Measuring Market Froth*

Rajeev Bhargava

Robin Greenwood

Michael Guidi

Zachary Crowell

November 2022

Abstract: We define equity markets and sectors to be "frothy" when the probability of a future drawdown in prices is high. Using simple panel regressions, we analyze data across 80 countries and 400 country-sectors to identify and evaluate which factors--including issuance, volatility, the price path, and flow-based factors-- are most predictive of future sector-level drawdowns. We translate our predictive model into indicators for sector- and market-level froth.

* Rajeev Bhargava, Michael Guidi and Zachary Crowell are at State Street Associates. Robin Greenwood is at Harvard Business School and an academic affiliate of State Street Associates. Additional disclosures at https://www.hbs.edu/ris/Profile%20Files/Outside%20Activities%20RG_ed358270-4d82-4c9e-8b46-f1f847ab381a.pdf.

I. Introduction

Financial market practitioners often use the terms “froth” and “bubble” interchangeably. Following periods of high stock returns, there is inexorably talk that the market is “frothy” or potentially in a bubble, portending an eventual crash. Figure 1 below plots the frequency of internet searches for the term “Stock market bubble” since 2004, using data from Google trends. The figure reveals elevated concerns about a bubble in 2007, 2013, 2015, 2018, and especially in 2020 and 2021, when the stock market entered a large boom following a large drawdown in March 2020 driven by news about Covid-19.

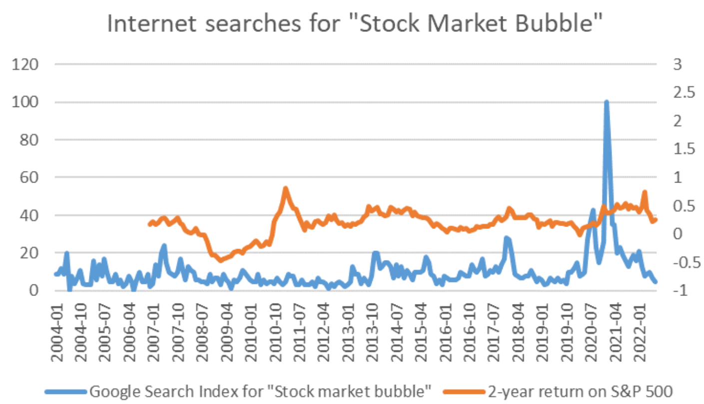

Figure 1: Plot of Google trends data for search term “stock market bubble” compared to 2-year return on the S&P 500

Although elevated past returns are a necessary condition for a bubble, they are not sufficient. Historical narratives of bubbles and crashes suggest financial froth is reflected in a variety of other factors, including elevated trading volume, stock price volatility, a speculative fever among market participants, security issuance, and more.[1] Shiller (2002) points to structural factors that start a bubble, “cultural factors” that sustain it, and psychological factors that help explain both the initial rise and crash. Kindleberger (1978), in his classic account of bubbles and crashes, describes booms that start with “displacement” based on strong fundamentals and transitions to “euphoria”. More recently, Greenwood, Shleifer, and You (2018) show that some of these additional factors can be quantified empirically to help

[1] See [add references]

distinguish whether an industry price run-up is truly a bubble. Studying 40 sector price run-ups in the United States between 1928 and 2014, they show that extreme price run-ups are more likely to end in a crash if they are also accompanied by increases in volatility, stock issuance, acceleration (a convex price path), an elevated market P/E ratio, and disproportionately high returns among new companies.

In this paper, we adopt a panel-regression approach to measuring financial froth in a sector, which we define as an elevated probability a subsequent large drawdown. In doing so, we follow Greenwood, Shleifer, and You (2018), who define a crash as the occurrence of a 40% drawdown occurring within a 2-year window of the forecast date. Under this definition, US technology-sector stocks crashed in 2000 and 2001, China Materials in 2007, and Netherlands Health Care in 2014, for some examples. Our goal is to produce simple indicators, akin to a credit rating, that indicate the probability of a future significant drawdown. Compared to Greenwood, Shleifer, and You (2018), we expand the analysis along three dimensions. First, Greenwood et al study a handful of only the most extreme run-up episodes throughout history, with price increases of 100% or more over the market; we expand the analysis to study all periods between 1990 and 2021 for 11 sectors across 80 countries. Second, rather than conditioning on extreme high past returns (and thus limiting the analysis to a small number of potential episodes), we include past returns as well as a host of other predictor variables to forecast the probability of a future drawdown. Third, we consider an expanded set of predictor variables, including measures of investor flows and positioning. These design choices are supported by the data, because we find that a recent price run-up, although indicative of financial froth, is far from the whole story.

