Does Accounting Information Identify Bubbles for Fama? Evidence from Accruals

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Draft: September 2023

ABSTRACT

Economists have long observed that stock price bubbles are associated with corporate overinvestment. We respond to Eugene F. Fama's challenge regarding the identification of bubbles (i.e. large price run-ups followed by crashes) by examining industry-level investments in net operating asset (NOA) accruals and stock returns for 49 countries around the world. Consistent with overinvestment in operating assets being key to bubble formation, we document five findings: (1) NOA accruals positively forecast the eventual crash of an industry price run-up; (2) NOA accruals negatively forecast stock returns following a run-up; (3) NOA accruals are positively associated with investor sentiment; (4) higher NOA accruals forecast more disappointing earnings relative to analysts' expectations for run-up industries; and (5) NOA accruals are sharply stronger predictors of crashes, returns and analyst forecast errors following run-ups compared to other periods. Our results provide the first evidence that accounting information can identify bubbles in Fama's sense.

*Corresponding author. We thank Ed deHaan (Editor), an anonymous referee, Ahmed Abdalla, Jung-Ho Choi, Michael Iselin, Yongtae Kim, Charles Lee, Christopher Jones, Jenny Zha Giedt, Angela Gore, Wenwei Lin, Scott Richardson, Yihan Song, Cameron Truong (discussant), Johnny Yeo, Paul Zarowin and seminar participants at the 2022 American Accounting Association Annual Meeting, George Washington University, University of Minnesota, Monash University, Rutgers University, Southern Methodist University, UT Arlington, University of Illinois Chicago and Egyptian Online Seminars in Accounting and Economics for helpful comments and feedback. We thank Malcolm Baker, Jeff Wurgler, and Yu Yuan for generously sharing their international investor sentiment indices.

Eugene F. Fama: The word "bubble" drives me nuts, frankly, because I don't think there's anything in the statistical evidence that says anybody can reliably predict when prices go down…
NPR: What would prove it to you that there were bubbles?
Eugene F. Fama: Empirical evidence.
NPR: Such as?
Eugene F. Fama: Well, that you could show me that you can predict when these things turn in some reliable way.
- What's A Bubble? (Nobel Edition), Planet Money, National Public Radio, November 1 2013

1. Introduction

Does accounting information identify stock price bubbles? The literature is largely silent on this important question despite extensive research on bubbles as well as the role of accounting information in capital markets (see reviews by Brunnermeier and Oehmke 2013 and Richardson, Tuna and Wysocki 2009, respectively). In fact, economists are divided on whether bubbles even exist. In his 2014 Nobel Prize lecture, Eugene F. Fama posits that bubbles may not exist, where a bubble is defined as an "irrational strong price increase that implies a predictable strong decline". The crux of his argument is that portfolios or stocks that have experienced significant appreciation do not on average experience unusually low returns in the future (Fama 2014).

Recently, Greenwood, Shleifer and You (2019; hereafter 'GSY') document evidence supporting the existence of bubbles by analyzing industry-level returns around the world. They find that industry crashes and returns following significant price run-ups are predictable using characteristics suggested by historical accounts of bubbles such as volatility, turnover and price acceleration. While they take an important first step in identifying bubbles, accounting information plays a limited role in their analysis.[1]

We build on GSY by investigating whether bubbles can be identified using bottom-up information about corporate investment from firms' financial statements. Economists have long

[1] GSY consider industry sales growth as an accounting variable but find that it has no predictive ability.

observed that managers overinvest during bubble periods, when stocks are overpriced, sentiment is exuberant, earnings expectations are inflated, and financing easy to obtain (e.g. Kindleberger 1978, Shiller 2000, Akerlof and Shiller 2010, Brunnermeier and Oehmke 2013). In other words, bubbles are not only associated with significant mispricing in financial markets but also distortions in real allocations. Moreover, such periods are followed by implosions in asset prices and disappointing corporate fundamentals as the consequences of the inefficient investment boom play out. We measure investment using changes in net operating asset (NOA) accruals, since prior work suggests that high levels of these accruals signal overinvestment and have negative implications for future performance (e.g. Hirshleifer et al 2004; Dechow et al 2008; Arif and Lee 2014). However, this prior work does not examine whether accruals identify bubbles. We fill this gap and also examine the underlying mechanism.

As Larson et al (2018) highlight, accruals reflect investment because investments generate future economic benefits and are typically recorded as assets. As firms change the scale of their operations, the amount of investment needed to support these operations also changes. To the extent that such investments are recorded as assets on the balance sheet, changes in the scale of operations generate accruals.[2] They also highlight that without a compelling reason to focus on working capital accruals alone, future researchers should include noncurrent operating accruals when measuring accruals since they are more economically significant than working capital accruals. Accordingly, our *ΔNOA* measure captures net investment in both working capital accruals and long-term operating accruals.

[2] Prior work adopting an investment perspective of accruals includes Fairfield et al (2003), Hirshleifer et al (2004), Zhang (2007), Dechow et al (2008), Bushman et al (2011), Momente et al (2015) and Arif et al (2016).

We focus our analysis on the industry level, in line with GSY as well as historical evidence that bubbles are often industry phenomenon. We use data from a large sample of countries to identify episodes in which industry-level stock prices increased over 100% in terms of both raw and net of market returns over the prior two years, consistent with GSY. To avoid picking up recoveries from periods of abnormally poor performance we also require raw returns of at least 50% over the past five years. Since the profitability of anomalies has decayed over time (e.g., Green et al 2011; McLean and Pontiff 2016) and because accounting data are only available starting in the early 1990's for non-US countries, we examine stock price run-ups that fall between 1992 and 2020.[3] This results in 18 US run-ups and 222 non-US run-ups, which we combine to create a single global sample of 240 industry run-ups across 49 countries. We study the characteristics of these industry run-ups and their future performance.

In line with Fama (2014) and GSY, we find that a sharp increase in stock prices at the industry level does not unconditionally predict low returns going forward. In other words, many industries that have experienced extreme price run-ups in the past continue to rise in the future. However, it is premature to conclude that bubbles do not exist solely because price run-ups are not on average followed by abnormally low stock returns. This is because the set of information available to investors is far broader than just past prices, and financial statement information may be particularly valuable. Accordingly, we conduct a series of tests to examine whether industry-level accruals forecast stock prices following industry run-ups using the four GSY performance measures: industry-level price crashes (defined as a 40% drawdown from any point in the two years after the initial price run-up), raw returns, returns net of the risk-free rate, and market-adjusted returns, all value-weighted at the industry level.

[3] Because we require five years of past returns and two years of subsequent returns, we use returns data dating back to 1987 and extending through 2022.

We find that industry-level NOA accruals forecast all four measures of stock price performance following run-ups. More specifically, accruals are significantly higher for price run-ups that subsequently crash compared to those that do not. In terms of economic magnitude, a one standard deviation increase in accruals is associated with a 12.4% greater probability of a stock price crash over the following two years, all else equal. Further, industry NOA accruals are a robust negative predictor of industry stock returns. Run-ups in the lowest decile of industry-level accruals experience positive industry-level raw returns of 16.0% on average over the following two years, while run-ups in the highest decile of industry-level accruals experience returns of -3.8% on average, and the difference of 19.8% is statistically significant.

We conduct a suite of robustness tests. First, we examine whether the industry-level predictive relation between accruals and future performance remains statistically significant after controlling for a battery of industry characteristics hypothesized by GSY to be associated with post-run-up returns, including volatility, changes in volatility, turnover, changes in turnover, age, age tilt, issuance, book to market, sales growth, price acceleration, CAPE ratio, as well as past returns. We find that even after including these potential bubble characteristics as control variables, NOA accruals significantly predict industry stock price crashes and stock returns.

Second, we examine the robustness of our results using the maximal false discovery rate procedure from Benjamini and Hochberg (1995). This procedure takes into account the fact that some characteristics may emerge as return predictors by chance because we consider many at the same time. As such, it statistically controls for the proportion of rejections expected to be false discoveries (i.e., Type 1 errors). We apply this approach to our tests examining the predictability of all four measures of stock price performance. Out of the thirteen industry characteristics we consider, NOA accruals are the only characteristic to survive all the false discovery tests using a false discovery rate of 5%. Third, we examine out-of-sample return predictability (e.g. Campbell and Thompson 2008) and find that accruals deliver positive out-of-sample R^2 when predicting each of the measures of post-run-up returns we examine. As such, the evidence suggests that accruals identify bubbles out of sample.

We next turn to validate the economic mechanism for why accruals identify bubbles. Under the overinvestment explanation, accruals identify bubbles because managers are more likely to overinvest when sentiment is buoyant. Consistent with this, we find a positive contemporaneous correlation between accruals and two investor sentiment proxies: the Baker, Wurgler and Yuan (2012) country-level sentiment index as well as the Dichev (2007) measure of investors' net equity market fund flows computed at the country-industry level.[4] A second prediction of the overinvestment channel is that the inefficiently high levels of investment are subsequently followed by more disappointing earnings realizations. Consistent with this, we find that higher accruals portend greater earnings shortfalls relative to analysts' EPS expectations. Taken together, our results are in line with historical bubble accounts in which managers overinvest during stock price bubbles, when capital market participants are exuberant, earnings expectations are inflated and financing easy to obtain (e.g. Kindleberger 1978, Shiller 2000, Akerlof and Shiller 2010).[5]

While the preceding tests focus exclusively on the 240 industry price run-ups in our global sample, we also zoom out to examine whether the predictive ability of accruals following price run-ups is significantly different from the predictive ability of accruals around non-run-ups. For these tests we analyze the entire sample of 98,187 industry-months across all 49 countries in which we identified at least one industry-level price run-up during our sample period. We find that the predictive ability of accruals for industry crashes, returns and forecast errors more than quintuples

[4] If the role of sentiment in shaping investment is elevated during stock price bubbles, then we expect the accruals-sentiment relation to be sharply higher during run-ups compared to other times. Consistent with this, we find that ΔNOA is more strongly associated with investor sentiment during run-up periods compared to non-run-up periods.
[5] As discussed in Section 4.6, we also investigated whether M&A or subcomponents of ΔNOA drive the ability of ΔNOA to identify bubbles but do not find conclusive evidence of this.

following run-ups compared to the baseline. This indicates that our results are not the product of accruals on average generically predicting future performance. Rather, our findings indicate that the misallocation of capital due to bubble-driven overinvestment has a distinctly negative impact on future asset prices and corporate fundamentals.

Finally, consistent with the conjecture that industry-level bubbles can have spillover effects on the aggregate stock market, we find that industry-level NOA accruals associated with price run-ups negatively forecast aggregate country-level returns, but industry-level accruals that are not associated with price run-ups do not forecast aggregate country-level returns. This indicates that industry bubbles have important aggregate-level effects, with the bursting of a bubble leading to a downturn in country-level stock prices.

Rational asset pricing is unlikely to drive our results for several reasons. First, it is hard for a risk-based story to explain why higher accruals forecast both higher crash risk and also lower future stock returns, on average. As Baron and Xiong (2017) observe, if shareholders anticipate the increased likelihood of stock price crash risk, they could demand higher expected returns by immediately lowering share prices and thus earn higher future average returns. Despite the increased crash risk, we find that higher accruals are followed by significantly lower, not higher, average future returns. Second, if time-varying discount rates or limits to arbitrage is the primary channel through which accruals forecast returns, accruals should not predict future cash flow "shocks". However, we find that higher accruals portend greater earnings disappointments in terms of earnings shortfalls relative to analyst forecasts. Finally, illiquidity effects are unlikely to explain the documented predictability of country- and industry-level market returns given the high liquidity and low adverse selection costs associated with trading country-level stock market indices and baskets of stocks using instruments such as index futures or industry ETFs (e.g. Subrahmanyam 1991; Liebi 2020). Nonetheless, we follow GSY in stressing that our paper focuses on whether accruals can identify bubbles, not how to optimally implement a trading strategy which takes advantage of predictability.

This paper makes several contributions. As Brunnermeier and Oehmke (2013) note, bubbles are of interest to economists not only because they significantly impact financial markets but also because they affect real allocations and investment in the economy. As a result, it is important to understand the circumstances under which bubbles arise. While GSY take an important first step towards identifying bubbles, we provide the first empirical evidence that corporate investment identifies bubbles. Consistent with an overinvestment channel, we find that corporate investment rises when investor sentiment around run-ups is more exuberant, yet such periods tend to be followed by price implosions and more disappointing corporate fundamentals.

