	4.84	0.0008
2	0.00	(0.10)	0.93	(0.35)	0.0030	1.66	0.0014	2.43	0.0008
3	0.00	(0.06)	0.62	(0.23)	0.0030	1.44	0.0014	1.62	0.0008
5	0.00	(0.04)	0.37	(0.14)	0.0030	1.26	0.0015	0.98	0.0008
10	0.00	(0.02)	0.19	(0.07)	0.0031	1.13	0.0015	0.49	0.0008

(c) Carhart model

γ	w_{NB}		w_B		p-value	V_B/V_{NB}	p-value	λ	p-value
0.5	0.50	(0.37)	3.50	(1.18)	0.011	3.42	0.0034	6.90	0.0061
1	0.25	(0.19)	1.81	(0.68)	0.011	2.24	0.0035	3.51	0.0060
2	0.12	(0.09)	0.91	(0.35)	0.010	1.63	0.0035	1.76	0.0060
3	0.08	(0.06)	0.61	(0.24)	0.010	1.42	0.0035	1.18	0.0060
5	0.05	(0.04)	0.36	(0.14)	0.010	1.25	0.0035	0.71	0.0061
10	0.02	(0.02)	0.18	(0.07)	0.010	1.12	0.0035	0.35	0.0061

This table reports the optimal portfolio w_{NB} (w_B) of a rational investor if she receives a negative (positive) bubble signal. Abnormal returns are based on the CAPM and the Fama-French and Carhart models. We assume that the investor has a power-utility function. We report optimal portfolios for varying levels of relative risk aversion γ for both cases. The investment opportunity is the typical industry with idiosyncratic volatilities equal to their pooled averages (CAPM, 4.17%; Fama-French model, 3.86%; and Carhart model, 3.81%). The risk-free rate equals its long-term average of 0.305% per month. We report the optimal portfolios as fractions of wealth. Based on the optimal portfolios, we calculate the ratio of expected utilities V_B/V_{NB}. We also calculate the certainty equivalent return λ that an investor requires for not changing her portfolio from w_{NB} to w_B in % per year. We use 10,000 temporal bootstraps to calculate standard errors (reported in parentheses) and p-values. We test $w_{NB} = w_B$, $V_B = V_{NB}$, and $\lambda = 0$ under the null hypothesis of no difference in distribution between the cases with positive and negative bubble signals.

Table 7: Descriptive Statistics of Bubbles

	CAPM			Fama-French model			Carhart model		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Bubbles per Industry	3.05	3.00	1.26	2.98	3.00	1.33	3.00	3.00	1.34
Raw Return	30.2	28.3	23.4	31.4	30.2	24.1	31.0	30.2	23.5
St. Abn. Return	0.489	0.418	1.18	0.506	0.435	1.20	0.516	0.446	1.24

This table reports the statistics on the number of bubbles per industry, their average raw return (in % per year), and the average standardized abnormal return per month. An observation belongs to a bubble if the investors receive a positive signal at t, that is, $B_t = 1$; and the observation is between t and the breakpoint $t - \zeta^*$. As long as the sequence of the bubble observations is not interrupted, we count them as belonging to the same bubble. We report the mean, median, and standard deviations.

Table 8: Correlation between Bubble Characteristics and Sentiment Indicators

Bubble Characteristic	Sentiment Indicator	CAPM		Fama-French model		Carhart model	
Number of Bubbles	Sentiment	0.17	(0.12)	0.46	(0.09)	0.46	(0.09)
Number of Bubbles	CCI	0.16	(0.11)	0.25	(0.12)	0.31	(0.10)
Difference in BE/ME	Sentiment	-0.52	(0.11)	-0.49	(0.08)	-0.49	(0.08)

This table reports correlation coefficients between the bubble characteristics and sentiment indicators. The variable Number of Bubbles is the number of industries that experience a bubble in a given month. The variable Difference in BE/ME is calculated as the BE/ME ratio of the portfolio of all industries experiencing a bubble in a given month minus the BE/ME ratio of the portfolio of the remaining industries. Both portfolios are value weighted. The BE/ME ratios for the industries are from French's data library. The variable Sentiment is the orthogonalized monthly investor sentiment indicator from Baker and Wurgler (2007), taken from Jeffrey Wurgler's homepage. The indicator ranges from July 1965 to December 2007. The variable CCI is the monthly Consumer Confidence Indicator of the University of Michigan, downloaded from the FRED-database of the Federal Reserve Bank of St. Louis. The indicator ranges from January 1978 to December 2009. We calculate correlation coefficients for months in which at least one industry experiences a bubble. HAC-standard errors based on Newey and West (1987) are reported in parentheses.