We estimate two baseline models. In the first, we predict sector-level drawdowns directly, where drawdowns can vary between 0% (if prices remain always at their peak) and 100% (if prices completely collapse, even if not immediately). In the second model, we predict the occurrence of a large drawdown, defined as a 40% or more fall from peak, occurring within two years of the prediction date.

Our main predictors include: past returns; stock issuance; past volatility of returns; turnover; “peak count” defined as the number of times that the sector has surpassed a prior peak; current drawdown; and two measures of financial market flows.

We report three main findings. First, although the predictive ability of any one of these variables in isolation for a future crash is limited – typical R-squared statistics associated with univariate predictive regressions are approximately 2% - their collective explanatory power is significantly higher, with R-squared of 12% in the main global sample and 28% in the US subsample. This suggests that market froth is inherently a function of several variables, and a model that attempts to predict it needs to use several inputs and account for the interactions between them. It is considerably easier to predict the incidence of crashes than it is to predict future average returns, because even sectors that have a high probability of a crash may avoid it, or the crash can come much later. Our multivariate panel regression predicts an average large drawdown probability of 29%, with the average predicted drawdown being 26%.

Second, we investigate the special role of past returns as a predictor, by isolating the sector-months in our data when past 2-year returns have exceeded 50%, which holds for approximately 17% of our sector-month observations. For most of the variables we study (such as issuance, for example), the predictive power is weakened in this subsample. This echoes the conclusions in Goetzmann (2016) who suggests that the probability of a crash conditional on a boom is only slightly higher than the unconditional probability.

Third, we investigate the statistical properties of the predictor that we build. We perform an analysis to determine the probability that certain levels of prediction will be followed by an actual drawdown event, as well as the probability that actual drawdown events are preceded by certain levels of prediction, in what is essentially a clinical investigation of Type 1 and Type 2 errors. We also investigate the timing of our predictions relative to actual drawdown events occurring during 2022.

Our paper is related to several lines of prior research. First, most directly related is Greenwood, Shleifer, and You (2018) who collect 40 episodes of industry price run-ups in the United States. They show that while high past returns predict an elevated probability of a future drawdown, high past returns alone do not predict future returns, because some price run-ups simply continue. Second, our paper joins a long tradition of historical and empirical work studying bubble and crash narratives, beginning with Mackay (1841) and Goetzmann (2016), but also including modern studies of the crash of 1929 (White 1990), and the internet bubble (Lamont and Thaler 2003). Third, our paper joins a smaller literature of papers forecasting increased volatility, or forecasting crashes (Engle and Ng 1993; West 1988; Chen, Hong and Stein 2001). Goetzmann and Dasol provide an account of what happens after a crash; Goetzmann, Kim and Shiller (2022) suggest that media narratives may also be helpful for studying crashes.

Section II describes our primary variable of interest, and the set of predictor variables that we consider. In Section III, we present results from our baseline regressions, as well as several variations such as conditioning on high past returns. Fitted values from these regressions constitute our measure of market froth. Section IV describes the statistical properties of our resulting model, focusing on the tradeoff between false positives and false negatives for an investor who is trying to avoid market crashes. Section V describes potential implications for trading strategies based on avoiding frothy markets. Section VI concludes.

II. Data and Predictors of Froth

Our primary variable of interest is the US dollar sector-level return, which we compute by aggregating individual stock returns of the companies in 12 sectors in 44 countries with liquid stock markets. We consider a country-sector as eligible for analysis as long as it has at least two listed firms in that month. While our original data is daily, we collapse to a monthly panel.

Our main variable of interest is a forward-looking maximum drawdown. This is the maximum drawdown experienced by a sector over the subsequent 24 months, based on closing prices at the end of month *t*. Formally, this is the maximum peak-to-trough drawdown in the returns index over the next two years. For example, if the highest peak in the returns index of the country-sector over the next two years is 100, and the lowest trough occurring *after* that peak is 25, then the reported country-sector 2 year forward looking maximum drawdown is 0.75. Because the maximum drawdown is, by construction, forward looking, there is no mechanical correlation between this and whether the sector is *currently* in a drawdown state in month *t*, although in the data these two events are correlated. On average, sectors are in a drawdown over 90% of the time, but only 25% of the time are they in a drawdown that exceeds 30% and only 10% of the time are they in a drawdown of more than 50%.