We are also the first to show that accounting information identifies bubbles. In particular, we extend the literature on accruals. Our finding that tracking *ΔNOA* yields powerful insights into bubble identification not only supports Larson et al's (2018) recommendation that accruals researchers include noncurrent operating assets in their measurement of accruals, but also underscores the recommendations of MBA financial statement analysis textbooks, which place special emphasis on NOA and advocate reformulating the financial statements to isolate NOA as a key step in the process of valuation (e.g. Penman 2010; Wahlen et al 2014).[6]

[6] We depart in several ways from prior research on aggregate accruals such as Arif and Lee (2014) and others which focus on forecasting aggregate (i.e. market-wide) returns using aggregate-level information. First, our objective is to examine whether NOA accruals identify bubbles. Specifically, we examine the predictability of stock prices and analyst forecast errors conditional on a rapid increase in stock prices. By contrast, Arif and Lee (2014) do not examine bubble identification and instead focus on the unconditional relation between NOA accruals and future returns. Second, we focus on predicting industry returns using industry accruals, while Arif and Lee (2014) focus on predicting aggregate returns using aggregate accruals. Third, we investigate the predictability of stock price crashes, while Arif and Lee (2014) do not.

2. Data and Sample Selection

We start our sample selection by gathering all firms with complete volume and returns data from the CRSP (for US firms) and Compustat Global Daily (for non-US firms) databases between 1987 and 2022. As our unit of analysis is an industry, we follow GSY and match US firms to sectors based on the Fama and French 49 industry classification scheme and international firms to sectors based on the Global Industry Classification Standard (GICS) code. The GICS sector is a broader industry definition (11 GICS sectors versus 49 Fama-French industries) which helps ensure that there is a meaningful number of firms in countries with smaller stock markets.

Returns are measured using US dollars and are value weighted within sectors at the monthly level. We merge the US sample with accounting data from Compustat North America. We primarily obtain accounting data for non-US firms from Compustat Global. To ensure maximal data coverage, if Compustat Global does not contain accounting information for the firm we use accounting data from Worldscope. We merge accounting data from the latest fiscal year-end prior to the monthly industry observation and allow for a four month reporting lag. We also require each country-industry-month observation to have at least ten firms with non-missing accruals data so that our industry-level observations are not driven by a small handful of firms.

We further require that each country-industry-month observation contain non-missing data for each of GSY's characteristics (defined in the following section). Each of the characteristics are computed using information from the databases mentioned above. The only exception is the country CAPE ratio, which comes primarily from Barclays Indices.[7] When the CAPE ratio is unavailable from Barclays, we directly compute it using data from Compustat Global.

[7] We download the CAPE ratio from https://indices.barclays/IM/21/en/indices/static/historic-cape.app

Episodes of price run-ups are identified following the methodology in GSY. All country-industry-month observations that have experienced value-weighted returns of 100% or more in the past two years, in both raw and net of market terms, as well as 50% or more raw returns over the past five years, compose our run-up sample. As this could lead to the identification of multiple overlapping run-ups, we choose only the first instance for which a run-up is observed and do not allow for a new run-up to be identified until two years later. Our requirement of large positive returns over a two-year horizon (100%) and a five-year horizon (50%) helps avoid falsely identifying recoveries from periods of poor performance rather than a price run-up.

We identify run-ups occurring between 1992 and 2020 because research indicates that the profitability of anomalies has decayed over time and because accounting data is available only starting in the early 1990's for non-US countries. Because we require each country-industry-month observation to have five years of prior returns and two years of subsequent returns, we use data on stock prices starting in 1987 and ending in 2022. After removing all country-industry-month observations that lack necessary data or have fewer than ten firms with non-missing accruals data in the industry, we obtain 18 US run-ups and 222 non-US run-ups, which we combine to create a single global sample of 240 run-ups from 1992-2020 across 49 countries.[8] By contrast, GSY use data on run-ups from 1926-2012 (1987-2012) to identify 40 (107) US (non-US) runups across 32 countries, and analyze the US and non-US samples separately.

The first US run-up in our sample was identified in December 1992 (Toys and Textiles), and the last US run-up was in November 2020 (Computer Hardware). The first international run-up was in January 1997 (Netherlands – IT), while the last international run-ups were identified in December 2020 (India – Utilities and Russia – Communication Services). We perform our primary

[8] The requirement for accounting data necessary to compute accruals, our examination of industry price run-ups from 1992-2020, and our use of both Compustat Global and Worldscope for accounting data are the main reasons why our set of run-ups do not exactly overlap with the set of run-ups in GSY.

analyses on a single run-up sample that combines US and non-US run-ups. Because we run multiple regression tests which include up to 13 independent variables, statistical tests involving just the US sample of 18 run-up observations would have weak statistical power. To mitigate this issue, we combine the US sample with the non-US sample to yield a single global sample.

The identification of crashes mirrors the methodology in GSY. We define a crash as a 40% or more drawdown in absolute terms beginning at any point after identification of the run-up in the subsequent two years. Of the 240 total run-ups, we identify 114 crashes (of which 10 crashes occurred in the US out of 18 total US run-ups).[9]

For our full sample analyses, we start with all country-industry-month observations in the 49 countries for which at least one run-up was identified during our sample period. After removing observations that have missing industry-month level variables or fewer than ten firms with non-missing NOA accruals, we are left with 98,187 total country-industry-month observations.

In our tests involving industry-level analyst optimism, we examine industry-level analyst forecast errors. We obtain monthly consensus analyst EPS forecasts for the upcoming fiscal year-end for US and international firms from I/B/E/S. Because of a lack of analyst coverage in certain country-industries, the sample size for these tests is slightly reduced. We are left with 228 run-ups and 95,308 country-industry-month observations with non-missing analyst forecast error data for our analyst optimism analyses. Furthermore, in our tests involving investor sentiment, we obtain our first sentiment proxy, the country-level aggregate sentiment index, from Baker et al (2012). We use data from CRSP and Compustat Global Daily to compute our second sentiment proxy, i.e. country-industry-month net capital inflows.

[9] Although several price run-up episodes and crashes, such as the dotcom bubble, are common across countries, the timing of the price booms and busts, as well as the specific industries affected, vary substantially. We obtain similar results after excluding the dotcom observations, suggesting that our results are not driven by the dotcom bubble.

3. Research Design

Our primary regression tests take the form:

$$Performance_{it\rightarrow t+24} = \alpha + \gamma_1 \Delta NOA_{it} + \sum \gamma_n \, Controls_{in} + \varepsilon$$

Performance is either a crash indicator (*CRASH*), which equals one if there is a 40% or more drawdown in raw industry returns beginning at any point after the identification of the industry price run-up over the subsequent 24 months, and zero otherwise; or a measure of industry stock returns over the next 24 months following identification of the price run-up; or industry-level consensus analyst EPS forecast error for the upcoming fiscal year-end (*IndAFError*), our proxy for analyst optimism. We examine three different measures of returns: raw industry value-weighted returns (*IndRet24*), industry value-weighted returns net of the risk-free rate (*IndRetRF24*), and industry value-weighted returns net of market value-weighted returns (*IndRetMAR24*). We run linear probability model regressions for the crash prediction models and OLS regressions for the return and analyst forecast error prediction models.[10]

We go beyond univariate regressions of future crashes and returns on each industry characteristic one at a time by also presenting results of multiple regression tests of future performance on accruals after controlling for all of the potential bubble characteristics. We aim to examine if industry accruals can predict future performance following run-ups above and beyond characteristics suggested by prior literature to be associated with bubbles.

There are several reasons for choosing to examine industry-level run-ups in the context of bubbles rather than individual stocks or entire stock markets. Many historical accounts of bubbles feature those that occur at the industry level (Kindleberger 1978; White 1990; Baker and Wurgler

[10] Our crash prediction results are robust to alternatively using a probit model for estimation. Inferences are also unchanged after controlling for country, industry, and year fixed effects. We do not include them in our prediction models to alleviate look-ahead bias.

2006). Further, while many run-ups occur during periods of favorable market performance, analyzing industries offers greater statistical power. For example, very rarely do market-level indices experience price run-ups of 100% or more during a two-year period. Studying industries also allows for comparisons of potential bubble industries with others trading at the same time, and many of the characteristics we study (including accruals) vary substantially across industries and over time. Hence, we can examine if accruals are especially likely to predict returns and crashes around price run-ups relative to other periods. Finally, short sale constraints and illiquidity issues tend to be alleviated at higher levels of aggregation such as at the industry or market level compared to the firm level.

Our main explanatory variable is net operating asset accruals, defined the change in net operating assets (*ΔNOA*). We compute this measure by first calculating firm-level accruals as the change in net operating assets scaled by average total assets.[11] We then percentile rank the firm-level accruals for each month in the full cross section of firms and calculate the value-weighted accruals percentile rank in each country-industry-month.

We include eleven control variables from GSY's set of asset pricing characteristics suggested by prior behavioral finance studies and accounts of bubbles. They include volatility (*Volatility*), the change in volatility (*Volatility-1yrChange*), turnover (*Turnover*), the change in turnover (*Turnover-1yrChange*), average firm age in an industry (*IndustryAge*), the difference between equal-weighted and age-weighted country-industry-month return to capture whether the price run-up occurred disproportionately among younger firms in the industry (*AgeTilt*), the percentage of firms in the industry that issued equity in the past year (*PercentIssuers*), the book-

[11] Net operating assets is defined as (total assets – cash and short-term investments – total liabilities + short-term debt + long-term debt). This is "AT" - "CHE" - "LT" + "DLC"+ "DLTT" using Compustat data and "ITEM2999" - "ITEM2001" - "ITEM3101" + "ITEM3051" + "ITEM3251" using Worldscope data. This definition of net operating assets is consistent with prior studies such as Richardson et al (2005).

to-market ratio (*BooktoMarket*), one-year sales growth (*SalesGrowth*), the difference between the two-year return and the first year of that two-year period leading up to the given month to measure the convexity or momentum of the price path (*Acceleration*), and the monthly cyclically adjusted price-earnings ratio (*CAPE*). All of these variables are value-weighted to the country-industry-month level, with the exception of the CAPE ratio, which is at the country-month level. Following GSY, we percentile rank *Volatility, Turnover, IndustryAge,* and *SalesGrowth* over the full cross section of firms prior to value-weighting them. Furthermore, we include an additional control for past two-year country-industry returns (*PastReturns*). Detailed definitions and calculations for these variables are presented in Appendix A.

For our full country-industry-month sample ("full sample") tests, we run multiple regression tests taking the form:

$$Performance_{it\rightarrow t+24} = \alpha + \gamma_1 \Delta NOA_{it} + \gamma_2 Runup_{it} + \gamma_3 \Delta NOA_{it}\ x\ Runup_{it} + \sum \gamma_n\, Controls_{in} + \varepsilon$$

As in the tests involving the run-up sample, *Performance* includes a crash indicator (*Crash*) and one of three different measures of returns: raw industry value-weighted returns (*IndRet24*), industry value-weighted returns net of the risk-free rate (*IndRetRF24*), and industry value-weighted returns net of market value-weighted returns (*IndRetMAR24*). We also examine industry value-weighted analyst forecast errors (*IndAFError*) and aggregate market value-weighted returns (*MktRet24*). We run linear probability model regressions for the crash prediction models and OLS regressions for the return and analyst forecast error prediction models.

In addition, we include an indicator variable that equals one if the country-industry-month was identified as a run-up (i.e., included in our run-up sample) and zero otherwise (*Runup*). We include an interaction term between ΔNOA and *Runup* to assess whether the predictive ability of industry-level NOA accruals for subsequent crashes, returns and analyst forecast errors following price run-ups is significantly different compared to non-run-up periods. A significant coefficient on γ_3 indicates that the ability of accruals to predict future performance following run-ups varies significantly from the baseline predictive ability of accruals.

4. Results

4.1 Descriptive Statistics

Table 1 lists all the countries for which we identified at least one industry run-up during our sample period. The table also presents the number of industry price run-ups as well as the number of run-ups that resulted in crashes for each country. We identify 49 total countries and 240 total industry price run-ups. The US experienced 18 run-ups from 1992-2020, while in the non-US sample, Thailand experienced the most run-ups over the same period, with 14 total run-ups. Of the 240 total run-ups identified, 114, or 47.5%, ended up crashing within the next two years. Of the 18 US run-ups, 10, or roughly 56%, subsequently crash. China and Hong Kong experienced the most crashes in the international sample with eight crashes each, followed closely by Brazil and India with seven.

Table 2 presents descriptive statistics for our sample for all industry-months as well as those that we classify as run-ups. For each sample, in Columns 2 and 3, we show the mean and standard deviation of the characteristic. While the average past two-year industry return in any given month is around 24.2% in the full panel, the average return is over 205% in the run-up sample. Note that in order to qualify as a run-up, the industry must experience value-weighted stock returns of 100% or more in the past two years (in both raw and market-adjusted terms), and raw returns of at least 50% over the past five years. The extremely positive average stock returns found in the run-up sample is consistent with the fact that a country-industry-month is categorized as a run-up if it experiences an economically large past return, given that Fama and other economists posit that bubbles (assuming they exist) begin with a significant run-up in stock prices. We also find that the run-up sample displays somewhat higher volatility, one-year changes in volatility and turnover, greater equity issuance, sales growth, CAPE ratio, convexity of price path (acceleration), and NOA accruals relative to the average country-industry-month. Run-ups are also associated with younger firms and lower book-to-market ratios.