Table 9: Returns after Bubble Signals with Industry Momentum Factor

(a) 6-Month Selection, 6-Month Holding

Signal	Negative		Positive		p-value
# obs	37849		1367		
mean	0.0060	(0.0083)	0.12	(0.045)	< 0.001
median	-0.020	(0.0077)	0.085	(0.045)	< 0.001
volatility	1.08	(0.014)	1.30	(0.034)	< 0.001
VaR(0.95)	1.67	(0.024)	1.96	(0.091)	< 0.001
ES(0.95)	2.31	(0.044)	2.68	(0.15)	0.001

(b) 12-Month Selection, 1-Month Holding

Signal	Negative		Positive		p-value
# obs	37890		1326		
mean	0.0075	(0.0083)	0.10	(0.044)	0.002
median	-0.017	(0.0079)	0.070	(0.046)	0.002
volatility	1.08	(0.014)	1.29	(0.032)	< 0.001
VaR(0.95)	1.67	(0.026)	1.93	(0.075)	0.002
ES(0.95)	2.31	(0.044)	2.68	(0.13)	< 0.001

This table reports the summary statistics and downside risk measures for the pooled set of standardized abnormal returns resulting from different momentum factors in our method to obtain positive bubble signals and compute abnormal returns. We base the abnormal returns on rolling regressions of the industry returns on the market return, the size portfolio SMB, and the value-growth portfolio HML from Fama and French (1993), and a momentum factor. In Panel A we construct the momentum factor of Moskowitz and Grinblatt (1999) in which industries are ranked at time t according to their performance over the period $t-6$ to $t-1$. The factor is based on equally weighted long positions in the seven best-performing industries and short positions in the seven worst-performing industries. The industries stay in this portfolio for six months, and every month we rebalance 1/6 of this portfolio. In Panel B we rank industries based on their performance over the period $t-12$ to $t-1$. We construct new portfolios every month. For each regression, we construct an abnormal return for the period after the estimation window, as in Equation (3). To correct for time-varying volatility, we standardize the abnormal return by a division by the residual volatility of the regression model. We split the abnormal returns according to the bubble signal. For each statistic, we construct standard errors, which we report in parentheses, and p-values based on 1,000 temporal bootstraps. The column titled p-value reports the results of tests for equality of the statistics based on the distribution without a bubble signal and those based on the distribution with a bubble signal under the null hypothesis of no distributional difference between the two cases.

Table 10: Characteristics of Abnormal Returns, Double-sorted on Positive Bubble Signals and Buy-Side Momentum

(a) CAPM, 6-Month Momentum

bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	728		1238		5254		
Average	0.186	(0.060)	0.195	(0.040)	0.054	(0.018)	0.441
Median	0.158	(0.084)	0.147	(0.039)	0.026	(0.020)	0.222
Volatility	1.28	(0.041)	1.12	(0.039)	1.04	(0.018)	0.169
VaR(0.95)	1.73	(0.105)	1.58	(0.098)	1.55	(0.031)	0.323
ES(0.95)	2.28	(0.115)	2.11	(0.097)	2.13	(0.063)	0.214

(b) CAPM, 12-Month Momentum

bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	899		1067		5088		
Average	0.219	(0.054)	0.169	(0.043)	0.104	(0.020)	0.209
Median	0.224	(0.064)	0.111	(0.042)	0.071	(0.017)	0.056
Volatility	1.26	(0.039)	1.12	(0.043)	1.06	(0.018)	0.229
VaR(0.95)	1.76	(0.096)	1.52	(0.105)	1.58	(0.041)	0.146
ES(0.95)	2.31	(0.118)	2.04	(0.101)	2.15	(0.061)	0.127

