Bubbles for Fama

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Q Group, May 2018

Bubbles for Fama

- Eugene Fama does not believe in bubbles, which he defines as "**irrational strong price increase that implies a predictable strong decline**."
- Fama's argument: if one looks at markets with large price increases, then going forward, returns on average are not unusually low

  "*For bubbles, I want a systematic way of identifying them. It's a simple proposition. You have to be able to predict that there is some end to it. All the tests people have done trying to do that don't work. Statistically, people have not come up with ways of identifying bubbles.*"
- Fama's conclusion at odds with a long literature on bubbles
- We examine the evidence: all episodes since 1928 in which stock prices of a US industry have increased over 100% in raw and net of market returns over the past two years
  - Most bubbles have a strong industry component– ".com" or new economy industries such as utilities during the 1920s
  - 40 such episodes in US data, so limited power
- Using these episodes, we analyze:
  - Average returns post price run-up
  - The likelihood of a crash after a large price run-up
  - Whether other features of the price run-up can help forecast a crash, and in doing so, help an investor earn abnormal returns from "timing the bubble"
- We repeat our analysis on international sector returns

Main Findings

1. **Fama is right about average returns**
   - Average raw returns post run-up are modestly positive
   - But *excess* returns are mediocre after big run-ups, and negative after extremely large run-ups
2. **However, high past returns are associated with a dramatically higher probability of a crash**
   - About half of the price run-ups we study end in a crash over the next 24 months, defined as a drawdown of 40% or more
   - If we increase the past return threshold, the probability of a crash increases even more
   - Elevated crash probability is perhaps just as important for, say, a regulator or central bank who is interested in the consequences of a crash

- Reasons for difference in results between #1 and #2
   - Some industries keep going up
   - Peaks are hard to tell: even when we correctly call a future crash, on average prices peak 5.4 months after we first identify the price run-up!

3. **Differences in characteristics between price run-ups that crash and price run-ups that do not**
   - We study turnover, volatility, issuance, book-to-market, age, market P/E, and the price path
   - For some – but not all – of these characteristics, we show significant differences between crashes and non-crashes
4. **These same characteristics can be used to “time” the bubble**
   - Several characteristics, in conjunction with the price increase, predict low returns over a 2-year horizon (Δvolatility, issuance, acceleration, CAPE, price increases among newer firms)

Overall, Fama is right only in the narrow sense of predicting average returns based on a run-up

Identifying Large Price Run-ups

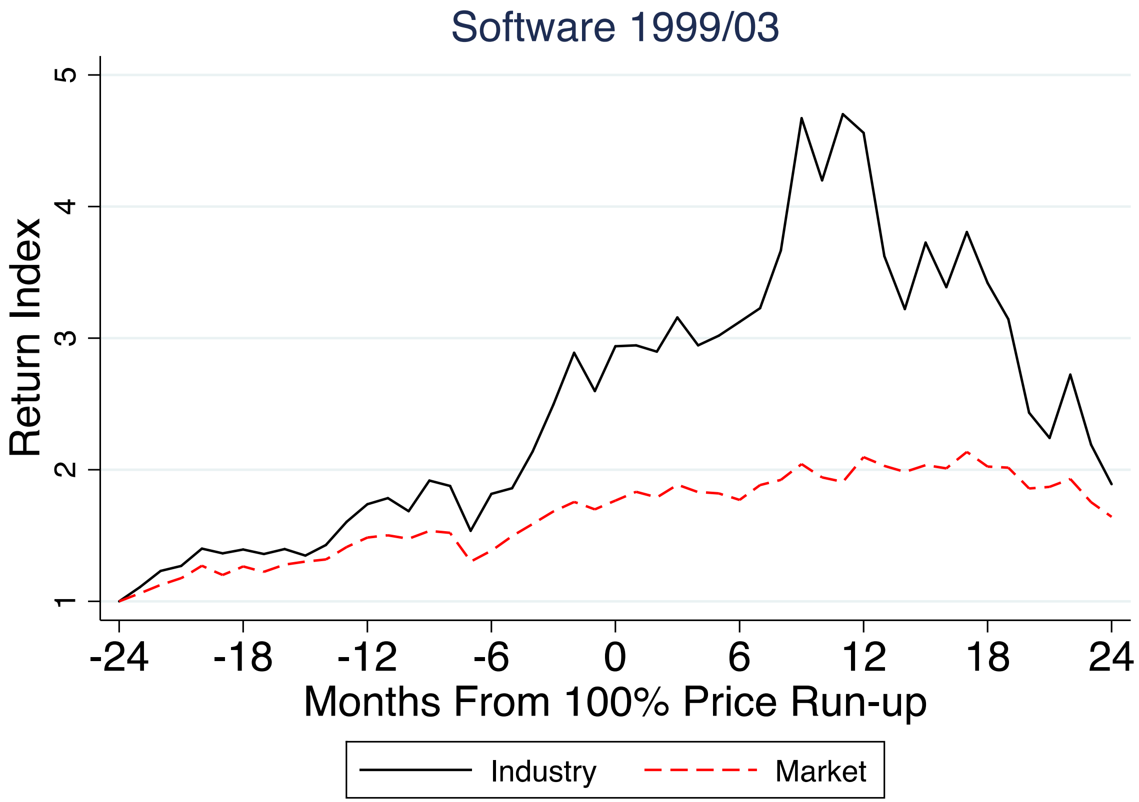
- We study industry returns
  - Industries defined according to Fama-French 49 classifications. We only consider industries with 10 firms or more
- We require that over the past two years
  - 100% or more raw return
  - 100% net of market return
- We also require that over the past five years
  - 100% or more raw return: this avoids us picking up recoveries from recent crashes
  - This additional screen is not important for our results, but helps us avoid identifying price run-ups that don't "look" like they might be a bubble
- These criteria identify **40 episodes** in US data
- In international data, we use identical criteria except that our "industries" are defined based in GICS sectors
  - All stocks with returns data in Compustat Xpressfeed 1985+ – returns in US$
  - Stocks matched to sectors based on GICS code
  - **107 price run-ups** in international data in 31 countries: 53 of these crash