4.2 Forecasting Crashes

Table 3 presents the results of univariate regressions predicting the incidence of crashes using industry-level accruals and other industry characteristics. The dependent variable is a crash indicator, which equals one if there is a 40% drawdown from any point in the two years after the initial price run-up, and zero otherwise. We find that our measure of industry-level NOA accruals, *ΔNOA*, are a statistically significant predictor of crashes, with a coefficient of 0.687 and t-statistic of 4.23, implying that a one standard deviation increase in accruals, all else equal, is associated with an 12.4% greater likelihood of a crash in the next two years. In line with GSY, we find that several other industry characteristics are statistically significant predictors of crashes. Specifically, these univariate tests indicate that crashes are significantly predicted by *Volatility*, *Volatility-1yrChange*, *IndustryAge*, *AgeTilt*, *PercentIssuers*, *BooktoMarket*, *Acceleration*, and *CAPE.*

Table 4 confirms that in a multiple regression setting, *ΔNOA* continues to positively forecast crashes (t-statistic 2.27). In particular, a one standard deviation increase in accruals, all else equal, is associated with an 8.3% greater likelihood of a crash. Further, while univariate tests in both GSY as well as our tests in Table 3 suggest that changes in volatility are significantly associated with crashes, Table 4 shows that this variable is no longer significant in a multiple regression setting. However, we find that in both univariate and multiple regression tests, industry-level NOA accruals, return volatility, average firm age of the industry, age tilt, percentage of firms in the industry issuing shares, book-to-market ratio, price acceleration and the CAPE ratio are all statistically significant predictors of crashes following price run-ups.

4.3 Forecasting Stock Returns

The preceding section documents that accruals have predictive ability for subsequent price crashes following industry price run-ups. However, this does not automatically imply that accruals can help an investor time the bubble since stock price gains before or after the crash may offset the negative return associated with the crash. In this section, we directly examine whether accruals forecast returns following price run-ups. We use three measures of future returns: the 24-month raw value-weighted industry return (*IndRet24*), the 24-month excess (net of risk-free rate) return (*IndRetRF24*), and the 24-month net of market return (*IndRetMAR24*).

Table 5 presents the results of univariate forecasting regressions of future returns on accruals and the GSY characteristics. Industry-level NOA accruals are a negative and statistically significant predictor of all three measures of future industry returns. Specifically, the coefficient on ΔNOA is -0.790 (t-statistic -4.02) for forecasting 24-month raw returns, -0.788 (t-statistic -4.04) for returns net of the risk-free rate, and -0.382 (t-statistic -3.02) for market-adjusted returns. In terms of economic magnitude, these results imply, for example, that a one standard deviation increase in accruals is associated with a decline in future raw returns of about 14.2% over the following two years. We also find that *Volatility, PercentIssuers, Acceleration,* and *CAPE* are generally negative and statistically significant predictors of all three measures of returns.

4.4 Robustness

We next conduct four sets of robustness tests to examine the predictability of future performance. We begin with multiple regression. Table 6 presents the results of multiple regression return forecasting tests, where we regress the three measures of future returns on *ΔNOA* after including controls for all the GSY characteristics as well as past 24-month returns (*PastReturns*). Across all regressions, *ΔNOA* remains a statistically significant negative predictor of future returns. Specifically, the coefficient on *ΔNOA* is -0.639 (t-statistic -2.81) in our tests forecasting 24-month raw returns, -0.636 (t-statistic -2.84) for forecasting returns net of the risk-free rate, and -0.254 (t-statistic -1.67) for forecasting market-adjusted returns. In terms of economic magnitude, these results imply, for example, that a one standard deviation increase in accruals is associated with a decline in future raw returns of about 11.5% over the following two years, all else equal.

Since GSY only present the results of univariate return forecasting regressions, it is unclear whether the characteristics they identify as return predictors remain statistically significant in a multiple regression setting. For instance, our results show that while *Volatility* is significant in univariate tests, it is no longer significant in multiple regression tests. In fact, our multiple regression reveals that only one variable besides *ΔNOA* consistently predict all three measures of future returns we examine. Specifically, *PercentIssuers* (i.e., equity issuance) is a negative and statistically significant predictor of industry raw returns, returns in excess of the risk-free rate, and market-adjusted returns. Our forecasting tests also reveal consistently significant F-tests, underscoring GSY's central message that bubbles do exist since crashes and returns are predictable when considering factors other than just past returns as potential bubble characteristics.

We also find that in both univariate and multiple regression return prediction tests, past 24-month returns are not significantly associated with subsequent 24-month returns. In fact, the results presented in Tables 5 and 6 suggest that past returns are positively, albeit statistically insignificantly, associated with future raw and risk-free rate adjusted returns. This is consistent with Fama's stance that a sharp price increase in a portfolio does not, on average, predict unusually low returns going forward. On the other hand, our results suggest that investors can obtain valuable insights from analyzing financial statements when identifying bubbles, as accruals are a robust predictor of future returns following price run-ups.

Further evidence on the predictive ability of NOA accruals for identifying bubbles is presented in Figure 1. This graph presents cumulative returns for country-industry level run-ups in the highest and lowest deciles of industry-level accruals from month -24 to month +30, where month 0 is the first month during which a price run-up is identified. The dark solid line represents returns for industries in the highest decile of accruals, while the red dashed line represents returns for industries in the lowest decile of accruals. We find that during the run-up period from month -24 to month 0, the returns of high-accrual industries are somewhat more volatile, but by month 0, cumulative returns are similar to that of low-accrual industries. Following month 0, the returns of the two portfolios are not significantly different early on, but high-accrual industries eventually experience a sharp drop in returns, especially from month +7 to +16. By month +23, or two years after the run-up was identified, high-accrual industries experience statistically insignificant average returns of -3.8% (t-stat -0.68), while low-accrual industries experience no sharp drops at any point during the subsequent two years and by month +23 experience average returns of 16.0% (t-stat 2.01) relative to the run-up identification in month 0. The 19.8% difference in average returns by month +23 between the high and low accrual portfolios is statistically significant, and persists through month +30. Taken together, Figure 1 presents evidence that among industries that experience price run-ups, those in the highest decile of accruals experience much lower future returns than industries in the lowest decile of accruals, although on average it takes around seven months before high accrual industries experience a precipitous stock price drop.

Our second set of robustness tests controls for the false discovery rate using the methodology developed by Benjamini and Hochberg (1995). This methodology imposes a tolerance level for false discovery across all the characteristics and indicates how many characteristics are predictive given this tolerance level. The procedure takes into account the fact that some characteristics may emerge as return predictors by chance because we consider many in separate tests at the same time. As such, the procedure statistically controls for the proportion of rejections expected to be false discoveries (i.e., Type 1 errors).

Following this methodology, we sort all 13 characteristic variables (industry-level NOA accruals, the bubble characteristics examined in GSY, and past returns) from low to high by *p*-value from the univariate regressions and compare the *p*-value with the adjusted *p*-value threshold, defined as $\frac{(\alpha * rank)}{13}$. We proceed sequentially, beginning with the characteristic with the highest *p*-value. If the *p*-value is greater than the adjusted *p*-value, the variable is deemed insignificant. If a characteristic has a *p*-value lower than the adjusted *p*-value, the methodology deems this variable and all variables with lower *p*-values to be significant.

We apply this false discovery procedure to the crash prediction tests shown in Table 3 as well as the return prediction tests in Table 5. Table 7, Panel A shows that with a false discovery rate of 5%, *CAPE, IndustryAge*, *Volatility*, *ΔNOA, PercentIssuers, Volatility-1yrChange*, *BooktoMarket*, and *Acceleration* all pass the false discovery test. Table 7, Panel B shows that *ΔNOA, CAPE, PercentIssuers,* and *IndustryAge* significantly predict raw returns beyond the false discovery threshold. Table 7, Panel C shows that the same four variables pass the false discovery test in significantly predicting excess returns. Meanwhile, Table 7, Panel D shows that *ΔNOA* is the only variable that has a p-value below the false discovery-adjusted p-value in predicting market-adjusted returns. Collectively, the results presented in Table 7 suggest that *ΔNOA* is the only variable to survive all the false discovery tests in predicting crashes and all measures of subsequent industry-level returns, demonstrating its robustness in identifying bubbles following industry price run-ups.

Third, we examine the out-of-sample forecasting ability of NOA accruals as well as the bubble characteristics nominated by GSY. Following Campbell and Thompson (2008), we require at least 20 years of return data to obtain initial coefficient estimates. As such, the initial coefficient is based on the sample of run-ups whose returns following the run-up fall between 1992 and 2011. Using this coefficient, we calculate forecasted two-year-ahead returns for all run-ups that occurred in 2012 and update the coefficient each year thereafter. Since our last run-up is identified in 2020, we have nine years of data over which to examine out-of-sample performance.

As documented in Table 8, we find that *ΔNOA* is associated with an out-of-sample R^2 of 9.01% when predicting raw industry returns, 9.45% when predicting industry returns net of the risk-free rate and 5.98% when predicting market-adjusted industry returns. The consistently positive out-of-sample R^2 indicates that the predictive regression has lower average mean-squared prediction error than the average historical post-run-up return. Table 8 also shows that *ΔNOA* exhibits consistently high out-of-sample R^2 when compared to the bubble characteristics nominated by GSY. Specifically, we find that *ΔNOA* has the second highest out-of-sample R^2 when predicting raw industry returns and risk-free adjusted returns, and the third highest out-of-sample R^2 when predicting market-adjusted returns. We note that while data limitations allow these tests to use only nine years of out-of-sample data, the findings collectively indicate that accruals identify bubbles out of sample.

To better assess the ability of NOA accruals to predict crashes out of sample, we also compute the area under the out of sample ROC (Receiver Operating Characteristic) curve when predicting crashes over the subsequent two years using only NOA accruals. Our test uses a maximum-likelihood ROC model for predicting crashes based on data from 1992-2011 for the initial estimation. The ROC curve is presented in Figure 3. The area under the ROC curve is 0.7285, which is statistically and economically significant given that an area under the curve of over 0.7 provides acceptable discrimination in predictive models of binary variables (e.g. Hosmer and Lemeshow 2000; Kedia et al 2015).[12] Further, untabulated analyses suggest that the area under the curve for NOA accruals when predicting crashes is the second highest compared to other industry characteristics.[13] In other words, the evidence indicates that *ΔNOA* has out of sample forecasting ability not only for future returns but also the incidence of crashes following price run-ups.

Fourth, in untabulated tests we find that our results are robust to considering industries with a larger minimum number of firms. In particular, industry-level NOA accruals are a statistically significant predictor of industry-level stock price crashes and returns when requiring at least 20 firms per country-industry to identify an industry run-up. We note, however, that the number of run-ups in these tests declines to 166, compared to 240 run-ups when requiring at least 10 firms for each country-industry.

4.5 Exploring the overinvestment mechanism

Our empirical tests thus far have focused on whether accruals forecast stock price performance following run-ups, and collectively suggest that accruals identify bubbles for Fama.

[12] We thank the anonymous referee for the suggestion to include the out-of-sample ROC curve analysis.
[13] The only characteristic with an area under the curve higher than NOA accruals is industry age, which yields an area under the ROC curve of 0.7423 when predicting crashes out of sample.

In this section, we examine the economic mechanism for why accruals identify bubbles. Under an overinvestment-based explanation, accruals identify bubbles because managers are more likely to overinvest when the sentiment of capital market participants is buoyant, capital is easy to obtain and earnings expectations are inflated.