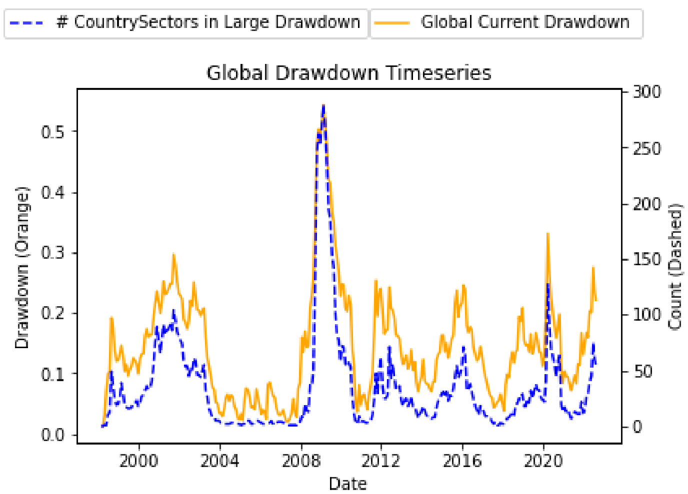

Figure 2: Global Drawdown Metrics

Predictor Variables

To conduct our analysis, we assemble a set of predictor variables motivated by previous work, including measures of issuance, volatility, trading volume, and the price path. We use a limited set of predictors to avoid the potential for overfitting, starting with variables suggested by Greenwood, Shleifer, and You (2019) but adapted for data availability in an international sample. There is surely potential to expand the set of potential predictors in future work.

Our predictor variables, summarized in Table 1, include:

- $R_{[t\text{-}24,t]}$: the market capitalization weighted contemporaneous 2-year return of a country-sector at time *t*. The average 2-year return is 22.7%, with a cross-sectional standard deviation of 62.9%.
- Fraction Large Issuance$_{[t\text{-}24,t]}$: the fraction of firms within a country-sector that issued greater than 10% common stock in the two years leading up to time t. Common stock issuance is based on the percentage change in split-adjusted shares outstanding from MSCI. As can be seen in Table 1, average issuance fraction is approximately 10.9% over a two-year period, but it varies significantly.
- Total Issuance (EW)$_{[t\text{-}24,t]}$: Using this firm level issuance calculation over the 24 month period leading up to t, we calculate as the equal weighted average issuance of the country-sector, winsorized at 100%. Average issuance is 5.5% with a standard deviation of 12.3%.
- $\sigma_{[t\text{-}24,t]}$ is the volatility in daily country-sector returns in the 24 months leading up to *t*. Average two year daily volatility is 1.8% with a standard deviation of .7%.
- $tv_{[t\text{-}24,t]}$ / $tv_{[t\text{-}48,t\text{-}25]}$ is the ratio of market-cap weighted country-sector turnover in the 24 months leading up to *t*, to the same calculation in the prior two year interval. This value is winsorized to have a maximum value of 3, and turnover at the firm level is calculated as the total volume over the specified time interval divided by the mean shares outstanding in the time interval. The average momentum is 1.28.
- Peak Count$_t$:is the number of times the market-cap weighted return index of the country-sector reaches an all-time peak in the 24 months leading up to *t*. Peak Count is closely related to a variable explored in Greenwood, Shleifer, and You (2019), which they call “convexity”, and which measures the price path. The average count is 2.8 with a standard deviation of 4.0.

- Drawdown_t is the *current* drawdown over the past 24 months that the Country-Sector is experiencing at *t*.

We supplement these price, volume, and issuance related predictor variables with time series measures of investor behavior and flows:

- IB_t is a binary flag variable based on the 5-year rolling Z-score of total sector flows and the 5-year rolling Z-score of excess country holdings. This flag is activated if the Z-scores for both of these IB variables is greater than 3. IB is a measure of whether investors have built up an extreme overweight position in the corresponding country and are continuing to buy the corresponding sector at a high level.
- BRS_t: The behavioral risk score, a composite measure of flows across many asset classes compiled by State Street based on their custody data. It measures institutional investors' risk appetite, with positive scores denoting "risk-on" and negative scores denoting "risk-off". We rescale BRS such that it is expressed as a percentage of its maximum value over the time series. The average value of this variable is .092 with s standard deviation of .345.
- Peak Count x BRS_t is an interaction variable between our peak count variable and the aggregate flows and holdings behavioral risk score

III. Forecasting Crashes

Tables 2-5 present forecasting regressions of the form

$$MaxDrawdown_{[it,i(t+24)]} = \beta_0 + \beta X_{it} + u_{it}, \qquad (1)$$

where *X* is a vector of predictive variables. Our main dependent variable is the maximum future drawdown, although we also later present regressions where the dependent variable is instead an indicator variable that takes a value of 1 when the maximum future drawdown exceeds 40%.