(c) Fama-French Model, 6-Month Momentum

bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	582		762		5400		
Average	0.039	(0.067)	0.170	(0.047)	0.054	(0.017)	0.754
Median	−0.002	(0.054)	0.131	(0.043)	0.036	(0.016)	0.792
Volatility	1.38	(0.047)	1.16	(0.037)	1.06	(0.018)	0.036
VaR(0.95)	2.11	(0.127)	1.64	(0.125)	1.58	(0.036)	0.101
ES(0.95)	2.84	(0.181)	2.27	(0.145)	2.15	(0.058)	0.095

(d) Fama-French Model, 12-Month Momentum

bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	720		624		5267		
Average	0.136	(0.056)	0.086	(0.056)	0.099	(0.019)	0.125
Median	0.083	(0.051)	0.061	(0.048)	0.076	(0.019)	0.198
Volatility	1.30	(0.041)	1.22	(0.045)	1.08	(0.019)	0.172
VaR(0.95)	1.92	(0.120)	1.83	(0.127)	1.60	(0.039)	0.333
ES(0.95)	2.54	(0.145)	2.60	(0.206)	2.17	(0.058)	0.650

(e) Carhart Model, 6-Month Momentum

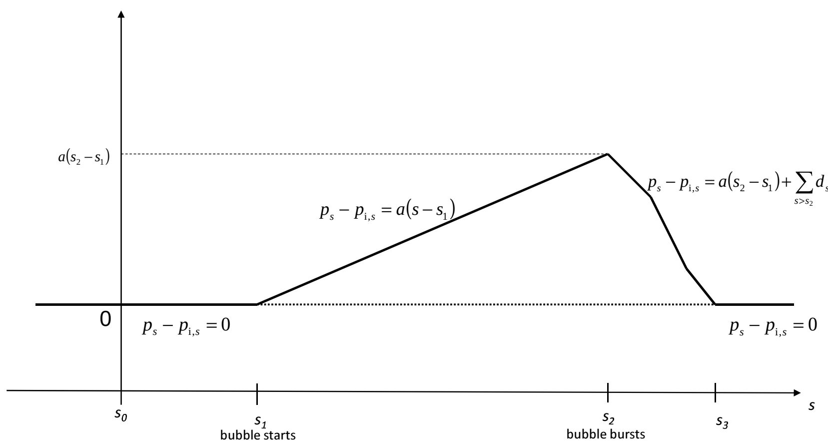
bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	472		865		5485		
Average	0.077	(0.064)	0.133	(0.050)	0.080	(0.018)	0.878
Median	0.034	(0.061)	0.104	(0.045)	0.037	(0.016)	0.856
Volatility	1.27	(0.045)	1.29	(0.040)	1.09	(0.018)	0.502
VaR(0.95)	1.99	(0.114)	1.84	(0.105)	1.59	(0.041)	0.141
ES(0.95)	2.51	(0.151)	2.61	(0.166)	2.18	(0.054)	0.400

(f) Carhart Model, 12-Month Momentum

bubble signal	positive		positive		negative		
buy-side mom.	yes		no		yes		p-value
# Obs.	614		723		5354		
Average	0.140	(0.054)	0.091	(0.057)	0.028	(0.017)	0.483
Median	0.082	(0.054)	0.085	(0.050)	−0.008	(0.018)	0.526
Volatility	1.22	(0.037)	1.33	(0.047)	1.08	(0.018)	0.871
VaR(0.95)	1.84	(0.101)	1.96	(0.151)	1.67	(0.048)	0.392
ES(0.95)	2.24	(0.096)	2.86	(0.214)	2.28	(0.057)	0.888