We empirically test the overinvestment explanation in two ways following the sentiment-based approach of Arif and Lee (2014). First, we examine the contemporaneous relation between accruals and investor sentiment. We draw on two proxies for investor sentiment. The first measure of investor sentiment, *Sentiment (BWY)*, is the country-year-level investor sentiment index calculated by Baker et al (2012) based on the first principal component of a variety of market-level sentiment proxies including the number of IPOs, IPO first-day returns, the valuation premium of high volatility stocks relative to low volatility stocks, and share turnover.[14] Since data for this measure is only available for six countries and ends in 2005, its coverage has limited overlap with the countries and years for which there are industry-level price run-ups in our sample. We calculate a second measure of investor sentiment based on investors' net equity fund flows, *Inflows*, by value-weighting firm-level net monthly capital inflows at the country-industry-month level based on the approach of Dichev (2007). This measure for deriving investor flows automatically adjusts for all capital contributions and distributions with no need to identify specific components. Further, it has minimal data requirements and can be calculated for all 240 run-up observations in our sample.[15]

We regress our measure of accruals, *ΔNOA*, on the investor sentiment proxies and the control variables. Results presented in Table 9, Panel A, Column 1 suggest that market-level

[14] We thank the authors of the Baker et al (2012) paper for providing us with the sentiment data used in their study.
[15] Because of the small number of observations in our sample, especially when using the Baker et al (2012) measure as our sentiment proxy, we do not include fixed effects in our specifications. However, the results presented in Column 2 are robust to including country, industry, and year fixed effects (untabulated).

investor sentiment is significantly and positively correlated with *ΔNOA* (coefficient 0.088, t-stat 2.57). Results presented in Table 9, Panel A, Column 2 suggest that *Inflows* is significantly and positively correlated with *ΔNOA* at the 1% level (coefficient 0.170, t-stat 3.80). Taken together, these results indicate that corporate managers invest more heavily in operating assets when investors are more optimistic and financing easy to obtain. In other words, our findings support the view that investor sentiment influences managers' real decisions and are inconsistent with the idea that sentiment is simply a "sideshow" for managerial investment decision making (e.g. Morck et. al. 1990).

A second prediction of the overinvestment explanation is that the inefficiently high levels of investment are subsequently followed by more disappointing realizations of corporate earnings. While GSY do not investigate whether analyst forecast errors are predicted by bubble characteristics, we believe it is important to examine this issue for at least two reasons. First, bubble episodes are characterized by overly optimistic expectations about future fundamentals among capital market participants. Given that sell-side analysts are among the most knowledgeable about a stock's fundamentals, examining their forecasts provides a window into the sentiment of a well-informed set of market participants and allows us to examine otherwise unobservable investor expectations (Hribar and McInnis 2012). If sophisticated market participants such as analysts do not anticipate the faltering fundamentals that follow periods of overinvestment, then higher accruals will portend greater earnings shortfalls relative to analyst expectations. The second reason for examining analysts' forecast errors is that if the predictive ability of accruals for future crashes and returns is not driven by mispricing but rather by rational asset pricing explanations such as time-varying expected returns, risk, illiquidity, or transaction costs (e.g., Khan 2008; Mashruwala et al 2006; Pontiff 2006; Core et al 2008), then accruals should not systematically predict analyst forecast errors.

We compute country-industry-level analyst forecast errors (*IndAFError*) by value-weighting firm-level analyst forecast errors at the country-industry-month level. Firm-level forecast error is defined as the difference between the median consensus analyst EPS forecast in a given month for the upcoming annual forecast period end and the actual EPS, scaled by the absolute value of actual EPS.[16] Table 9 Panel B presents regressions of analyst forecast error on accruals and the control variables. The number of observations in these tests declines to 228 due to limitations in IBES coverage. We find that *ΔNOA* is a positive and statistically significant predictor of forecast errors, with a coefficient of 1.756 and t-statistic of 2.11. This evidence suggests that sophisticated market participants (i.e., analysts) do not anticipate ex-ante the faltering fundamentals that are realized following periods of corporate overinvestment.

Taken together, our results are in line with historical bubble accounts which suggest that managers' investment decisions are affected by the same waves of investor euphoria that mark stock price bubbles (e.g. Kindleberger 1978, Shiller 2000, Akerlof and Shiller 2010). More specifically, our findings are consistent with the view that managers overinvest during periods of buoyant investor sentiment, only to be subsequently followed by greater corporate earnings disappointments relative to expectations.

4.6 Predictive Ability of Accrual Components

The results of the preceding analyses indicate that *ΔNOA* positively predicts crashes and negatively predicts stock returns following price run-ups. However, it is unclear whether these results are driven by a specific component of *ΔNOA*, and prior work examining firm-level data suggests that working capital accruals and long-term net operating asset accruals negatively

[16] Results are robust to using the mean consensus forecast rather than the median.

forecast returns and earnings (e.g. Sloan 1996; Richardson et al 2005; Allen et al 2013; Dechow et al 2006; Fairfield et al 2003). Since ΔNOA is equal to the sum of working capital accruals and long-term net operating asset accruals, we conduct a series of tests to investigate the predictive ability of these components of ΔNOA.

We examine multiple regression tests investigating the predictive ability of long-term net operating asset accruals and working capital accruals for future performance. Table 10 presents the results of tests investigating whether industry-level working capital accruals (*ΔWC*) or long-term net operating asset accruals (*ΔLTNOA*) have predictive ability for industry-level stock price crashes and the three measures of future industry-level stock returns. We compute *ΔWC* by first calculating firm-level working capital accruals, i.e., the change in working capital (current assets minus current liabilities) over the past fiscal year scaled by average total assets.[17] We then percentile rank firm-level working capital accruals each month in the full cross section of firms and calculate the value-weighted working capital accruals percentile rank for each country-industry-month observation. We compute *ΔLTNOA* in a similar manner by computing the country-industry-month level value-weighted percentile rank of firm-level noncurrent net operating asset accruals, i.e., the change in noncurrent assets minus noncurrent liabilities.[18]

[17] Working capital is defined as the change in current operating assets minus the change is current operating liabilities plus depreciation and amortization expense. Current operating assets is defined as current assets – cash and short term investments, or "ACT"-"CHE" using Compustat data and "ITEM2201"-"ITEM2001" using Worldscope data. Current operating liabilities is defined as current liabilities – short-term debt – taxes payable, or "LCT" – "DLC" – "TXP" using Compustat and "ITEM3101" – "ITEM3051" – "ITEM3063" using Worldscope. Depreciation and amortization expense is "DP" using Compustat and "ITEM1151" using Worldscope. This definition is consistent with many prior studies that focus on working capital accruals, including Hirshleifer et al (2009).

[18] Noncurrent assets is defined as total assets – current assets – deferred taxes, or "AT" – "ACT" – "TXDB" using Compustat data and "ITEM2999" – "ITEM2201" – "ITEM3263" using Worldscope data. Noncurrent liabilities is defined as total liabilities – current liabilities – long term debt – deferred taxes, or "LT" – "LCT" – "DLTT" – "TXDB" using Compustat data and "ITEM3351" – "ITEM3101" – "ITEM3251" – "ITEM3263" using Worldscope data. This definition is consistent with that in Richardson et al (2005).

In Table 10 Panel A, we examine the predictive ability of industry-level working capital accruals for post-run-up performance after controlling for the battery of variables suggested by GSY. Across each dependent variable, the coefficient on working capital accruals suggests that higher working capital is followed by worse performance, but the coefficients are generally not statistically significant. Overall, Panel A shows that working capital accruals do not significantly predict any performance measure, echoing prior work which does not find conclusive evidence of a significant predictive relation between working capital accruals and future returns at the industry level (e.g. Heater et al 2021; Hirshleifer et al 2009).[19]

Table 10 Panel B documents that *ΔLTNOA* is a statistically significant predictor of future performance for two of the four measures of stock price performance. Specifically, *ΔLTNOA* is a statistically significant predictor of raw returns (coefficient -0.712, t-stat -2.49) and returns net of the risk-free rate (coefficient -0.708, t-stat -2.50). However, *ΔLTNOA* does not significantly predict crashes (coefficient 0.143, t-stat 0.90) or market-adjusted returns (coefficient -0.108, t-stat -0.59).

We also examine the predictive ability of *ΔWC* and *ΔLTNOA* when they are both included in the regressions along with the GSY controls. In untabulated analyses, we find that the Spearman (Pearson) correlation between *ΔWC* and *ΔLTNOA* is only 0.085 (0.057). Consistent with the low correlation between *ΔWC* and *ΔLTNOA*, Table 10 Panel C shows that across all the regressions, the coefficients and statistical significance for *ΔLTNOA* are similar across Table 10 Panel B and Panel C. Likewise, the coefficients and statistical significance for *ΔWC* are similar across Table

[19] For example, Hirshleifer et al (2009) find that the relationship between industry-level working capital accruals and future industry returns is positive for seven industries at the 5% significance level or better, negative for five industries, and statistically insignificant for the remaining 36 industries. Heater et al (2021) also fail to find a robust predictive relation between industry-level working capital accruals and future industry returns in their cross-sectional tests.

10 Panel A and Panel C. As such, the implications of ΔWC and $\Delta LTNOA$ for future stock prices are largely independent. Further, in Panel C we examine whether there is a statistical difference in the coefficients on $\Delta LTNOA$ and ΔWC when forecasting crashes and all the return measures. We find that across all four measures of future stock price performance, we cannot reject the null that $\Delta LTNOA$ and ΔWC have the same coefficient. In other words, we obtain similar coefficients on $\Delta LTNOA$ and ΔWC when predicting future stock prices. As such, we do not find clear-cut evidence that $\Delta LTNOA$ (or ΔWC) exclusively drives the ability of ΔNOA to identify bubbles.

We also graph the average returns of industries in the extreme deciles of $\Delta LTNOA$ and ΔWC around run-ups. Figure 2, Panel A shows that in the first 24 months following a run-up, the highest $\Delta LTNOA$ decile outperforms the lowest $\Delta LTNOA$ decile (5.16% versus 0.71%) but the difference in returns is statistically insignificant (t-stat = 1.37). Figure 2, Panel B shows that the highest ΔWC decile continues to run-up for 3 months after run-up identification, but these industries tend to crash over the following eight months. The two-year average industry return from month 0 (when the run-up is first identified) until month 23 is -11.48% for the lowest ΔWC decile and -18.36% for the highest ΔWC decile. However, the difference in these portfolio returns is statistically insignificant (t-stat = 0.99). In other words, while run-ups in the highest decile of ΔWC are somewhat more likely to crash within the first year after run-up identification, overall return performance is not statistically different for high and low ΔWC industries over the full 24 month window. This contrasts with the return differential based on extreme deciles of ΔNOA (Figure 1) in which industries in the highest decile of ΔNOA significantly underperform the industries in the lowest decile of ΔNOA over the 24-month period following the run-up.

While these return plots depict purely univariate results and do not permit the inclusion of control variables, we draw two conclusions. First, the graphs indicate that timing the peak of a bubble is difficult. Second, the fact that sorting run-ups according to extreme deciles of *ΔWC* or *ΔLTNOA* does not lead to a statistically significant difference in future stock returns over the following 24 months reinforces the view that *ΔNOA* is a more useful return predictor than either *ΔLTNOA* or *ΔWC* given that run-ups in the highest decile of *ΔNOA* significantly underperform run-ups in the lowest decile by a statistically significant 19.8% over the 24 months following run-up identification (Figure 1).

In untabulated analyses we investigate whether any specific accrual component drives the overall predictive relation between industry-level ΔNOA and future performance. Specifically, we include changes in accounts receivables, inventory, other current assets, PP&E, goodwill, intangibles, other long-term assets, accounts payables, other current liabilities, and other long-term liabilities in our forecasting regressions along with all the GSY controls. While some individual operating accruals components have predictive ability for some measures of future performance, when taken together, the evidence does not suggest that a single operating accrual drives the overall ability of ΔNOA to identify bubbles.[20]

Overall, the results of the above tests suggest that both long-term NOA accruals and working capital accruals contribute to the predictive ability of ΔNOA. While long-term NOA accruals are a somewhat stronger predictor of future performance than working capital accruals, the fact that ΔNOA is a reliably significant predictor of all the stock price-based performance

[20] In further untabulated analyses we investigate whether M&A drives our results. Heater et al (2021) show that aggregate M&A activity is responsible for the ability of aggregate working capital accruals to predict market-level aggregate returns (as originally documented by Hirshleifer et al 2009), where M&A is based on the total number of target firms that are merged or acquired. We measure M&A activity in four ways: the raw number of M&As in the industry over the fiscal year ('industry M&A'), industry M&A scaled by the total number of firms in the country-industry, the aggregate number of M&As in the whole country over the fiscal year, and the number of cross-industry M&As in the country-industry scaled by the number of firms in the country-industry. None of these measures of M&A subsume the ability of accruals to identify bubbles.

measures we examine indicates that ΔNOA more consistently identifies bubbles for Fama than either subcomponent.