A few comments are in order about this specification. First, to reduce the risk of overfitting, we constrain coefficients to be identical across countries and sectors. Second, except for our flow measure, all variables are included in linear form without interactions. Third, we are not limiting the sample to high past return episodes; we estimate it informed by all market conditions.

Panel A of Table 2 shows the main results. We first summarize univariate specifications and then describe the multivariate results. Column (1) shows the results using past returns alone. Past returns attract a coefficient of 0.025, which means that a 100% past return increases expected drawdown by 2.5 percentage points, compared to its unconditional return of 30%. This coefficient increases to .034 when returns is used with other predictors in a multivariate specification.

Column (2) shows the results when using the large run-up return binary flag variable with just the % return predictor in a bivariate regression. In this case, the binary flag return variable attracts a coefficient of .063, meaning that when the two-year country-sector return greater than 100% increases the predicted drawdown by 6.3 percentage points. Interestingly, when this variable is regressed with the rest of our predictor variables in our multivariate regression, the sign flips, driven substantially by its correlation with the continuous measure of past returns.

We see a similar phenomenon with the fraction of firms in the country-sector that issue more than 5% of their stock in the 2 years leading up to an observation. In univariate predictive regressions (column 3), this measure of issuance attracts a coefficient of 0.06, a relatively modest effect meaning that if 100% of the firms in a country issuing greater than 10% of stock, that this increases the predicted drawdown by six percentage points. However, when this variable is included with the rest of our predictor variables it attracts a coefficient of -.006. This change in coefficient sign is likely due to the inclusion of the next predictor variable, namely the Equal Weighted Issuance of the country-sector, with which it is 72% correlated. Equal weighted issuance attracts a coefficient of .149 (statistically significant at the 1% level), meaning that an equal weighted issuance of 10% increases the predicted drawdown by 1.5 percentage points. This coefficient moves to .111 in the multivariate regression.

Column (5) shows that past return volatility is a strong predictor of future drawdowns: the coefficient of 6.474 implies that a 1% standard deviation in daily country-sector returns in the 2 years leading up to an observation increases the predicted drawdown by a sizeable 6.5%. In the multivariate specification with other predictors, the coefficient is similar.

Column (6) shows that elevated turnover is also helpful for forecasting drawdowns. The regression of our turnover momentum variable with our return (%) variable in column (6) returns a coefficient of .029 for turnover momentum. This implies that if turnover momentum at an observation is 100%, the predicted drawdown will increase from 26% to 28.9%. When regressed with the rest of our predictors, the coefficient becomes .014.

Column (7) shows that current drawdowns predict future additional drawdowns. Column (8) shows that our measure of the price path, "peak count", which varies from 0 to 24, strongly predicts future drawdowns.

Last, we turn to measures of investor behavior. Column (9) shows that BRS attracts a coefficient of -0.073. This corresponds to a negative one standard deviation change leading to a 7.3 percentage point increase in predicted drawdown. A similar coefficient obtains in the multivariate specification. Column (10) shows that there is an interaction between BRS and a measure of the price path. Column (11) shows that that IB attracts a coefficient of .231. Thus, when both excess country holdings and total sector flows have Z-scores greater than 3, admittedly a rare event, the predicted drawdown increases by 23.1%. Similar effects obtain in the multivariate specification.[2]

The results of our multi-variate panel regression for our full global sample offer some rather intuitive results. An increase in country-sector returns and return volatility implies a larger impending drawdown, as well as increases in issuance and turnover. In what follows, we treat the full multivariate specification in Column (12) as the "baseline" model.

The next panel of Table 2 repeats our analysis on the US-only sample of sector drawdowns. As can be seen, the results on this smaller sample are largely similar, but with some interesting differences vis-à-vis the global sample. For example, the coefficient of the large run up return binary flag variable is .104 with a t-statistic of 1.366 for the US-only sample (Table 2.B) in the multivariate regression. In the global sample, this coefficient is -.014, telling us that in the US model the large return binary flag variable being activated is a much stronger indicator of a larger impending drawdown, consistent with Greenwood, Shleifer and You (2019)'s results. Because this result does not hold in the global sample. We see a similar phenomenon occur when using past volatility as a predictor: the effect is much stronger in the global sample.

In repeating the multivariate regression in Table 2.B for the rest of the countries in the G10, we see similar results. It is also a noticeable trend that the R-squared of regressions at the country level are significantly higher than at the global level.