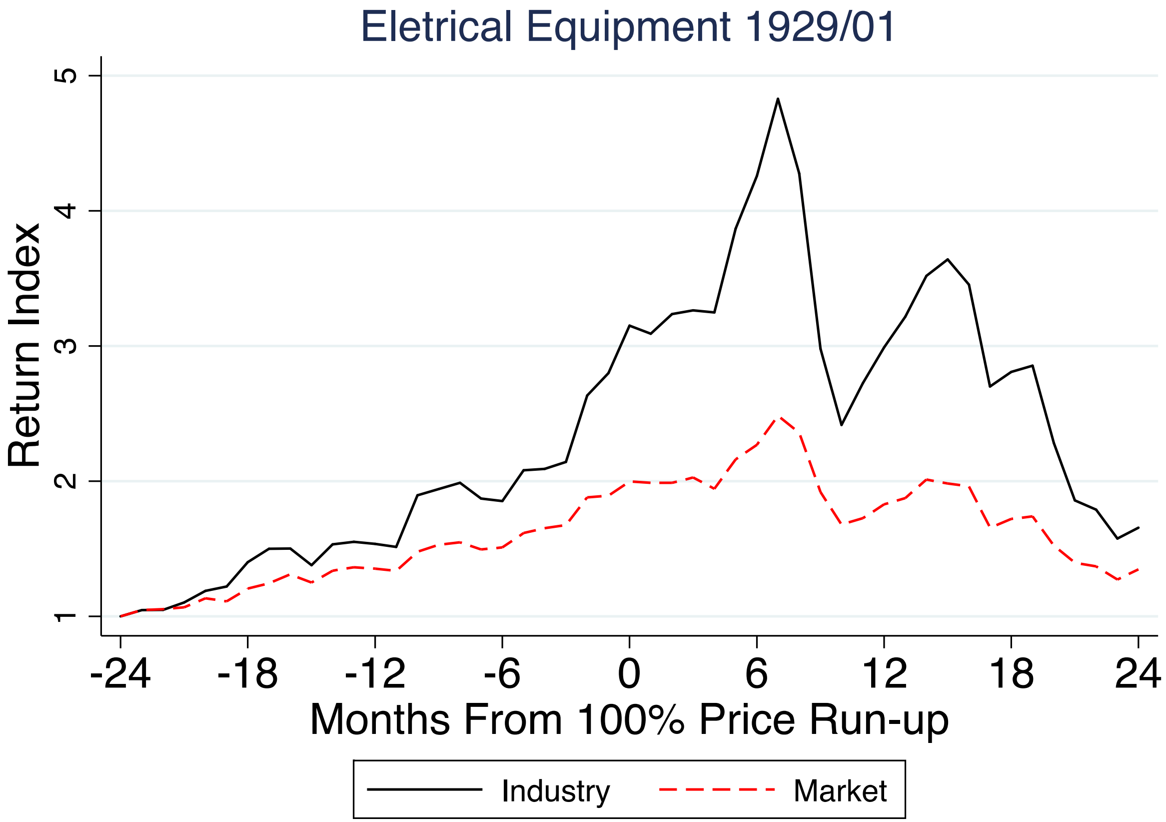
IDENTIFYING LARGE PRICE RUN-UPS: DETAILS

- We study industry returns
  - Industries defined according to FF-49 classifications.
  - We include newly listed firms, so the portfolios are not fixed on a calendar year basis
  - Our returns are over 97% correlated with the FF returns on French's website
- Correlation of episodes
  - The FF-49 definitions are quite narrow, meaning that in 1999, for example, we identify 4 potential bubble candidates that are in fact part of a larger episode
  - This is an issue of standard errors, since these episodes are not independent: we cluster by calendar-year