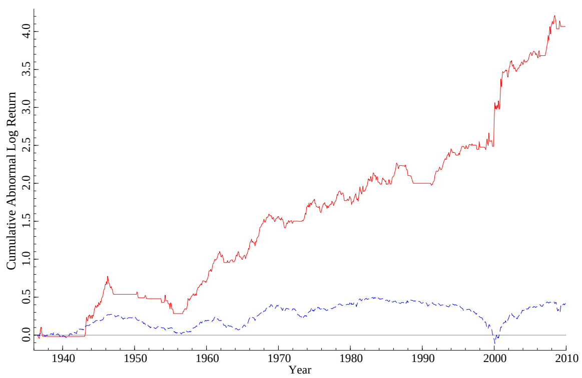
This table reports the summary statistics and downside risk measures for the pooled set of standardized abnormal returns. We sort returns on whether a positive bubble signal exists in the previous month t, and on whether returns correspond with industries that are selected for a buy-side momentum portfolio. The seven industries that perform the best over a specific past horizon constitute this portfolio. For Panels a, c, and e, this horizon is from $t-1$ to $t-6$; for Panels b, d, and f, the horizon is from $t-1$ to $t-12$. We report standard errors based on a temporal bootstrap in parenthesis. The final column contains p-values for a test on the equality of statistics for the combination of a positive bubble signal and buy-side momentum (positive, yes) and the combination of a positive bubble signal and no buy-side momentum (positive, no). The p-values correspond with the one-sided alternative that the first statistics are larger than the second statistics. We construct the p-values by a temporal bootstrap under the null-hypothesis of equality in distribution.

Figure 1: A Stylized Example of the Bubble Model

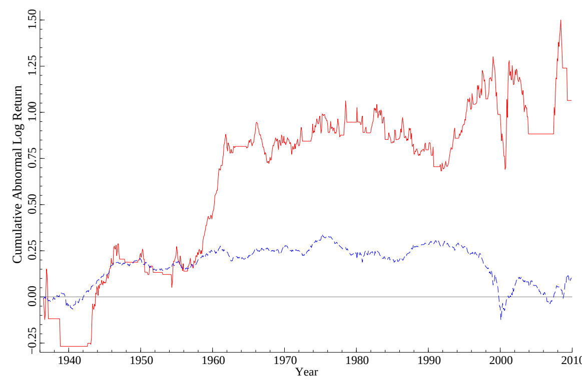


This figure presents a stylized example of the bubble model. The size of the bubble is determined as the difference between the log price of asset p_s and the log fundamental or intrinsic value $p_{\mathrm{i},s}$. Until s_1, the growth rate of the price and of the fundamental value coincide. From s_1 to s_2, the growth rate of the fundamental value drops to $r_{\mathrm{e},s}$, but the asset price grows at the higher rate $r_{\mathrm{e},s} + a$. A bubble arises as its log size grows by a. At s_2, a correction sets in, and the asset price falls towards the fundamental value at rate d_s. The correction lasts until s_3. In the graph, we assume pricing errors are absent.

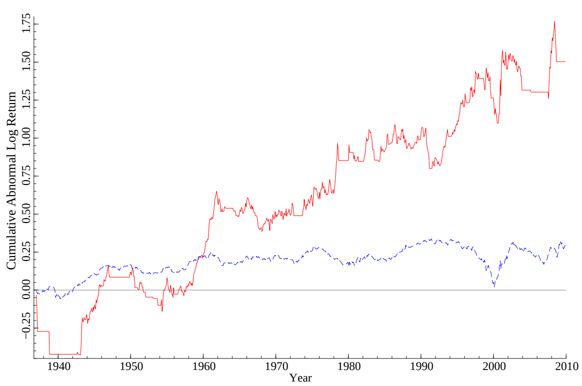
Figure 2: Abnormal Return of Bubble Portfolio and No-bubble Portfolio