Perhaps the most interesting conclusion from our multivariate global full sample panel regression (Table 2.A, column 12) is found in the coefficient of our Peak Count x BRS interaction variable. The Behavioral Risk Scorecard aggregates several flows and holdings indicators to gauge the global appetite for risk amongst investors. This score has a range between -1 and 1, with -1 reflecting high investor risk aversion, and 1 reflecting investor "risk on". The Peak Count x BRS interaction variable is simply the product of this risk score with the number of times that the monthly return index of the country-sector has hit an all-time high in the 24 months leading up to an observation, and thus can take on any value between -24 and 24. The statistical significance of this interaction term can be interpreted as saying that crashes are very likely if prices have risen rapidly *and* investors are bearish. A nice illustration of this point comes from looking at the US financial sector during the 2008-2009 financial crisis.

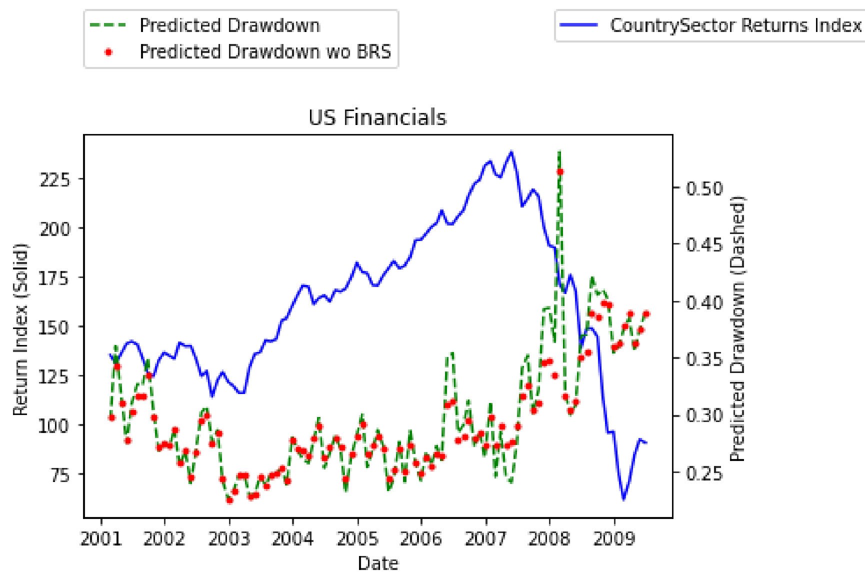

Figure 9: US Financials Froth Predictions with and without Peak Count x BRS variable

The predicted drawdown for the US financial sector (green) spikes to high relative levels in the months leading up to the global crash in 2007. This prediction is in large part driven by investor flow variables. Specifically, if we consider our predictions without the Peak Count x BRS interaction variable (red), we see that our drawdown predictions increase much more gradually, not raising alarm until well after the actual drawdown begins.[3]

We next vary the dependent variable to be a binary measure of whether the sector experiences a large drawdown over the next 24 months, where "large" is defined as 40% or more. We estimate specifications of the form:

[3] More generally, beyond this bit of anecdotal evidence, we see that the inclusion of the BRS in predicting drawdowns increases the probability that a large drawdown event is preceded by a large drawdown prediction, as seen in Table 7. We can also see that removing the BRS variable from our predictions increases the mean number of months prior to a drawdown event that a large drawdown prediction is first made, if it is made at all. This implies that the Peak Count x BRS serves effectively in timing these predictions so that they first occur closer to when drawdown events occur.

$$MaxDrawdown_{[it,i(t+24)]} > 40\% = \beta_0 + \beta X_{it} + u_{it}, \quad (2)$$

These results are shown in Table 3A, 3B, and 3C, and adopt a parallel structure to Table 2, where we estimate regressions first on the full sample, and then on narrower country-specific samples. In a direct comparison of R-Squared values, the probability model is a little over half the predictive power of the size model, with an R-squared of .073. Most of our variables in both multivariate models have comparable signs and t-statistics, implying that their predictive power for each model is similar.

In Table 4, we perform the same regression in Table 2.A, only we limit our input data to observations in which the two-year run-up returns of the country sector exceed 50%. In the bivariate regressions shown in columns (1) through (11) in Table 4, we see coefficients and *t*-statistics largely similar to those in the same columns of Table 2.A. The results of the multivariate regression in column 12 of Table 4 are also mostly similar to that of Table 2.A, with a few notable exceptions, namely that past returns and the current drawdown variables are less statistically significant.