Episodes

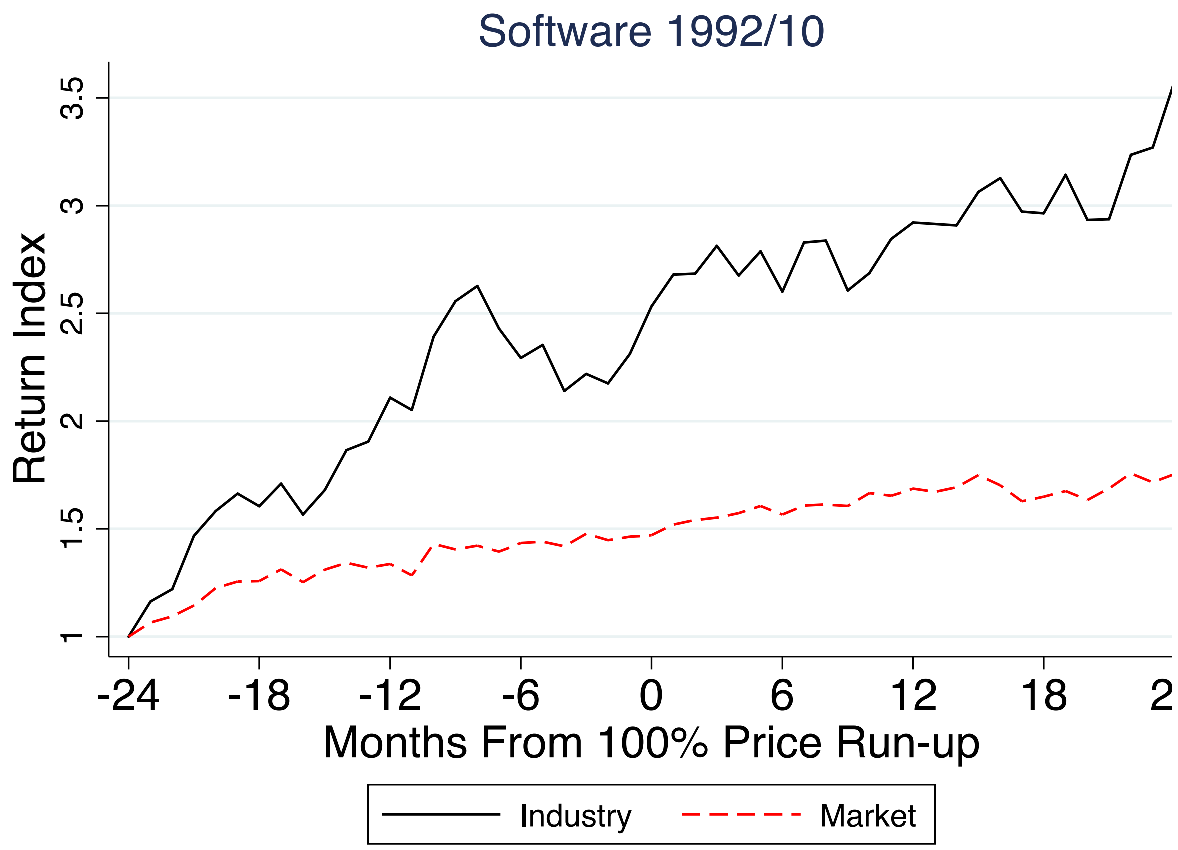
- Familiar Crashes

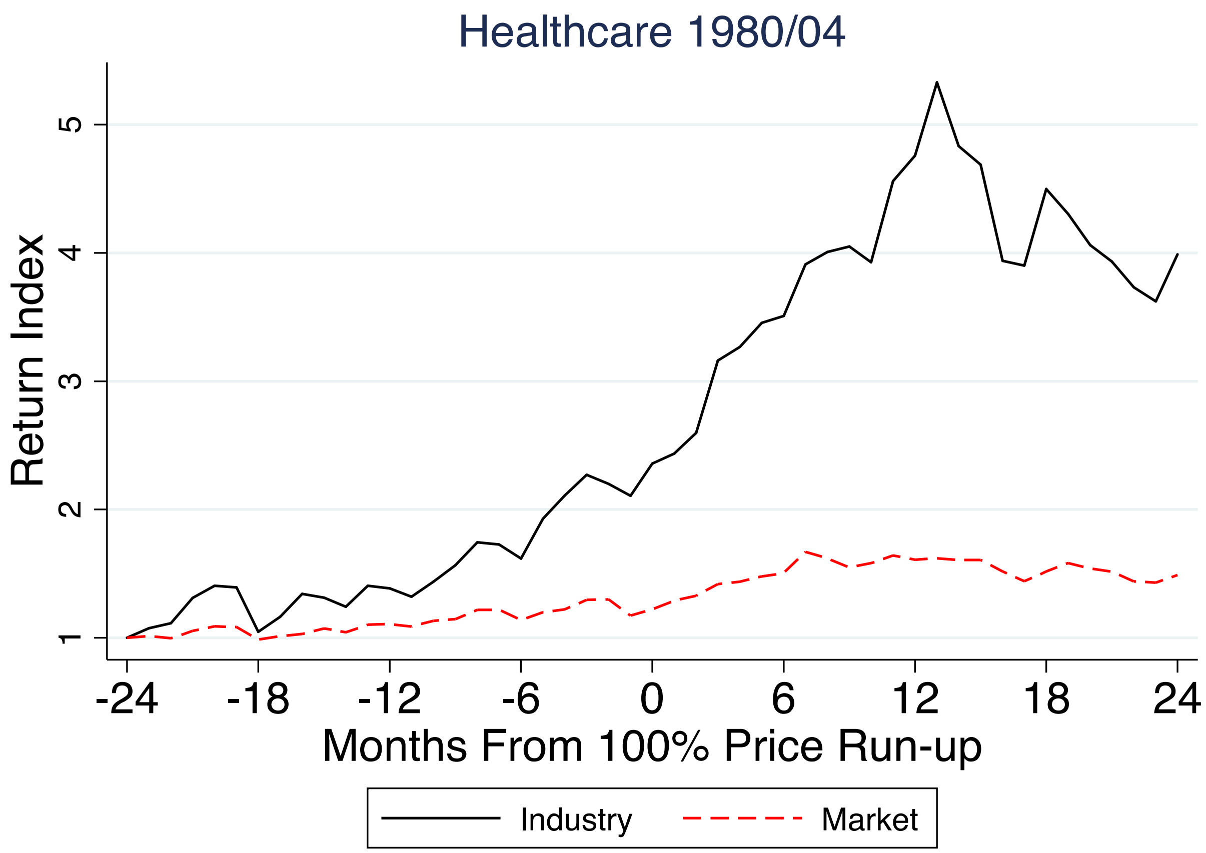




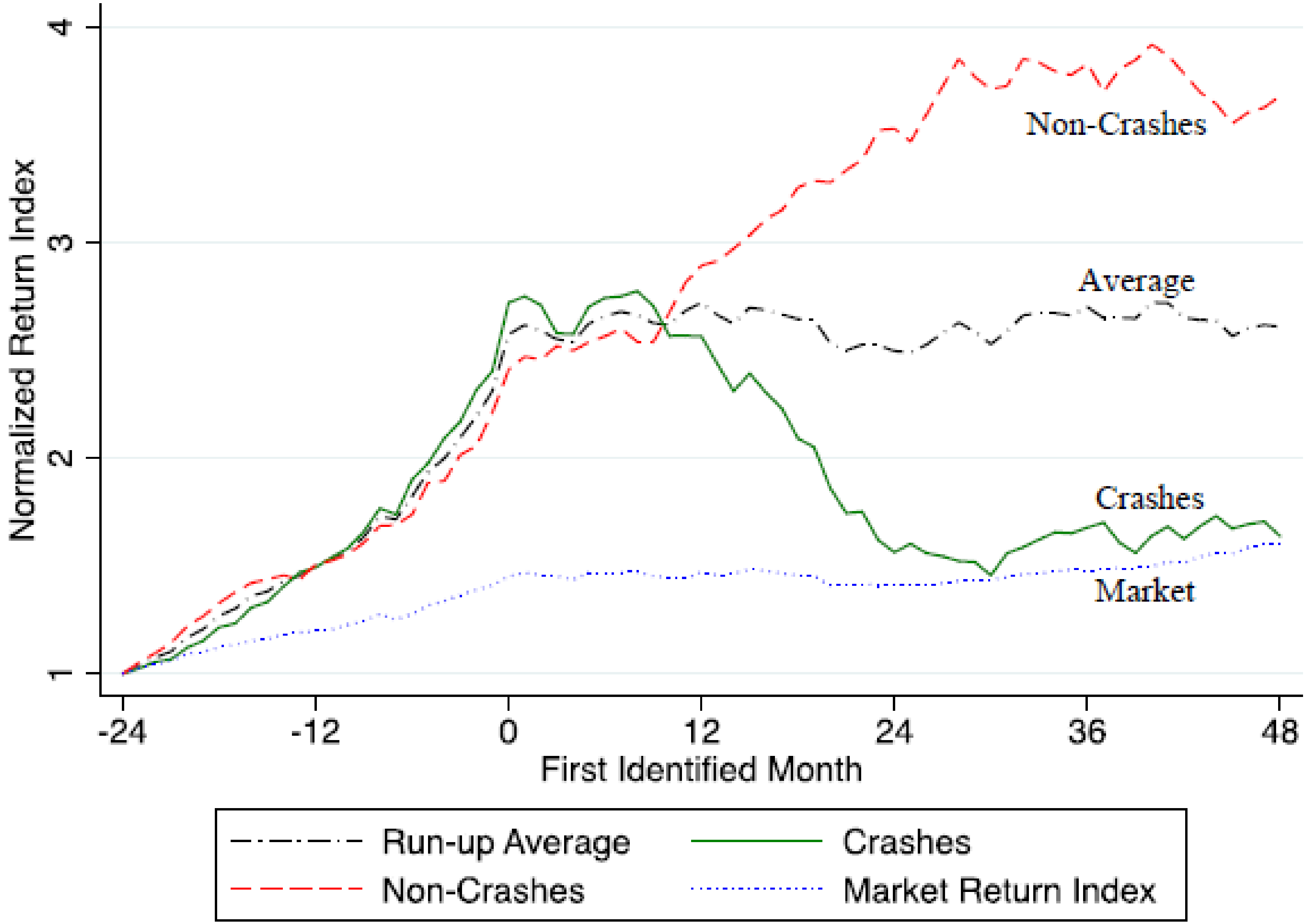
Episodes

- Perhaps less familiar non-crashes

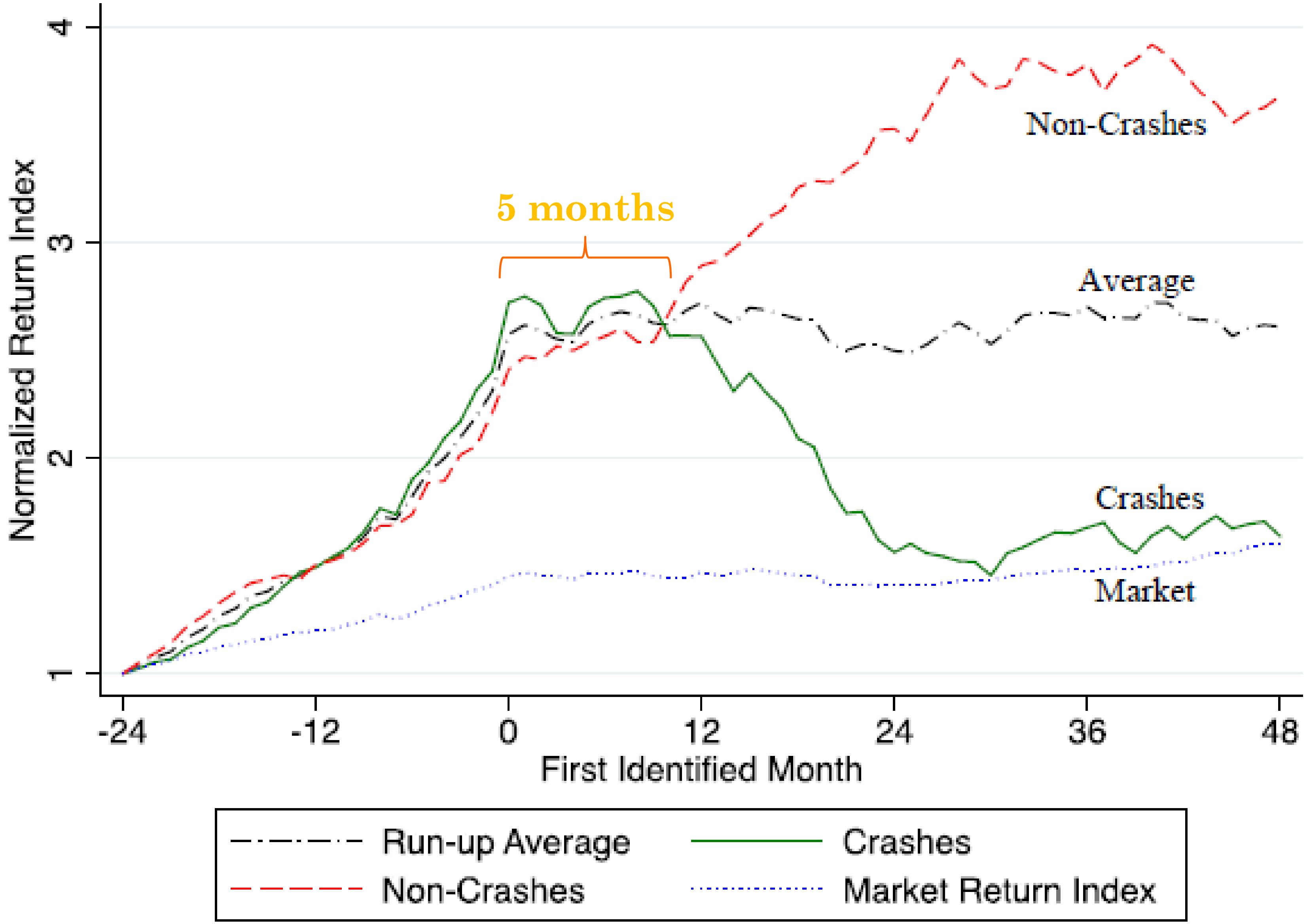




AVERAGE RETURNS



AVERAGE RETURNS



- Even in the cases where we have correctly identified a run-up that will crash, on average, it takes another five months before the industry hits peak price
- During these five months, the average return is 30%