4.7 Full Sample Results

The empirical tests in the preceding analyses focus exclusively on the 240 price run-ups in our global sample. To investigate whether the results obtained using the run-up sample reflect a generic predictive relation between accruals and future performance or instead reflect a more unique predictive relation, in this section we analyze the entire sample of 98,187 industry-months across all 49 countries in which at least one price run-up was identified. We define a dummy variable, *Runup*, which takes the value one if the country-industry-month observation was one of the 240 run-ups that we identified in our sample used in the preceding analyses, and zero otherwise. As before, we choose the first month for which a run-up is observed and do not allow for a new run-up to be identified until two years later.[21]

Table 11 presents the results of regressions forecasting returns and crashes using our full country-industry-month sample. We use a total of five measures of future industry performance: the *Crash* indicator, *IndRet24*, *IndRetRF24*, *IndRetMAR24*, and *IndAFError*. The variable of interest is the interaction term *ΔNOA*Runup*, which is the interaction of industry-level accruals and a run-up indicator. We control for all the GSY characteristics including past returns.

We find that industry-level accruals that are associated with price run-ups have significantly stronger predictive ability for industry returns and crashes than industry-level

[21] Since we use a two-year window when computing future returns, our full sample tests have many overlapping returns when computing future returns in consecutive months for the same industry-country. However, this would bias against us finding results of stronger predictive ability for the identified run-up months (i.e., the consecutive months after the first month for which a run-up is observed are classified as non-run-up months). Nevertheless, we run robustness tests in which we delete observations in the same industry-country within a 12 or 24-month period surrounding an identified run-up month, and untabulated results suggest that these results are not only robust, but marginally stronger than those that are tabulated.

accruals that are not associated with price run-ups.[22] Specifically, the coefficient on *ΔNOA*Runup* when predicting *Crash* is 0.434 (t-statistic 2.85). The coefficient on *ΔNOA*Runup* when predicting *IndRet24* is -0.691 (t-statistic -2.58). The coefficient on *ΔNOA*Runup* when predicting *IndRetRF24* is -0.690 (t-statistic -2.58), and the coefficient on *ΔNOA*Runup* when predicting *IndRetMAR24* is -0.204 (t-statistic -1.26). The coefficient on *ΔNOA*Runup* when predicting *IndAFError* is 1.305 (t-statistic 2.35). In terms of magnitude, the predictive ability of accruals for future industry price crashes, industry raw returns, returns in excess of the risk-free rate, and analyst forecast errors more than quintuples following price run-ups compared to non-runup periods. Taken together, these results indicate that our core findings are not simply the product of a generic accrual-performance predictive relation.

The results presented in the first four columns of Table 11 suggest that following price run-ups, industry-level accruals incrementally and significantly predict crashes, raw industry returns as well as industry returns net of the risk-free rate following price run-ups, but not market-adjusted industry returns. One possible reason for this null result is that accruals negatively forecast both industry-level returns as well as country-level market returns following run-ups, leading to lack of predictability of market-adjusted industry returns following run-ups. Indeed, while GSY conjecture that industry bubbles may be intertwined with overall market valuation, they do not empirically test this conjecture. Accordingly, we test whether industry-level accruals forecast country-level aggregate returns following run-ups by regressing subsequent 24-month market-level value-weighted stock returns on *ΔNOA*Runup* and all of the other independent variables.

Using our full sample of 98,187 industry-months, the last column of Table 11 documents that industry-level accruals associated with price run-ups negatively forecast aggregate country-

[22] Results are robust to inclusion of country and year fixed effects. We do not include them to mitigate look-ahead bias.

level stock market returns. We find that industry-level accruals do not predict subsequent market aggregate returns on average, with a coefficient on *ΔNOA* of 0.008 (t statistic 0.23). Importantly, however, the coefficient on *ΔNOA*Runup* is -0.534 with a t-statistic of -2.49, and the F-statistic for the combined coefficient *ΔNOA+ΔNOA*Runup* is 6.22 (p-value 0.01), indicating that industry-level accruals associated with price run-ups are a statistically significant predictor of future country-level stock market returns. As such, our empirical evidence provides support for the conjecture by GSY that industry bubbles are likely intertwined with overall market valuation. Combined with our earlier results, our evidence demonstrates that industry price run-ups are not only followed by significantly lower returns at the industry level, but also at the aggregate country level.

Panel B of Table 11 examines full sample results for our sentiment tests. If sentiment plays an especially important role in shaping investment during stock price bubbles, then we expect the accruals-sentiment relation to be significantly stronger during run-up periods compared to other times. As such, we examine if *ΔNOA* is incrementally more strongly associated with investor sentiment during run-up periods compared to non-run-up periods. As we document in Panel B of Table 11, for both measures of investor sentiment, the positive association between sentiment and *ΔNOA* is incrementally stronger during run-up periods than during non-run-up periods, given that the interaction term *Sentiment (BWY)*Runup* is positive and statistically significant (coefficient 0.043, t-statistic 2.25) and the interaction term *Inflows*Runup* is also positive and statistically significant (coefficient 0.151, t-statistic 2.22). In fact, the results indicate that during non-run-up periods, net capital inflows from investors are not significantly associated with *ΔNOA* given that the coefficient on *Inflows* has a t-statistic of 0.006.[23] Overall, these results are consistent with the

[23] We include country, industry, and year fixed effects in both tests presented in Table 11, Panel B.

view that managers are prone to overinvesting when sentiment around stock price run-ups is buoyant.

5. Conclusion

Stock price bubbles have long intrigued economists, yet prior empirical work is largely silent on the role of accounting information in bubbles. Our study investigates whether investments in net operating asset accruals identifies bubbles. Using a large global dataset, we document that net operating asset accruals reliably forecast future performance following price run-ups. Specifically, higher levels of industry-level NOA accruals portend sharply lower future industry stock returns and greater likelihood of crashes following rapid price appreciation.

The predictive ability of accruals for future performance strengthens sharply around run-ups compared to non-run-up periods, indicating that our results are not the product of a generic relation between accruals and future performance. Further, we find that industry accruals around run-ups negatively forecast market-level returns, consistent with the bursting of a bubble leading to a downturn in the overall country-level market index. Overall, our results provide new support for historical accounts suggesting that bubbles have important economic consequences because the misallocation of capital due to bubble-driven investment booms is followed by faltering fundamentals and implosions in asset prices which can even extend to the aggregate stock market (e.g. Kindleberger 1978, Shiller 2000, Akerlof and Shiller 2010).

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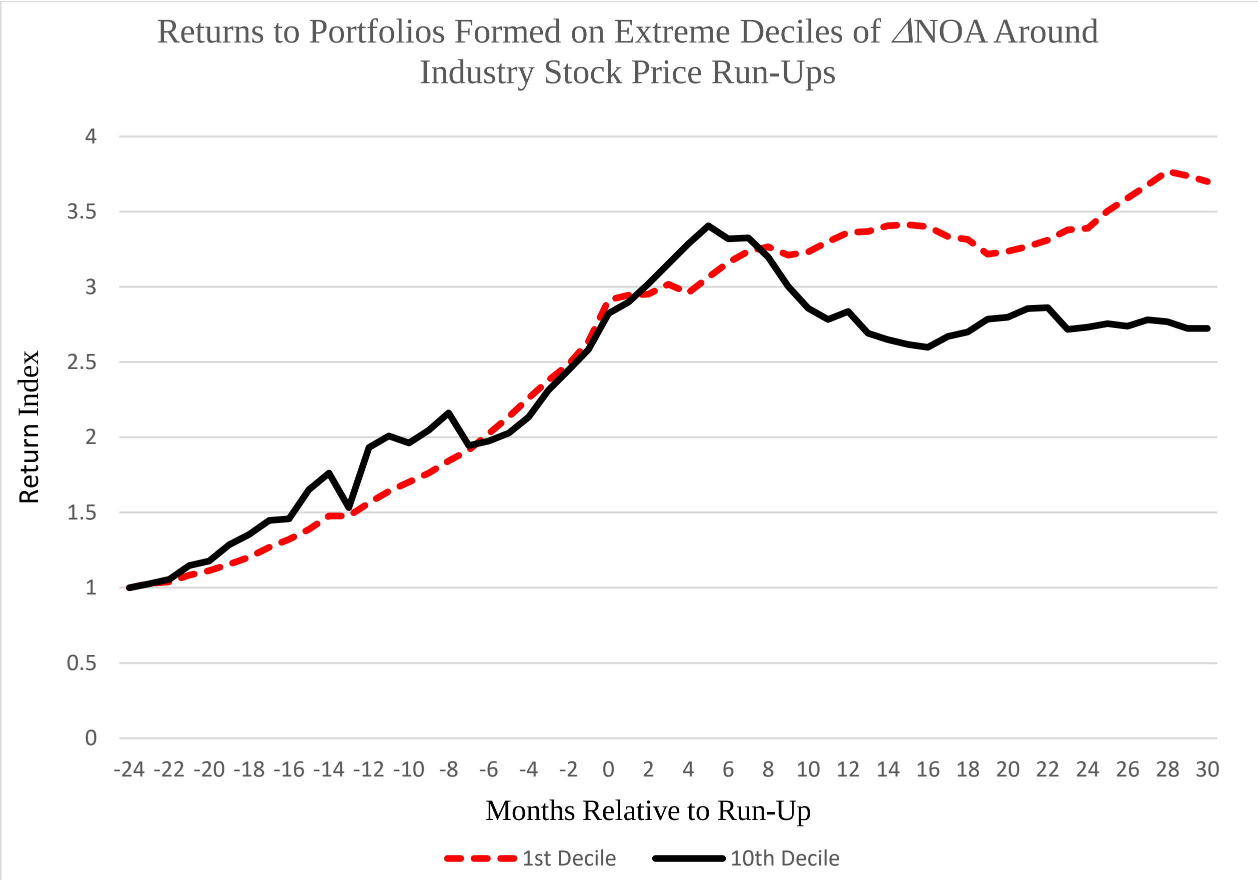
Appendix A. Variable Definitions

CRASH	Indicator variable that equals one if there is a 40% or more drawdown in raw country-industry value-weighted returns beginning at any point after the identification of the industry price run-up over the subsequent 24 months, and zero otherwise
IndRet24	Raw country-industry returns over the subsequent 24 months. Monthly firm returns are value-weighted in each month for each country-industry
IndRetRF24	Raw country-industry value-weighted returns over the subsequent 24 months net of the risk-free rate
IndRetMAR24	Raw country-industry value-weighted returns over the subsequent 24 months net of market value-weighted returns
ΔNOA	Percentile rank of firm-level net operating asset accruals in the full cross section of firms value-weighted in each month for each country-industry. Firm-level accruals are computed as the change in net operating assets over the past fiscal year scaled by average total assets from the most recent and the prior fiscal years. Net operating assets is defined as total assets – cash and short term investments – total liabilities + short-term debt + long-term debt.
Volatility	Percentile rank of firm volatility in the full cross section of firms value-weighted in each month for each country-industry. Firm volatility is computed as the monthly standard deviation of daily returns.
Volatility – 1yrChange	Percent change of monthly *Volatility* (defined above) compared with its average value in the year prior
Turnover	Percentile rank of firm turnover in the full cross section of firms value-weighted in each month for each country-industry. Firm turnover is computed by dividing the number of shares traded by the number of shares outstanding in each month. NASDAQ stocks are then further divided by two because of double-counting.
Turnover-1yrChange	Percent change of monthly *Turnover* (defined above) compared with its average value in the year prior.
IndustryAge	Percentile rank of firm age in the full cross section of firms value-weighted in each month for each country-industry. Firm age is computed as the number of months since the firm first appeared on either Compustat North America or CRSP (US) or on Compustat Global (international).
AgeTilt	Difference between the equal-weighted country-industry return and the age-weighted country-industry return over the past two years.
PercentIssuers	Percentage of firms in the country-industry that issued equity in the past year. A firm is defined as having issued equity if the split-adjusted share country increased by 5% or more.
BooktoMarket	Monthly value-weighted firm book-to-market ratio in each country-industry. Firm book-to-market is computed as the ratio of book value of equity at the most recent fiscal year end to market value of equity in a given month.
SalesGrowth	Percentile rank of firm-level one-year sales growth over the most recent fiscal year in the full cross section of firms value-weighted in each month for each country-industry.