IV. How Predictable are Drawdowns?

In this section, we evaluate the predictive power of the model for drawdowns. In some sense, we have already done so, by reporting R-squared, the simplest measure of model fit, which varies between .073 (Table 3.A) and .116 (Table 2.A) in our multivariate specifications. Below we go beyond simple measures of fit and evaluate the model according to three additional tests. First, how well does the model predict global average drawdowns? Second, what is the nature of false positives and false negatives? Third, we perform an out-of-sample exercise to evaluate how effective the model was at predicting the cross-section of market drawdowns experienced in 2022.

Predicting global drawdowns

Figure 3 plots average global predicted drawdown, based on fitted values of Eq. (1) averaged across all country-sectors, against the average realized drawdown. A good model would generate elevated drawdown probability at some point in the 24 months prior to an actual large drawdown. We see such a trend in Figure 3, with global average predicted drawdowns elevating to significant levels in the months leading up to elevated actual drawdown levels. Take the 2008 global financial crisis for example. Actual drawdown levels begin to spike in 2008, but actual global drawdown prediction levels reach significant levels in 2007.

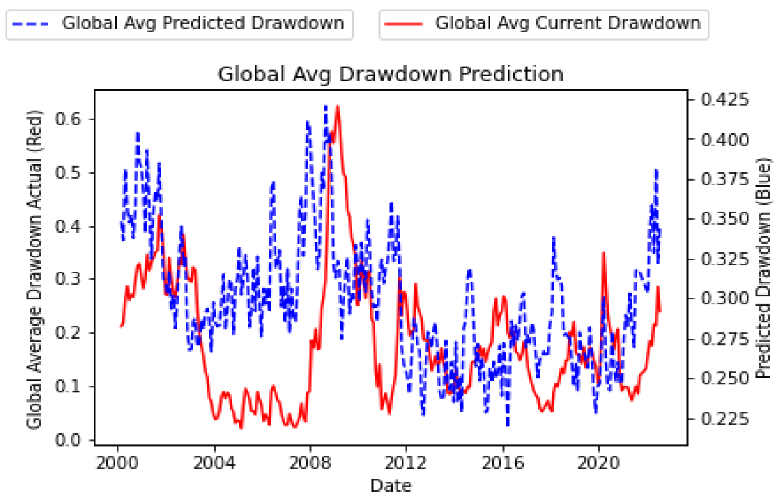

Figure 3: Global Average Prediction Timeseries

Type 1 and Type 2 errors

While the model has substantial predictive power, there are still large prediction errors, in the sense that the model fails to flag some large drawdowns, and identifies warning signs in other cases when no price collapse subsequently occurs. The tradeoff between these different type-1 and type-2 prediction errors depends on how the model is used, and the disutility the investor associates with false negatives and false positives. Table 6 digs into the predictions of the global full sample panel model, seeking to understand the frequency with which our model correctly identifies crashes that ultimately materialize within 24 months, as well as studying the events in which a substantial crash in stock prices occurs, but the model did not provide much warning.

Table 6 shows these results. Note that because the model is continuous, we much specify a threshold under which the model identifies a frothy sector. To incorporate this into our analysis, we set various cutoffs for which we consider our model to be predicting a large drawdown. It must also be noted that not all crashes are of the same severity and the severity of a crash is influenced by overall market froth. Thus, we also analyze prediction accuracy in consideration of drawdowns at the 20%, 40%, and 50% level.

We begin in Panel A by analyzing the proportion of our predictions of the model in column (12) of Table 2 that are followed by a true drawdown event. As the prediction cutoff increases, the likelihood of a large drawdown event increases, but the likelihood of drawdown decreases with drawdown size.

We have analyzed carefully a number of episodes in which the model has performed well, and when it has performed less well, and offer some examples below. Consider for example Figure 4, which shows the prediction dynamics of the China materials sector through time, and is an excellent case study of how the model in column (12) of Table 2.A measures market froth. We can clearly see that as the return index of the sector spikes when the sector is being highly valued, so too does the predicted drawdown of the sector, indicating that the models is measuring higher levels of froth. The predicted drawdown tends to peak right as the return index begins to crash, showing that our froth measure is useful predictor of crashes.