AVERAGE RETURNS

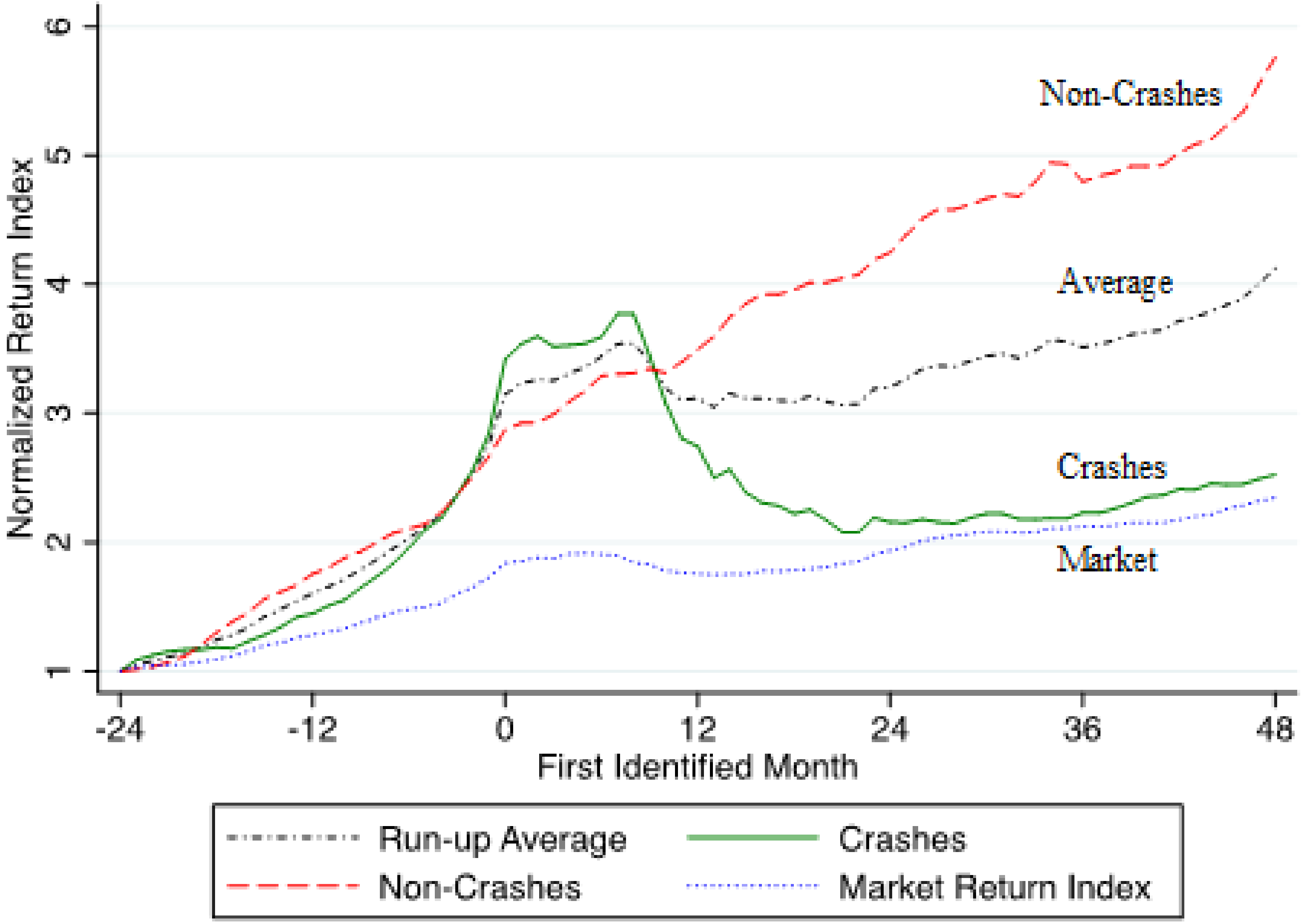
	Subsequent Performance over next 2-years						
	12mo Raw Return (%)	24mo Raw Return (%)	12mo net-of-RF Return (%)	24mo net-of-RF Return (%)	12mo net-of-market Return (%)	24mo net-of-market Return (%)	24mo Maximal Drawdown
Crash Mean	-5%	-42%	-10%	-53%	-3%	-29%	-60%
All Run-ups	**7%**	**0%**	**3%**	**-10%**	**5%**	**0%**	**-41%**

These mediocre average returns occur in spite of well-documented industry momentum effect, which goes the other way

MARKET RETURNS

- We have not made any attempt here to disentangle periods of market overvaluation with that of the industry
- Most historical narratives of bubbles, such as during the 1920s and 1990s (and many prior) suggest that the two are intertwined
- In the data, average market excess returns post industry run-up are poor:
  - -3% excess market returns in the first year

International Data

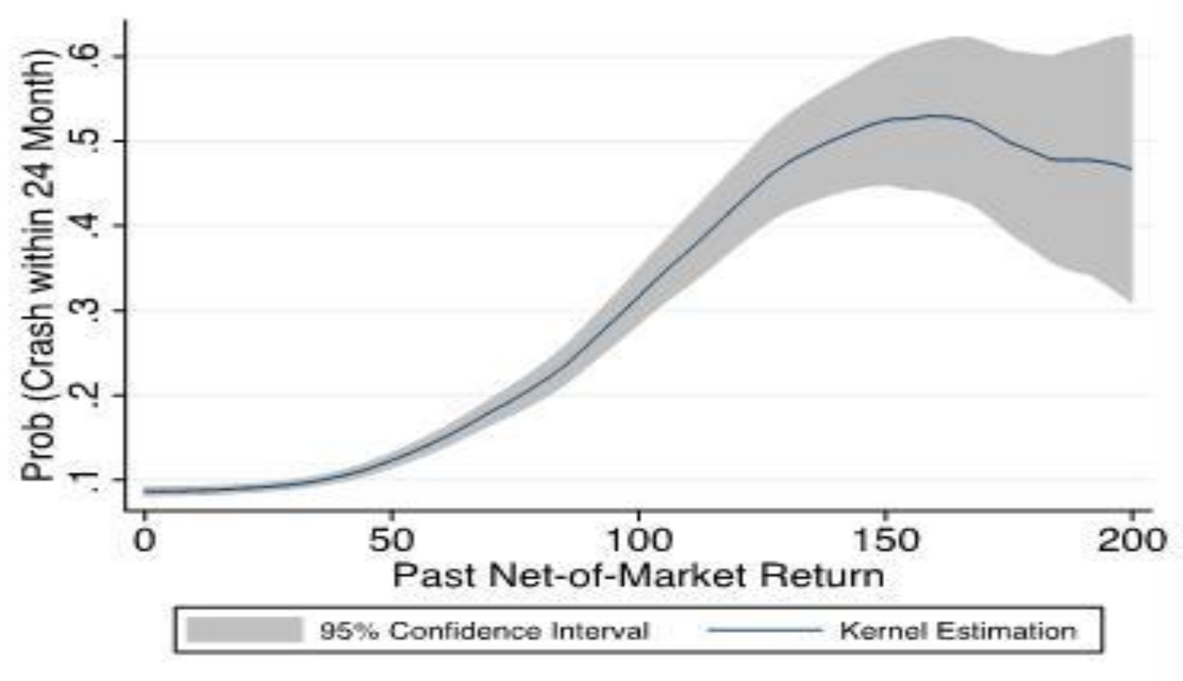


Finding 2:
Price Run-ups are Associated with high likelihood of crashes

LIKELIHOOD OF A CRASH

- We define a crash as a 40% drawdown
  - Experienced from moment of run-up, or from any high experienced in the 24 months thereafter
  - This means you an have a crash even if returns from the moment of run-up are modest
- Under this definition, about half of the price run-ups we look at crash!
  - Comparison: Unconditional probability of an industry crash is about 14%