(a) CAPM



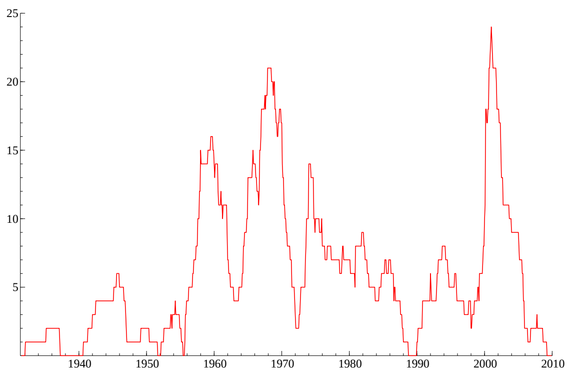
(b) Fama-French model



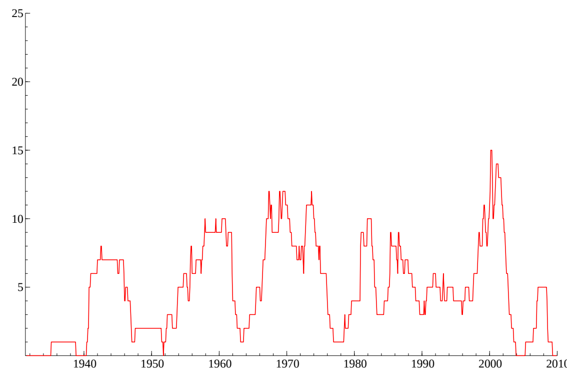
(c) Carhart model

This figure shows the cumulative abnormal log returns of $1 invested in the bubble portfolio (red, solid) or the no-bubble portfolio (blue, dashed) starting in July 1936 for the CAPM and Fama-French models. For the Carhart model, we start in January 1937. The bubble (no-bubble) portfolio is invested in every month $t+1$ in all industries for which we have a positive (negative) bubble signal at t. If there are no positive bubble signals, then the bubble portfolio is not invested. Both portfolios are equally weighted across industries.

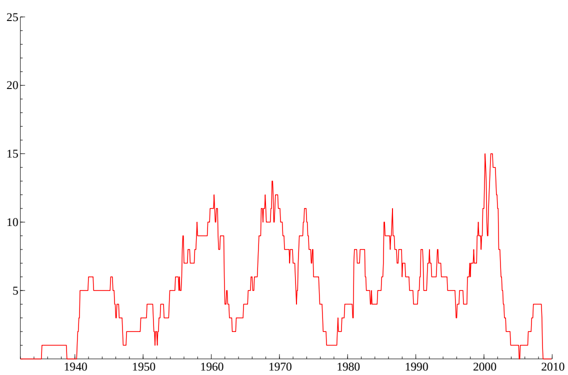
Figure 3: Number of Bubbles over Time



(a) CAPM



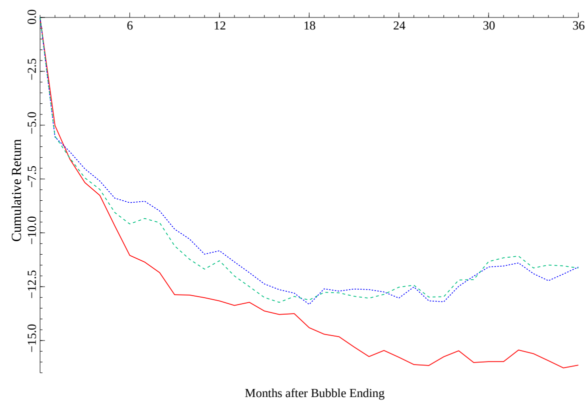
(b) Fama-French Model



(c) Carhart Model

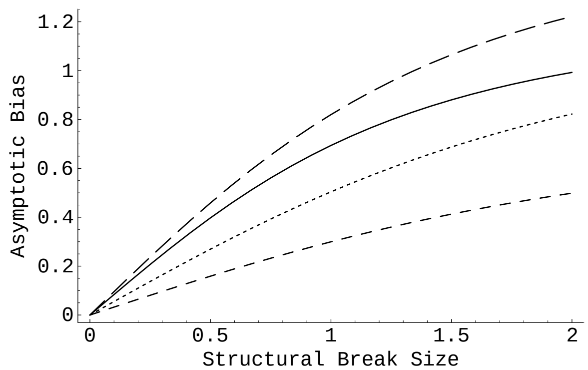
This figure shows the evolution of the number of industries in a bubble over time for the different factor models. An industry i encounters a bubble in month $\tau < t$, if the investors receives a positive signal at t, i.e., $B_{i,t} = 1$, and month τ is between t and the breakpoint $t - \zeta^*$. We show results based on the CAPM (panel A), the Fama-French model (panel B) and the Carhart model (panel C).