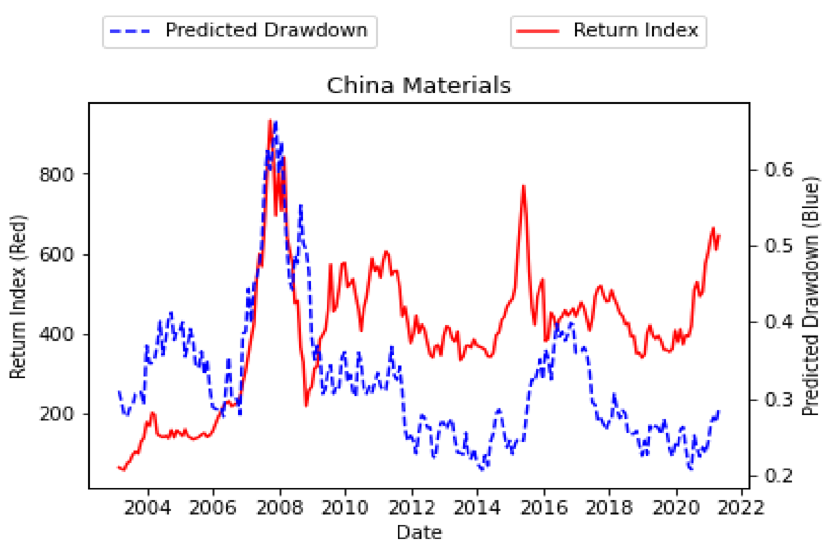

Figure 4: China Materials Sector Predicted Drawdown Timeseries

There are many drawdowns that our model doesn't detect simply because it isn't designed to do so. This is most commonly seen in Energy sectors. Such sectors are often heavily exposed to commodity prices and other market-external factors. Consider as an example US energy sector in Figure 5.

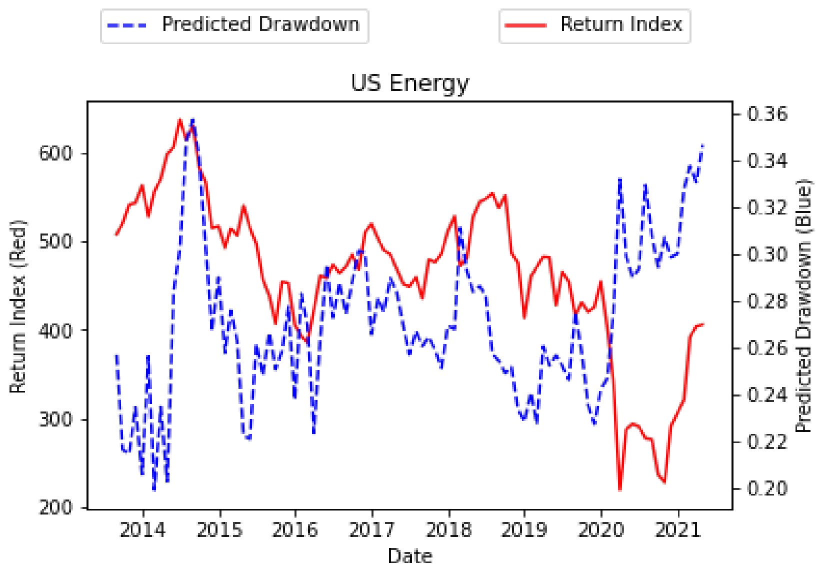

Figure 5: US Energy Sector Predicted Drawdown Timeseries

Here we can see that the predicted drawdown never really reaches a high level, barely scratching 30% on a few occasions. That being said, the sector undergoes some significant drawdowns in 2014, 2018, and 2020 that perfectly coincide with major drops in oil future prices. Our model is not built to anticipate such events, and thus causes us to miss drawdowns driven by commodity prices from time to time.

Another potential test of the model is to subject it to an out-of-sample analysis. As an out of sample test, we compare the most recent market drawdowns experienced in nearly all markets and sectors in 2022 to those predicted by our model. Figure 6 shows such an analysis. To do so, we plot the actual drawdowns of 568 sectors in 78 countries between June 2021 and September 2022 against the model maximum predicted drawdown based on June 2021 data. There is a 37% correlation between predicted drawdowns and actual drawdowns for this period: sectors that have a larger predicted drawdown tend to experience larger actual drawdowns.