Kernel density of crash likelihood as a function of past net of market returns



Distribution of Post-Run-up returns

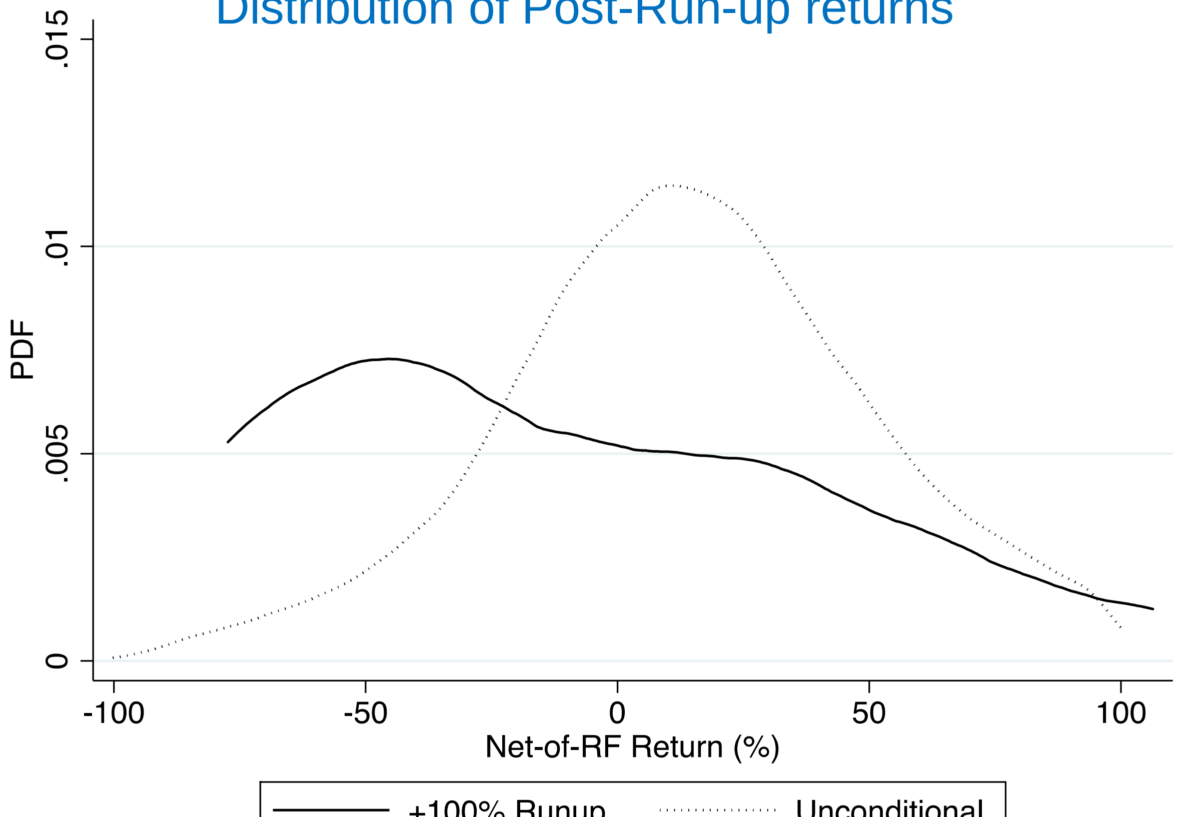


Table 3: Run-ups and Crashes

	Probability of a Subsequent Crash & Drawdown				
Pickup threshold	Number of Run-ups Identified	Number of Crashes	% Crashes	Drawdown of Crashes (%)	Average Drawdown (%)
50%	168	34	20%	-53% [-28.40]	-27% [-13.03]
75%	77	28	36%	-54% [-32.87]	-34% [-11.02]
100%	40	21	53%	-60% [-31.08]	-41% [-8.27]
125%	21	16	76%	-60% [-17.64]	-51% [-9.91]
150%	15	12	80%	-62% [-17.39]	-54% [-10.48]

80% of these price run-ups ultimately crash!

Finding 2*: with very high price run-ups, our earlier conclusions about average returns must be modified

Pick-up Threshold	Subsequent Average Returns					
	Raw Return		Net of Risk-Free Returns		Net of Market Returns	
	12-month Raw Return (%)	24-month Raw Return (%)	12-month Net of Risk-Free Return (%)	24-month Net of Risk-Free Return (%)	12-month Net of Market Return (%)	24-month Net of Market Return (%)
Panel A: US Industries 1926-2012						
50%	12%	21%	7%	11%	2%	3%
	[3.07]	[3.61]	[1.79]	[1.89]	[0.83]	[0.63]
75%	10%	11%	5%	0%	3%	1%
	[2.14]	[1.51]	[1.10]	[0.04]	[0.95]	[0.32]
100%	7%	0%	3%	-10%	5%	0%
	[0.95]	[-0.04]	[0.53]	[-0.89]	[0.90]	[-0.03]
125%	-5%	-17%	-11%	-30%	-6%	-14%
	[-0.62]	[-0.98]	[-1.32]	[-1.72]	[-1.02]	[-1.04]
150%	-10%	-13%	-17%	-28%	-9%	-10%
	[-1.22]	[-0.52]	[-2.23]	[-1.22]	[-1.45]	[-0.57]

Finding 3:
Conditional on a price run-up, Crashes and non-crashes differ in their characteristics

CHARACTERISTICS

- We measure characteristics of firms involved in the price run-up
- We are not trying to reinvent the wheel here or to come up with new characteristics
  - What's new is that we are conditioning on a large price run-up
  - Data mining is a huge concern
- Data issues
  - We are constrained in looking at data that is available over the full sample
  - Because we are comparing episodes over a 90 year period, we must be careful to construct our variables in a way that preserves comparability across episodes
  - For example, volume during the 1920s is not comparable to volume in the 1990s or 2000s.
  - For now, we measure turnover and volatility as percentile ranks, but we are open to suggestions

Characteristics

- **Volatility of returns** (level and 12-month changes)
  - Value-weighted percentile rank in the cross-section of firms
- **Turnover** (level and 12-month changes)
  - Value-weighted percentile rank in the cross-section of firms
- **Firm Age:**
  - Number of years since the firm first appeared on Compustat or on CRSP, whichever came first. Computed as a percentile rank for each stock in CRSP, then VW
- **Age tilt:**
  - Equal weighted return minus Age weighted return
  - Higher when industry return driven by the younger firms
- **Issuance:**
  - % of firms that issued stock during run-up
  - Issuance is 5% or more increase in split-adjusted shares outstanding
- **Book-to-market ratio**
  - VW across firms in the industry
  - We use Ken French's book equity data in the early years

CHARACTERISTICS

- **Cyclically Adjusted P/E Ratio:**
  - Market level
- **Sales Growth:**
  - Use all firms with Sales data in year t and t-1
  - Measure Sales growth as a percentile rank (1=highest gr; 0=lowest gr)
- **Acceleration:**
  - Convexity of the Price Path
  - $R_{t\text{-}24,t} - R_{t\text{-}24,t\text{-}12}$