Acceleration	Difference between the two-year return and the return for the first year of that two-year period leading up to the given month.
CAPE	Country-level monthly cyclically adjusted price-earnings ratio from Barclays Indices. Missing data from Barclays is filled in using information on stock prices as well as average earnings over the past 10 years at the country level.
PastReturns	Raw country-industry value-weighted returns in the past two years.
ΔWC	Percentile rank of firm working capital accruals in the full cross section of firms value-weighted in each month for each country-industry. Firm working capital accruals is defined as the change in working capital over the past fiscal year scaled by average total assets from the most recent and the prior fiscal years. Working capital is computed as the change in current assets – cash and short term investments (current assets) minus the change in current liabilities – short-term debt – taxes payable (current liabilities), plus depreciation and amortization expense.
ΔLTNOA	Percentile rank of firm noncurrent operating accruals in the full cross section of firms value-weighted in each month for each country-industry. Firm noncurrent operating accruals is defined as the change in the difference between noncurrent assets and noncurrent liabilities over the past fiscal year scaled by average total assets from the most recent and the prior fiscal years. Noncurrent assets is computed as total assets – current assets – deferred taxes. Noncurrent liabilities is computed as total liabilities – current liabilities – long-term debt – deferred taxes.
IndAFError	Monthly value-weighted firm-level analyst forecast error in each country-industry. The firm-level analyst forecast error is defined as the difference between the median consensus analyst EPS forecast in a given month for the upcoming annual forecast period end and the actual EPS, scaled by the absolute value of actual EPS.
Sentiment (BWY)	Yearly market sentiment index from Baker, Wurgler, and Yuan (2012)
Inflows	Country-industry net capital inflows over the most recent fiscal year, computed as the value-weighted firm-level net capital inflow aggregated at the country-industry level. Firm-level net capital inflows are computed as the sum of the monthly net capital inflows over the most recent fiscal year, defined as $-1 * \left(\mathrm{MV}_{\mathrm{i,m-1}} * \left(1 + \mathrm{r}_{i,m}\right) - \mathrm{MV}_{\mathrm{i,m}}\right)/TA$ where $\mathrm{MV}_{\mathrm{i,m}}$ is the market capitalization of firm *i* at the end of month *m* and $\mathrm{r}_{\mathrm{i,m}}$ is the stock return of firm *i* in month *m* (including dividends) and TA is total assets for the firm as of the most recent fiscal year end.
Runup	Indicator variable that equals one if the country-industry-month observation has experienced value-weighted returns of 100% or more in the past two years, in both raw and net of market terms, as well as 50% or more raw returns over the past five years. Only the first instance for which a run-up is observed is defined as a run-up and a new run-up cannot be identified until at least two years later. This follows the methodology in Greenwood et al (2019).
MktRet24	Aggregate value-weighted market returns over the subsequent 24 months

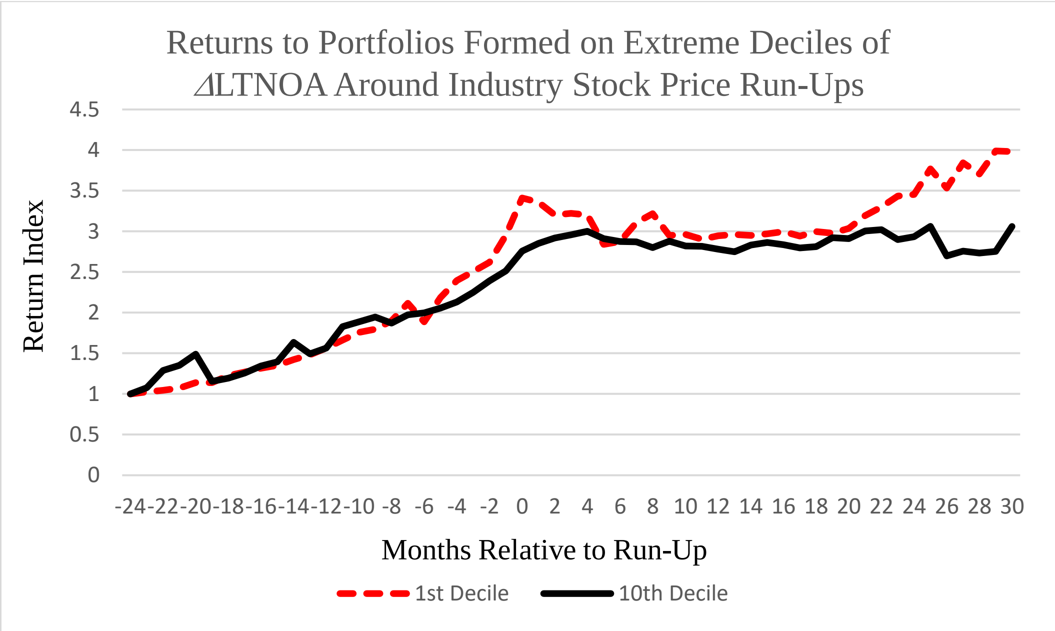
Figure 1. NOA Accruals and Returns in Months Around Industry Price Run-Ups



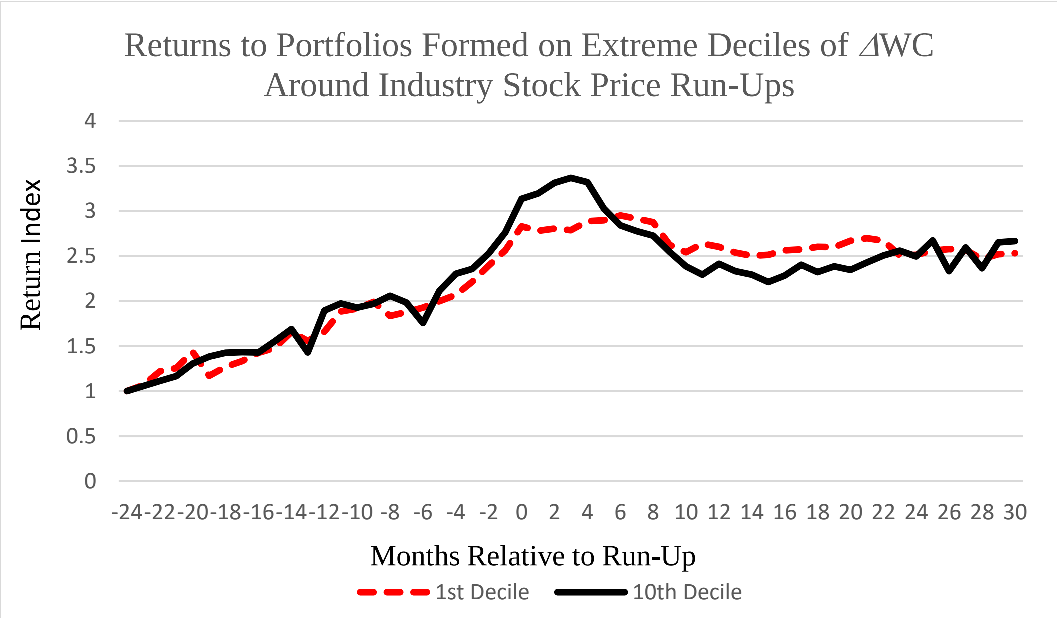
This figure presents cumulative returns to all country-industries that experienced a large price run-up between month -24 and month 0, where month 0 is the first month during which a price run-up is identified. The red dashed line depicts the average return index for run-up industries in the lowest decile of industry-level NOA accruals. The black solid line depicts the average return index for run-up industries in the highest decile of industry-level accruals. We include 240 total episodes of price run-ups across 49 countries. The return index at month -24 is normalized to 1.

Figure 2. Decomposed Accruals and Returns in Months Around Industry Price Run-Ups

Panel A – Long Term Net Operating Asset (LTNOA) Accruals



Panel B – Working Capital (WC) Accruals



This figure presents cumulative returns to all country-industries that experienced a large price run-up between month -24 and month 0, where month 0 is the first month during which a price run-up is identified. In Panel A (Panel B), the red dashed line depicts the average return index for run-up industries in the lowest decile of industry-level LTNOA (WC) accruals, and the black solid line depicts the average return index for run-up industries in the highest decile of industry-level LTNOA (WC) accruals. We include 240 total episodes of price run-ups across 49 countries. The return index at month -24 is normalized to 1.

Table 1: List of Sample Countries with Number of Run-Ups and Crashes

Country	Runups	Crashes
Argentina	5	4
Australia	3	2
Austria	3	2
Belgium	3	1
Bulgaria	1	1
Brazil	9	7
Switzerland	4	1
Chile	3	0
China	12	8
Cayman Islands	1	1
Cyprus	1	0
Germany	5	2
Denmark	5	0
Egypt	2	1
Spain	5	1
Finland	4	0
France	3	3
United Kingdom	4	2
Greece	6	4
Hong Kong	12	8
Indonesia	6	3
India	13	7
Israel	2	2
Italy	2	1
Jordan	2	1
Japan	2	2
South Korea	7	2
Sri Lanka	4	2
Mexico	2	0
Malaysia	3	2
Nigeria	2	1
Netherlands	5	3
Norway	3	2
New Zealand	3	2
Pakistan	5	0
Peru	2	1
Philippines	7	2
Poland	5	3
Romania	2	2
Russia	7	6
Saudi Arabia	1	0
Singapore	10	4
Sweden	1	1
Thailand	14	1
Turkey	3	1
Taiwan	2	2
United States	18	10
Vietnam	3	2
South Africa	13	1
Total	240	114
Mean	4.90	2.33

Table 2: Descriptive Statistics

	All Industry-Months			Run-Ups		
Industry Characteristic	**N**	**Mean**	**Std**	**N**	**Mean**	**Std**
PastReturns	98187	0.2415	0.59	240	2.0557	0.87
ΔNOA	98187	0.5289	0.16	240	0.5519	0.18
Volatility	98187	0.3455	0.17	240	0.4774	0.18
Volatility-1yrChange	98187	0.0537	0.50	240	0.2120	0.57
Turnover	98187	0.4735	0.22	240	0.4585	0.21
Turnover-1yrChange	98187	0.0942	0.57	240	0.2588	0.63
IndustryAge	98187	0.6583	0.17	240	0.5902	0.19
AgeTilt	98187	-0.0031	0.08	240	-0.0148	0.16
PercentIssuers	98187	0.1606	0.13	240	0.1888	0.14
BooktoMarket	98187	0.4331	0.34	240	0.2314	0.15
SalesGrowth	98187	0.5209	0.15	240	0.5902	0.16
CAPE	98187	27.1756	18.82	240	32.9796	22.11
Acceleration	98187	-0.0238	12.73	240	1.3643	1.13
Crash	98187	0.1999	0.40	240	0.4750	0.50

This table presents descriptive statistics for our full country-industry-month sample and the run-up sample. Within each sample, the number of observations, mean, and standard deviation are presented for the variables. The past two-year return is the cumulative return over the past 24 months for any given country-industry-month. The other variables are value-weighted percentile ranked accruals, value-weighted percentile ranked volatility and its one-year change, value-weighted percentile ranked turnover and its one-year change, value-weighted percentile ranked firm age, age tilt, percentage of issuers, value-weighted book-to-market ratio, value-weighted percentile ranked sales growth, market cyclically adjusted price-earnings ratio, acceleration, and crash indicator. Definitions of variables are presented in Appendix A.

Table 3: Crash Predictability – Univariate Linear Probability Model Analysis

	Crash	R^2
ΔNOA	0.687*** (4.23)	0.06
PastReturns	0.093 (1.63)	0.03
Volatility	1.028*** (5.72)	0.13
Volatility-1yrChange	0.154*** (3.69)	0.03
Turnover	0.164 (1.00)	0.00
Turnover-1yrChange	-0.027 (-0.52)	0.00
IndustryAge	-0.773*** (-6.78)	0.09
AgeTilt	0.337* (1.70)	0.01
PercentIssuers	0.969*** (3.86)	0.07
BooktoMarket	-0.880*** (-2.97)	0.07
SalesGrowth	0.254 (1.25)	0.00
Acceleration	0.085** (2.22)	0.04
CAPE	0.007*** (7.76)	0.11

This table presents results of univariate linear probability model regressions predicting the incidence of industry crashes with industry-level NOA accruals and other bubble characteristics using our global sample of 240 run-up-identified country-industry-months. The dependent variable is a crash indicator, which equals one if there is a 40% drawdown from any point in the two years after the initial price run-up, and zero otherwise. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 4: Crash Predictability – Multiple Linear Probability Model Analysis Including Controls

	Crash
ΔNOA	0.462**
	(2.27)
PastReturns	0.013
	(0.35)
Volatility	0.536***
	(3.05)
Volatility-1yrChange	0.003
	(0.06)
Turnover	-0.120
	(-0.74)
Turnover-1yrChange	-0.026
	(-0.50)
IndustryAge	-0.554***
	(-3.81)
AgeTilt	0.273*
	(1.69)
PercentIssuers	0.771***
	(3.35)
BooktoMarket	-0.462**
	(-2.02)
SalesGrowth	-0.306
	(-1.58)
Acceleration	0.019*
	(1.70)
CAPE	0.005***
	(4.42)
N	240
R^2	0.35
F-statistic	77.76

This table presents results to multiple linear probability model regressions predicting the incidence of industry stock price crashes using industry-level NOA accruals and controlling for various bubble characteristics. The dependent variable is a crash indicator, which equals one if there is a 40% drawdown from any point in the two years after the initial price run-up, and zero otherwise. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 5: Predictability of Returns – Univariate Regressions