Figure 4: Returns after Bubbles

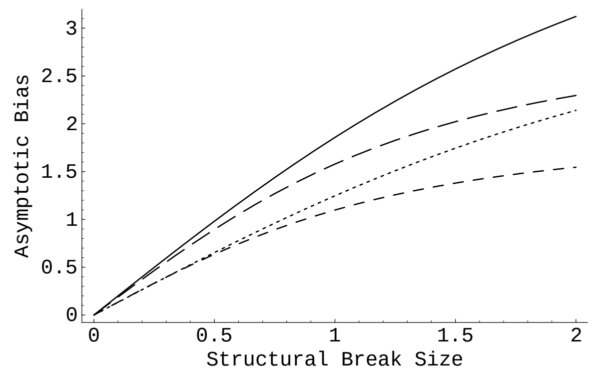


This figure shows the cumulative abnormal returns of a typical industry (in %) up to 36 months after a bubble has ended. Based on the full time series of positive bubble signals, we construct bubbles for each industry. The end of one bubble is the first month that is no longer classified as a positive bubble signal. We show abnormal returns based on the CAPM (solid red line), the Fama-French model (dotted blue line) and the Carhart model (dashed green line). For each post-bubble month we calculate the average standardized abnormal return, multiplied by the average idiosyncratic volatility (CAPM, 4.17%; Fama-French model, 3.86%; and Carhart model, 3.81%). The averages are then summed up to produce the cumulative abnormal return series in the figure.

Figure 5: Effect of Model Misspecification



(a) Long-run Factor Moments



(b) Maximum Factor Average

This figure shows how the asymptotic bias in the t-statistic (y-axis) for a structural break in the intercept is affected by the size of the structural break (x-axis) in a factor exposure in the true model. We assume that the true model is given by

$$r_{i,t-\tau} = \alpha_{i,t} + \beta_{i,t,\tau} f_{1,t-\tau} + \boldsymbol{\gamma}_{i,t}\, \tilde{\boldsymbol{f}}_{t-\tau} + \varepsilon_{i,t,\tau},\ \mathrm{E}[\varepsilon_{i,t,\tau}] = 0,\ \mathrm{E}[\varepsilon^2_{i,t,\tau}] = \sigma^2_{i,t},\ \tau = 0, 1, \ldots, T-1$$

$$\beta_{i,t,\tau} = \begin{cases} \beta^{\mathrm{a}}_{i,t} & \text{for } \tau = \zeta+1, \zeta+2, T-1 \\ \beta^{\mathrm{p}}_{i,t} & \text{for } \tau = 0, 1, \ldots, \zeta, \end{cases}$$

while the estimated model is given by

$$r_{i,t-\tau} = a_{i,t,\tau} + b_{i,t} f_{1,t-\tau} + \boldsymbol{c}'_{i,t} \tilde{\boldsymbol{f}}'_{t-\tau} + e_{i,t,\tau},\ \mathrm{E}[e_{i,t,\tau}] = 0,\ \tau = 0, 1, \ldots, T-1$$

$$a_{i,t,\tau} = \begin{cases} a^{\mathrm{a}}_{i,t} & \text{for } \tau = \zeta+1, \zeta+2, T-1 \\ a^{\mathrm{p}}_{i,t} & \text{for } \tau = 0, 1, \ldots, \zeta. \end{cases}$$

We plot the expected value of the t-statistic on the difference $a^{\mathrm{a}}_{i,t} - a^{\mathrm{p}}_{i,t}$

$$\chi = \frac{\sqrt{T}\Delta\, \mathrm{E}[f_1]}{\sqrt{\Delta^2 \mathrm{Var}[f_1] + \frac{1}{\xi(1-\xi)}\sigma^2_{i,t}}},$$

as a function of the size of the true structural break $\Delta = \beta_2 - \beta_1$. Panel A shows this relation for the long-run factor moments: CAPM, solid ($\mu = 0.61\%$, $\sigma = 5.46\%$); SMB, dashed ($\mu = 0.24\%$, $\sigma = 3.33\%$); HML, dotted ($\mu = 0.402\%$, $\sigma = 3.59\%$); and MOM, long dashed ($\mu = 0.70$, $\sigma = 4.83\%$). In Panel B, we use the largest ten-year average in our sample: CAPM, solid ($\mu = 1.46\%$, $\sigma = 3.21\%$); SMB, dashed ($\mu = 0.99\%$, $\sigma = 5.73\%$); HML, dotted ($\mu = 0.97\%$, $\sigma = 2.94\%$); and MOM, long dashed ($\mu = 1.37$, $\sigma = 5.20\%$). We have $\xi = 1/2$, $T = 120$, and $\sigma^2_{i,t} = 4\%$.

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