Example: Volatility

- Price volatility increases among the episodes that crash…

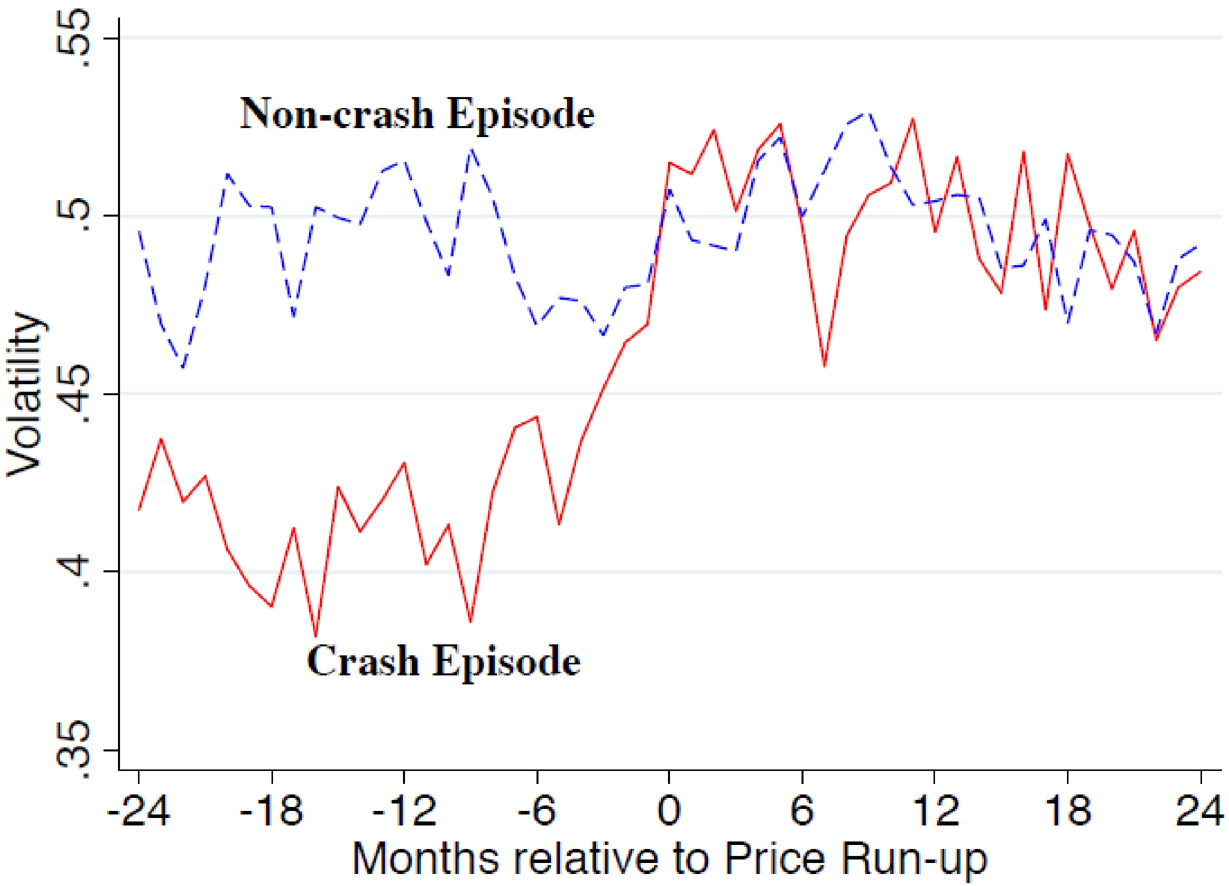


TABLE 4 (US)

	All industry-months		Run-ups		Run-ups with Crash		Run-ups with no Crash		Crash minus no Crash	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Difference**	**[*t*]**
Past 2-year Return	0.272	(0.42)	1.574	(0.33)	1.722	(0.34)	1.411	(0.22)	0.311	[3.14]
Excess Past 2-year Return	0.023	(0.32)	1.123	(0.15)	1.138	(0.17)	1.108	(0.13)	0.030	[0.64]
Turnover and Volatility:										
Volatility (VW)	0.328	(0.14)	0.498	(0.12)	0.508	(0.12)	0.487	(0.12)	0.021	[0.46]
Volatility (VW)- 1yr- Δ	-0.002	(0.10)	0.039	(0.14)	0.093	(0.16)	-0.028	(0.07)	0.113	[2.61]
Turnover (VW)	0.545	(0.19)	0.684	(0.16)	0.667	(0.17)	0.703	(0.14)	-0.036	[-0.67]
Turnover (VW)- 1yr- Δ	0.002	(0.09)	0.032	(0.10)	0.029	(0.10)	0.034	(0.10)	-0.005	[-0.15]
Age:										
Firm Age (VW)	0.740	(0.17)	0.652	(0.21)	0.724	(0.21)	0.574	(0.17)	0.150	[2.30]
Age tilt	-0.002	(0.06)	0.017	(0.12)	0.053	(0.14)	-0.022	(0.08)	0.075	[2.46]
Issuance:										
% Issuers	0.245	(0.18)	0.285	(0.17)	0.343	(0.18)	0.221	(0.14)	0.122	[2.17]
Fundamentals vs. Price:										
Book to Market (VW)	0.603	(0.65)	0.367	(0.21)	0.291	(0.19)	0.439	(0.20)	-0.148	[-1.75]
Sales Growth	0.197	(0.41)	0.257	(0.15)	0.289	(0.18)	0.229	(0.12)	0.061	[1.04]
CAPE	18.272	(7.56)	22.438	(9.34)	25.454	(11.32)	19.104	(4.90)	6.350	[1.87]
Acceleration:										
Acceleration	N/A	N/A	1.074	(0.34)	1.228	(0.26)	0.905	(0.33)	0.323	[2.99]
Joint F-stat										[3.62]
p-value (Prob>F)										0.000

TABLE 4 (INTERNATIONAL)

	Crash minus no Crash	
	Differenc	**[*t*]**
Past 2-year Return	0.532	[2.98]
Excess Past 2-year Return	0.282	[2.80]
Turnover and Volatility:		
Volatility (VW)	0.154	[5.50]
Volatility (VW)- 1yr- Δ	0.060	[1.77]
Turnover (VW)	0.015	[0.44]
Turnover (VW)- 1yr- Δ	0.021	[1.03]
Age:		
Firm Age (VW)	-0.087	[-2.25]
Age tilt	0.848	[2.25]
Issuance:		
% Issuer	0.147	[1.57]
Fundamentals vs. Price:		
Book to Market (VW)	-0.174	[-4.02]
Sales Growth	0.032	[1.10]
CAPE	10.882	[4.63]
Acceleration:		
Acceleration	0.806	[5.18]
Joint F-stat		[5.74]
p-value (Prob>F)		0.000

Joint test of significance accounting for correlation between hypotheses

Predicting Returns

- In conjunction with the price increase, do characteristics of the run-up forecast future returns?