	IndRet24	R^2	IndRetRF24	R^2	IndRetMAR24	R^2
ΔNOA	-0.790***	0.04	-0.788***	0.04	-0.382***	0.02
	(-4.02)		(-4.04)		(-3.02)	
PastReturns	0.010	0.00	0.012	0.00	-0.066	0.01
	(0.22)		(0.26)		(-1.59)	
Volatility	-0.484**	0.01	-0.474**	0.01	-0.290**	0.01
	(-2.06)		(-2.02)		(-2.06)	
Volatility-1yrChange	-0.002	0.00	-0.001	0.00	-0.060	0.00
	(-0.03)		(-0.01)		(-1.40)	
Turnover	-0.500**	0.02	-0.521**	0.02	-0.128	0.00
	(-2.23)		(-2.32)		(-1.05)	
Turnover-1yrChange	0.049	0.00	0.049	0.00	0.040	0.00
	(0.79)		(0.79)		(1.15)	
IndustryAge	0.847***	0.05	0.842***	0.05	0.269	0.01
	(3.17)		(3.21)		(1.52)	
AgeTilt	-0.517**	0.01	-0.523**	0.01	-0.271	0.01
	(-2.12)		(-2.14)		(-1.69)	
PercentIssuers	-1.299***	0.06	-1.314***	0.07	-0.614**	0.03
	(-3.70)		(-3.74)		(-2.24)	
BooktoMarket	1.184**	0.08	1.175**	0.08	0.339	0.02
	(2.11)		(2.10)		(1.08)	
SalesGrowth	-0.415*	0.01	-0.414*	0.01	-0.299	0.01
	(-1.67)		(-1.67)		(-1.23)	
Acceleration	-0.107*	0.03	-0.108*	0.03	-0.025*	0.00
	(-1.65)		(-1.69)		(-1.72)	
CAPE	-0.006***	0.04	-0.006***	0.04	-0.004***	0.03
	(-3.87)		(-3.85)		(-2.66)	

This table presents results to univariate OLS regressions predicting future industry-level stock price performance using industry-level NOA accruals (*ΔNOA*) and various bubble characteristics using a global sample of 240 run-ups. The dependent variables are 24-month industry raw return (*IndRet24*), 24-month industry net of risk-free return (*IndRetRF24*), and 24-month industry net of market return (*IndRetMAR24*), all value-weighted at the industry level. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 6: Predictability of Returns – Multiple Regression

	IndRet24	IndRetRF24	IndRetMAR24
ΔNOA	-0.639***	-0.636***	-0.254*
	(-2.81)	(-2.84)	(-1.67)
PastReturns	0.086	0.088	-0.057
	(1.23)	(1.27)	(-0.89)
Volatility	0.041	0.054	0.035
	(0.12)	(0.16)	(0.13)
Volatility-1yrChange	0.102	0.101	-0.045
	(1.12)	(1.14)	(-0.74)
Turnover	-0.217	-0.240	-0.015
	(-1.07)	(-1.18)	(-0.14)
Turnover-1yrChange	-0.020	-0.021	0.045
	(-0.33)	(-0.35)	(1.08)
IndustryAge	0.670**	0.662**	0.132
	(2.20)	(2.20)	(0.61)
AgeTilt	-0.451*	-0.456*	-0.255
	(-1.87)	(-1.88)	(-1.48)
PercentIssuers	-0.870***	-0.879***	-0.509*
	(-2.91)	(-2.97)	(-1.92)
BooktoMarket	0.950*	0.934	0.131
	(1.70)	(1.69)	(0.35)
SalesGrowth	0.203	0.199	-0.054
	(0.92)	(0.93)	(-0.22)
Acceleration	-0.094	-0.096	0.002
	(-1.15)	(-1.18)	(0.07)
CAPE	-0.004***	-0.004***	-0.002
	(-2.97)	(-3.01)	(-1.35)
N	240	240	240
R^2	0.23	0.24	0.09
F-statistic	151.29	172.19	4.91

This table presents results to multiple OLS regressions predicting future industry-level stock prices using industry-level NOA accruals (*ΔNOA*) and controlling for various bubble characteristics. The dependent variables are 24-month raw return (*IndRet24*), 24-month net of risk-free return (*IndRetRF24*), and 24-month net of market return (*IndRetMAR24*), all value-weighted at the industry level. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 7: False Discovery Tests

Panel A – Crash Prediction

Characteristic	t statistic	P value	Rank	5% Threshold	
CAPE	7.76	0	1	0.0038	TRUE
IndustryAge	-6.78	0	2	0.0077	TRUE
Volatility	5.72	0	3	0.0115	TRUE
ΔNOA	4.23	0	4	0.0154	TRUE
PercentIssuers	3.86	0	5	0.0192	TRUE
Volatility-1yrChange	3.69	0	6	0.0231	TRUE
BooktoMarket	-2.97	0.003	7	0.0269	TRUE
Acceleration	2.22	0.027	8	0.0308	TRUE
AgeTilt	1.70	0.089	9	0.0346	FALSE
PastReturns	1.63	0.103	10	0.0385	FALSE
SalesGrowth	1.25	0.212	11	0.0423	FALSE
Turnover	1.00	0.318	12	0.0462	FALSE
Turnover-1yrChange	-0.52	0.603	13	0.0500	FALSE

Panel B – 2-year Industry Returns

Characteristic	t statistic	P value	Rank	5% Threshold	
ΔNOA	-4.02	0	1	0.0038	TRUE
CAPE	-3.87	0	2	0.0077	TRUE
PercentIssuers	-3.70	0	3	0.0115	TRUE
IndustryAge	3.17	0.002	4	0.0154	TRUE
Turnover	-2.23	0.026	5	0.0192	FALSE
AgeTilt	-2.12	0.034	6	0.0231	FALSE
BooktoMarket	2.11	0.035	7	0.0269	FALSE
Volatility	-2.06	0.04	8	0.0308	FALSE
SalesGrowth	-1.67	0.095	9	0.0346	FALSE
Acceleration	-1.65	0.099	10	0.0385	FALSE
Turnover-1yrChange	0.79	0.43	11	0.0423	FALSE
PastReturns	0.22	0.826	12	0.0462	FALSE
Volatility-1yrChange	-0.03	0.976	13	0.0500	FALSE

Panel C – 2-year Risk-Free Rate-Adjusted Industry Returns

Characteristic	t statistic	P value	Rank	5% Threshold	
ΔNOA	-4.04	0	1	0.0038	TRUE
CAPE	-3.85	0	2	0.0077	TRUE
PercentIssuers	-3.74	0	3	0.0115	TRUE
IndustryAge	3.21	0.001	4	0.0154	TRUE
Turnover	-2.32	0.021	5	0.0192	FALSE
AgeTilt	-2.14	0.033	6	0.0231	FALSE
BooktoMarket	2.10	0.036	7	0.0269	FALSE
Volatility	-2.02	0.044	8	0.0308	FALSE
Acceleration	-1.69	0.091	9	0.0346	FALSE
SalesGrowth	-1.67	0.095	10	0.0385	FALSE
Turnover-1yrChange	0.79	0.43	11	0.0423	FALSE
PastReturns	0.26	0.795	12	0.0462	FALSE
Volatility-1yrChange	-0.01	0.992	13	0.0500	FALSE

Panel D - 2-year Market-Adjusted Industry Returns

Characteristic	t statistic	P value	Rank	5% Threshold	
ΔNOA	-3.02	0.003	1	0.0038	TRUE
CAPE	-2.66	0.008	2	0.0077	FALSE
PercentIssuers	-2.24	0.025	3	0.0115	FALSE
Volatility	-2.06	0.04	4	0.0154	FALSE
Acceleration	-1.72	0.086	5	0.0192	FALSE
AgeTilt	-1.69	0.091	6	0.0231	FALSE
PastReturns	-1.59	0.112	7	0.0269	FALSE
IndustryAge	1.52	0.129	8	0.0308	FALSE
Volatility-1yrChange	-1.40	0.162	9	0.0346	FALSE
SalesGrowth	-1.23	0.219	10	0.0385	FALSE
Turnover-1yrChange	1.15	0.25	11	0.0423	FALSE
BooktoMarket	1.08	0.28	12	0.0462	FALSE
Turnover	-1.05	0.294	13	0.0500	FALSE

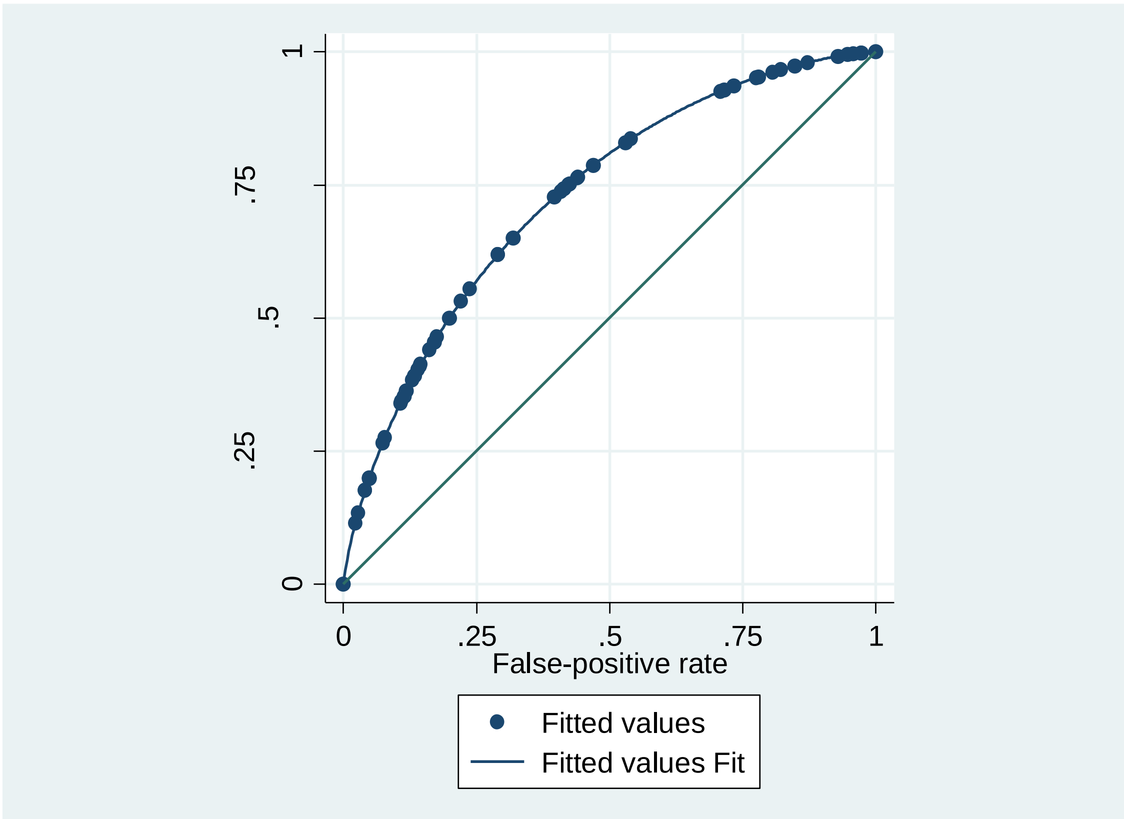
This table tests the significance of industry-level NOA accruals and other bubble characteristics in predicting crashes (Panel A), 24-month raw returns (Panel B), 24-month returns net of the risk-free rate (Panel C), and 24-month net of market return (Panel D) allowing for a maximal false discovery rate of 5%. We adopt the maximal false discovery rate procedure from and Bejamini and Hochberg (1995) to compute the probability of false discovery. We rank all variables by their p-values from the univariate regressions. We display the p-value thresholds for 5% and report whether the independent variables pass the false discovery test. "True" suggests that the characteristic individually passes the false discovery test at 5% significance. Definitions of variables are provided in Appendix A.

Table 8: Out-of-Sample R^2

Out-of-sample R^2			
	IndRet24	*IndRetRF24*	*IndRetMAR24*
ΔNOA	9.01%	9.45 %	5.98%
Volatility	4.10%	4.02%	2.20%
ΔVolatility	-1.13%	-1.08%	0.45%
Turnover	-14.78%	-15.37 %	-1.28%
ΔTurnover	1.41%	1.37%	0.81%
Age	12.38%	11.90%	2.72%
Age Tilt	3.50%	3.47%	1.18%
Issuance	7.35%	7.85%	8.49%
Book-to-Market	-3.65%	-3.21%	-5.83%
Sales Growth	5.86%	5.83%	3.01%
Price Acceleration	-1.20%	-1.13 %	0.38%
CAPE Ratio	2.27%	2.88%	9.12%
Past Returns	0.00%	0.00%	1.08%

This table presents out-of-sample R^2 from testing the out-of-sample predictability of *ΔNOA*, the GSY bubble characteristics, and past 24-month industry raw returns for future 24-month raw industry returns (*IndRet24*), 24-month risk-free-adjusted industry returns (*IndRetRF24*), and 24-month market-adjusted industry returns (*IndRetMAR24*) across Columns 1-3, respectively. We use observations between 1992 and 2011 to obtain initial in-sample coefficient estimates. Using these coefficients, we calculate forecasted two-year-ahead returns for all run-ups that occurred in 2012, and update the coefficients each year thereafter through run-ups that occurred in 2020. The computed out-of-sample R^2 for all characteristics in predicting all three measures of future industry returns are presented in the table.

Figure 3: Maximum likelihood ROC Curve for out-of-sample crash prediction using NOA Accruals



Area Under Curve: 0.7285 (standard error = 0.071)

Table 9: Economic Mechanism – Tests of Overinvestment Explanation

Panel A: Association between ΔNOA and Investor Sentiment

	ΔNOA	*ΔNOA*
Sentiment (BWY)	0.088**	
	(2.57)	
Inflows		0.170***
		(3.80)
Volatility	0.243	0.236***
	(0.34)	(3.71)
Volatility-1yrChange	-0.028	-0.017
	(-0.45)	(-0.80)
Turnover	-0.007	0.002
	(-0.02)	(0.04)
Turnover-1yrChange	0.258	0.022
	(1.35)	(1.26)
IndustryAge	0.671	0.036
	(1.61)	(0.50)
AgeTilt	-0.030	-0.067
	(-0.19)	(-0.94)
PercentIssuers	0.296	0.085
	(0.39)	(0.97)
BooktoMarket	0.109	-0.004
	(0.46)	(-0.04)
SalesGrowth	0.628	0.416***
	(1.11)	(4.14)
Acceleration	-0.239	-0.012
	(-0.76)	(-1.19)
CAPE	0.001	0.001*
	(0.24)	(1.83)
PastReturns	0.099	-0.007
	(0.34)	(-0.94)
N	17	240
R^2	0.89	0.23

Panel B: Predicting Analyst Forecast Errors

	IndAFError
ΔNOA	1.756**
	(2.11)
Volatility	-1.636
	(-0.85)
Volatility-1yrChange	-0.017
	(-0.04)
Turnover	0.178
	(0.29)
Turnover-1yrChange	0.325
	(1.15)
IndustryAge	-1.501
	(-1.24)
AgeTilt	-2.265*
	(-1.72)
PercentIssuers	-0.468
	(-0.37)
BooktoMarket	1.153
	(0.87)
SalesGrowth	-0.674
	(-0.84)
Acceleration	0.035
	(0.27)
CAPE	0.018**
	(2.35)
PastReturns	0.099
	(0.65)
N	228
R^2	0.13

This table presents results to multiple OLS regressions linking investor sentiment to NOA Accruals in Panel A and predicting analyst earnings forecast errors in Panel B. The dependent variable in Panel A is *ΔNOA*, while the dependent variable in Panel B is the country-industry value-weighted analyst forecast error (*IndAFError*). The main explanatory variables are two measures of sentiment in Panel A – the country-year market sentiment index from Baker, Wurgler, and Yuan (2012) (*Sentiment (BWY)*) in Column 1 and country-industry net capital inflows (*Inflows*) in Column 2 – and the main explanatory variable is *ΔNOA* in Panel B. Controls for the GSY bubble characteristics and past 24-month raw industry returns are included in both panels. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 10: Predictability of Future Stock Prices using Components of ΔNOA Accruals – Multiple Regression including GSY Controls

Panel A: Working Capital Accruals				
	Crash	IndRet24	IndRetRF24	IndRetMAR24
ΔWC	0.177	-0.135	-0.136	-0.214
	(1.18)	(-0.77)	(-0.77)	(-1.02)
N	240	240	240	240
R^2	0.33	0.21	0.22	0.09
Controls	Y	Y	Y	Y

Panel B: Long-Term Net Operating Asset Accruals				
	Crash	IndRet24	IndRetRF24	IndRetMAR24
ΔLTNOA	0.143	-0.712**	-0.708**	-0.108
	(0.90)	(-2.49)	(-2.50)	(-0.59)
N	240	240	240	240
R2	0.33	0.24	0.25	0.08
Controls	Y	Y	Y	Y

Panel C: Long-Term Net Operating Asset Accruals & Working Capital Accruals				
	Crash	IndRet24	IndRetRF24	IndRetMAR24
ΔLTNOA	0.142	-0.712**	-0.707**	-0.106
	(0.91)	(-2.47)	(-2.47)	(-0.58)
ΔWC	0.176	-0.131	-0.132	-0.213
	(1.17)	(-0.80)	(-0.81)	(-1.02)
N	240	240	240	240
R^2	0.34	0.24	0.25	0.09
Controls	Y	Y	Y	Y
F-stat: Diff in coefficients	0.02	2.49	2.51	0.16
p-val: Diff in coefficients	(0.89)	(0.13)	(0.13)	(0.69)

This table presents results of multiple linear probability model regressions predicting the incidence of future industry-level crashes (*Crash*) and OLS regressions predicting future industry-level 24-month returns using industry-level working capital accruals (*ΔWC*) in Panel A, LTNOA accruals (*ΔLTNOA*) in Panel B, and both working capital and LTNOA accruals in Panel C, controlling for the GSY bubble characteristics. The dependent variable in Column 1 is a crash indicator, which equals one if there is a 40% drawdown from any point in the two years after the initial price run-up, and zero otherwise. The dependent variables in Columns 2-4 are the 24-month raw return (*IndRet24*), 24-month net of risk-free rate return (*IndRetRF24*), and 24-month net of market return (*IndRetMAR24*), respectively, all value-weighted at the industry level. Control variables included in all specifications are volatility (*Volatility*), change in volatility (*Volatility-1yrChange*), turnover (*Turnover*), change in turnover (*Turnover-1yrChange*), average firm age in the industry (*IndustryAge*), age tilt (*AgeTilt*), percentage of firms in the industry that issue equity (*PercentIssuers*), the book-to-market ratio (*BooktoMarket*), sales growth (*SalesGrowth*), acceleration (*Acceleration*), the CAPE ratio (*CAPE*), and past two-year raw industry returns (*PastReturns*), but the coefficients to the control variables are not tabulated for brevity. Panel C also presents the F-statistic and p-value from testing the significance in the difference between coefficients of *ΔLTNOA* and *ΔWC*. Standard errors are clustered by calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.

Table 11: Full Sample Tests

Panel A: Predictability of Future Performance using All Country-Industry-Months

	Crash	IndRet24	IndRetRF 24	IndRet MAR24	IndAF Error	MktRet24
ΔNOA	0.085***	-0.098***	-0.096***	-0.105***	0.216***	0.008
	(3.57)	(-2.88)	(-2.84)	(-4.74)	(2.65)	(0.23)
ΔNOA *Runup	0.434***	-0.691**	-0.690**	-0.204	1.305**	-0.534**
	(2.85)	(-2.58)	(-2.58)	(-1.26)	(2.35)	(-2.49)
Volatility	0.571***	0.140**	0.149**	0.086**	0.568***	0.140
	(12.46)	(1.97)	(2.12)	(2.51)	(3.81)	(1.34)
Volatility-1yrChange	-0.030**	-0.027	-0.029	-0.001	0.004	-0.042
	(-2.28)	(-1.21)	(-1.31)	(-0.11)	(0.10)	(-1.60)
Turnover	-0.106**	0.018	0.015	-0.043*	-0.427***	0.046
	(-2.28)	(0.34)	(0.27)	(-1.82)	(-7.57)	(0.76)
Turnover-1yrChange	-0.001	0.027**	0.021*	-0.004	0.194*	0.035**
	(-0.08)	(2.29)	(1.78)	(-0.67)	(1.71)	(2.37)
IndustryAge	-0.121***	0.157**	0.154**	0.058**	0.078	0.143**
	(-3.90)	(2.48)	(2.45)	(1.99)	(0.68)	(2.12)
AgeTilt	0.078	-0.103	-0.107	-0.010	-0.118	-0.066
	(1.62)	(-1.32)	(-1.38)	(-0.25)	(-0.92)	(-0.63)
PercentIssuers	0.234***	-0.234***	-0.253***	-0.153***	-0.071	-0.064
	(4.45)	(-3.14)	(-3.46)	(-4.71)	(-0.42)	(-0.86)
BooktoMarket	-0.022	0.204***	0.199***	0.039**	0.309***	0.154***
	(-1.33)	(7.11)	(6.96)	(2.55)	(5.88)	(5.09)
SalesGrowth	-0.010	0.194***	0.196***	0.040	-0.054	0.156***
	(-0.37)	(3.85)	(3.92)	(1.55)	(-0.58)	(3.15)
Acceleration	0.001**	-0.000	-0.000*	0.000	0.000	-0.001
	(2.20)	(-1.58)	(-1.67)	(1.20)	(1.16)	(-1.33)
CAPE	0.001***	-0.002***	-0.002***	-0.000	0.002	-0.002
	(3.33)	(-2.59)	(-2.73)	(-0.64)	(1.48)	(-1.04)
PastReturns	0.066***	-0.039**	-0.042**	-0.026***	0.016	0.008
	(5.43)	(-1.98)	(-2.15)	(-2.74)	(0.37)	(0.28)
Runup	-0.188**	0.310*	0.315**	0.114	-0.676***	0.177
	(-2.22)	(1.96)	(2.00)	(1.16)	(-2.59)	(1.44)
N	98187	98187	98187	98187	95308	98187
R^2	0.09	0.03	0.04	0.01	0.02	0.02
F Statistic	27.21	9.73	9.68	5.51	13.26	5.88
*ΔNOA +ΔNOA*Runup*	11.55	8.60	8.59	3.52	7.43	6.22
Joint F-statistic (p-value)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.06)*	*(0.01)*	*(0.01)*

Panel B: Association between ΔNOA and Investor Sentiment using all Country-Industry-Months

	ΔNOA	*ΔNOA*
Sentiment (BWY)	0.025***	
	(4.32)	
*Sentiment (BWY)*Runup*	0.043**	
	(2.25)	
Inflows		0.006
		(0.76)
*Inflows*Runup*		0.151**
		(2.22)
Volatility	0.128**	-0.033**
	(2.65)	(-2.42)
Volatility-1yrChange	-0.015	0.011***
	(-1.28)	(3.03)
Turnover	-0.021	0.039***
	(-0.34)	(2.88)
Turnover-1yrChange	0.019***	-0.000
	(5.57)	(-0.06)
IndustryAge	-0.024	-0.063***
	(-0.70)	(-5.18)
AgeTilt	0.029	-0.015
	(0.97)	(-0.89)
PercentIssuers	0.097***	0.072***
	(2.86)	(4.65)
BooktoMarket	-0.049*	-0.028***
	(-1.71)	(-4.78)
SalesGrowth	0.334***	0.306***
	(8.83)	(26.79)
Acceleration	-0.010	-0.000
	(-0.76)	(-0.38)
CAPE	-0.001	0.000*
	(-0.89)	(1.81)
PastReturns	-0.036***	-0.025***
	(-2.85)	(-8.37)
Runup	-0.017	-0.050
	(-0.54)	(-1.37)
N	12474	98178
R^2	0.33	0.17
F Statistic	25.57	70.65
Fixed Effects	C, I, Y	C, I, Y
*Sent +Sent*Runup*	12.26	5.21
Joint F-statistic (p-value)	*(0.00)*	*(0.02)*

This table presents results to multiple regressions using the full sample of country-industry-month observations in 49 countries. Panel A presents results to regressions in which the dependent variables are future industry-level crashes (*CRASH*), 24-month raw industry returns (*IndRet24*), 24-month risk-free adjusted industry returns (*IndRetRF24*), 24-month market adjusted industry returns (*IndRetMAR24*), industry-level analyst earnings forecast errors (*IndAFError*), and market aggregate returns (*MktRet24*) across Columns 1-6, respectively. Panel B presents results to regressions in which the dependent variable is *ΔNOA*. The main explanatory variable is *ΔNOA* in Panel A and two measures of sentiment in Panel B – the country-year market sentiment index from Baker, Wurgler, and Yuan (2012) (*Sentiment (BWY)*) in Column 1 and country-industry net capital inflows (*Inflows*) in Column 2, and their interactions with *Runup*, an indicator variable that equals one if the country-industry-month was first identified as a price run-up, and zero otherwise. Controls for the GSY bubble characteristics and past 24-month raw industry returns are included in both panels. Country, Industry, and Year fixed effects are included in both specifications. Standard errors are clustered by country-calendar year. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Definitions of variables are provided in Appendix A.