$$R_{it\rightarrow t+24} = a + b \cdot Char_{it} + u_i$$

Dependent Variables	24mo Raw Return			24mo Net of Risk-Free Return		
	b	[*t*]	R-square	*b*	[*t*]	R-square
Volatility (VW)	0.012	[0.02]	0.000	-0.140	[-0.18]	0.001
Volatility (VW)- 1yr-Δ	-1.288	[-3.67]	0.106	-1.346	[-3.87]	0.120
Turnover (VW)	0.764	[1.12]	0.049	0.777	[1.20]	0.052
Turnover (VW)- 1yr-Δ	0.824	[0.64]	0.022	0.743	[0.62]	0.019
Firm Age (VW)	-0.758	[-1.37]	0.084	-0.748	[-1.43]	0.084
Age tilt	-1.651	[-2.26]	0.129	-1.765	[-2.70]	0.152
% Issuers	-1.058	[-2.42]	0.110	-0.994	[-2.37]	0.101
Book to Market (VW)	1.151	[2.37]	0.165	1.017	[1.90]	0.131
Sales Growth	0.642	[0.83]	0.027	0.429	[0.56]	0.012
CAPE	-0.025	[-2.54]	0.192	-0.022	[-2.19]	0.156
Acceleration	-0.434	[-1.71]	0.074	-0.463	[-1.85]	0.087
Joint F-stat		[3.43]			[4.00]	
p-value (Prob>F)		0.006			0.002	

TABLE 6 (INTERNATIONAL)

Dependent Variables	24mo Raw Return			24mo Net of Risk-Free Return		
	b	[*t*]	R-square	*b*	[*t*]	R-square
Volatility (VW)	-1.677	[-5.36]	0.146	-1.722	[-5.43]	0.152
Volatility (VW)- 1yr-Δ	-0.646	[-1.39]	0.025	-0.641	[-1.34]	0.024
Turnover (VW)	-0.651	[-1.58]	0.023	-0.698	[-1.67]	0.026
Turnover (VW)- 1yr-Δ	0.113	[0.16]	0.000	0.080	[0.11]	0.000
Firm Age (VW)	0.994	[2.47]	0.080	1.026	[2.50]	0.084
Age tilt	-0.055	[-1.72]	0.024	-0.059	[-1.84]	0.028
% Issuers	-0.261	[-2.81]	0.035	-0.261	[-2.76]	0.035
Book to Market (VW)	1.176	[3.071	0.163	1.220	[3.16]	0.173
Sales Growth	0.321	[0.71]	0.005	0.307	[0.67]	0.004
CAPE	-0.026	[-4.92]	0.206	-0.027	[-5.04]	0.219
Acceleration	-0.201	[-4.65]	0.068	-0.210	[-4.79]	0.073
Joint F-stat		[6.17]			[6.75]	
p-value (Prob>F)		0.000			0.000	

Assessing Statistical Significance

- We present results based on many different bubble features
- How should we interpret the statistical significance of the results?
- Two main issues
  - **What is the joint significance of the variables we examine?**
    - We implement a SUR-type test that incorporates the fact that characteristics are correlated across bubble episodes
    - Test that net-of-benchmark returns from each strategy are zero
  - **"False Discovery" problem, aka "Data Mining"**
    - Because we look at several characteristics, even at a strict Type 1 error threshold (say 5% or 10%), it is possible that one or more of them arise because of data mining
    - This is a well understood problem in statistics, we implement the algorithm to determine *how many* are likely significant
    - We apply Benjamini and Hochberg (1995) algorithm at 10% threshold
      - At 10% threshold, this means maximal percent of hypotheses that are false discoveries
    - This is a modification of the well-known Bonferroni (1936) correction

False discovery Tests

- False discovery rate formula in Benjamini and Hochberg (1995) to compute the probability of false discovery.
- We rank all 13 variables by their p-value and experiment the maximal false discovery rate below 10%
- 5 of the variables pass at the 10% level, compared to 7 that would pass individually

Dependent Variables	24mo Raw Return			24mo Net of Risk-Free Return		
	[*t*]	*p*-value	10% Significance	[*t*]	*p*-value	10% Significance
Volatility (VW)	[0.02]	0.984	FALSE	[-0.18]	0.858	FALSE
Volatility (VW)- 1yr-Δ	**[-3.67]**	**0.001**	**TRUE**	**[-3.87]**	**0.000**	**TRUE**
Turnover (VW)	[1.12]	0.270	FALSE	[1.20]	0.237	FALSE
Turnover (VW)- 1yr-Δ	[0.64]	0.526	FALSE	[0.62]	0.539	FALSE
Firm Age (VW)	[-1.37]	0.179	FALSE	[-1.43]	0.161	FALSE
Age tilt	[-2.26]	0.029	TRUE	[-2.70]	0.010	TRUE
% Issuers	[-2.42]	0.020	TRUE	[-2.37]	0.023	TRUE
Book to Market (VW)	[2.37]	0.023	TRUE	[1.90]	0.065	FALSE
Sales Growth	[0.83]	0.412	FALSE	[0.56]	0.500	FALSE
CAPE	[-2.54]	0.015	TRUE	[-2.19]	0.035	TRUE
Acceleration	[-1.71]	0.095	FALSE	[-1.85]	0.072	FALSE

From Predictability to Trading Strategy

- The ability to forecast of returns implies an ex post trading strategy
- In all strategies, an investor chooses to either hold the industry or to exit and hold another asset, alternatively the broader market or the risk-free rate.
- Benchmark Portfolio = Hold all industry in all periods.
- The “sell” signal for each strategy is to exit the industry if the feature is greater than the corresponding mean of among crashed price run-ups in Table 4. Never buy back the industry after selling.
- Note – some lookback bias here
- In principle, we could use multiple characteristics to develop more complex trading strategies, but we do not do this because of concerns about data mining that we have tried to avoid

LESSONS FROM FORMING TRADING STRATEGIES

- At a horizon of one-year, nearly impossible to generate outperformance
  - Even if you call the bubble, miss the peak by 5 months and over 30%
- At a two-year horizon, conditioning on price Δ and one of:
  - volatility,
  - issuance,
  - and age,

  generates outperformance
- Turnover of little use in calling a bubble, even though turnover elevated during price run-ups
- Outperformance tends to be larger if we switch into R_f rather than R_m
  - Price run-ups tend to occur during broader market rallies
- Tradeoff between false positives and false negatives: setting higher thresholds tends to reduce false positives but at the expense of more false negatives

CONCLUSIONS

- Fama has set a bar for identifying bubbles
  - We believe our evidence clears this preliminary bar, using price run-up episodes that appear to be “ex ante bubbles”
- But there are ways to raise this bar further
  - Will the future be like the past?
  - Arbitrage profits vs. predictability
  - Can the results be reconciled with the logic of conventional asset pricing?

Behavioral Finance and Financial Stability Website at Harvard