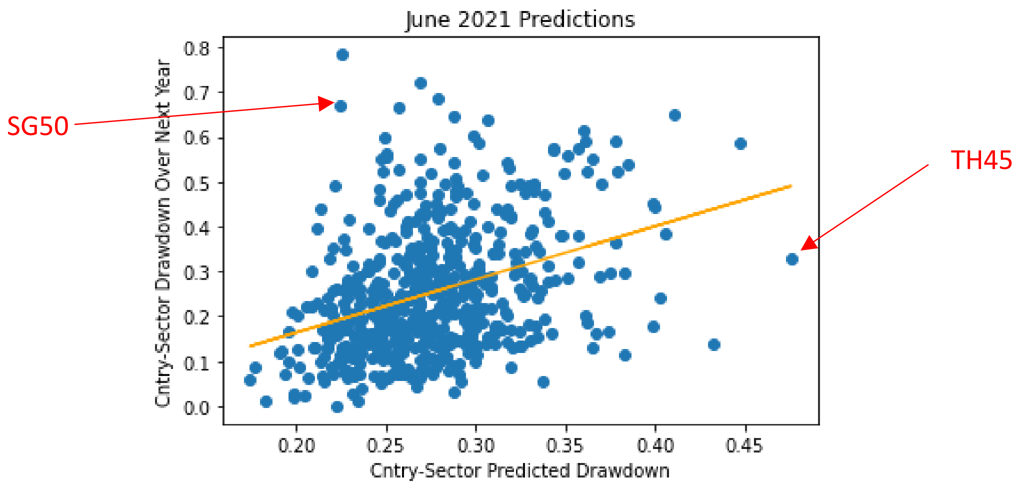

Figure 6: Country-Sector Level Drawdown Predictions for next 2 years for June 2021

We now analyze the evolution of drawdown predictions on a few out-of-sample examples; Singapore Communications Services (SG50) and Thailand Technology (TH45).

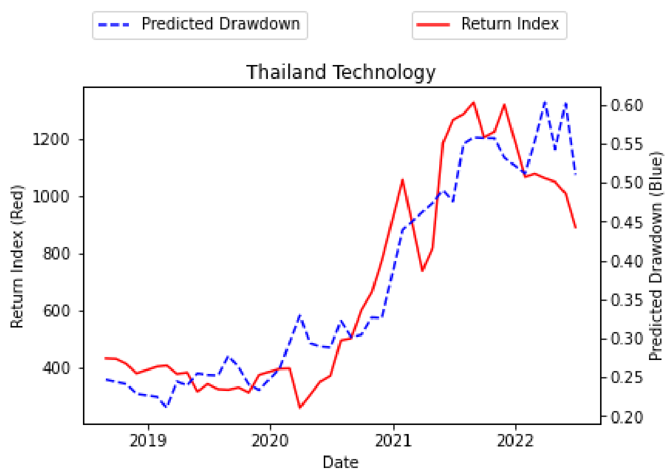

Figure 7: Thai Technology Froth Predictions

Figure 7 clearly shows the froth predictions of the TH45 country-sector tracking its returns index, and reaching a significant predicted drawdown level of approximately 55.8% at the peak of the return index.

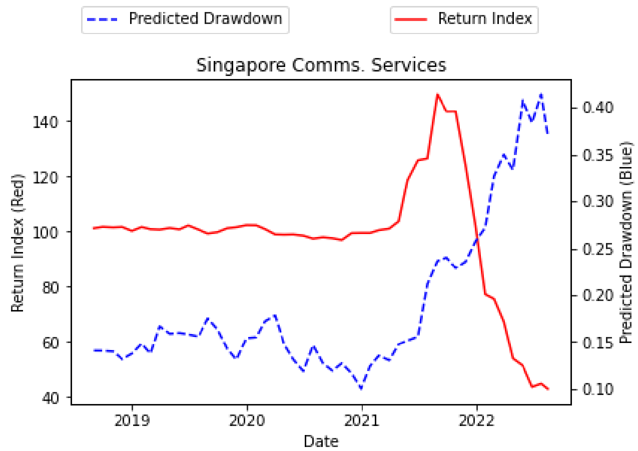

Figure 8: Singapore Comms. Services Froth Predictions

Singapore communications services provides an excellent example of a missed drawdown prediction. The predictions fail to reach any significant level and lag the return index of the country-sector, not reaching a significant level until well into the drawdown event.

V. Trading strategies

We have emphasized that predicting drawdowns is not the same as predicting returns – even in the cases where we correctly identify a future drawdown, our timing may be off, or perhaps the sector continues to run up before it crashes. Nevertheless, it seems plausible that if the model can inform avoiding the most extreme potential bubbles, that analyzing the resulting return implications is worthwhile.

We analyze a trading strategy based on the idea of avoiding sectors with high propensity for a future drawdown. As a benchmark, we consider simply the market-cap weighted global return index based on all countries in our sample.

The first strategy we consider is based on eliminating the top quartile of frothy sectors from the portfolio in each month. A second type of strategy is based on the idea that we could exclude sectors for which predicted future drawdowns exceed 30%. Cumulative returns to both strategies are shown in Figure

10, and summarized in Table 7, which reports average month returns, as well as estimates from a CAPM regression of monthly returns on a constant and the value-weighted global market. The cutoff strategy provides the largest alpha to the benchmark return index, 0.002. The quartile strategy also attracts a positive alpha, but is much smaller at 0.0005.

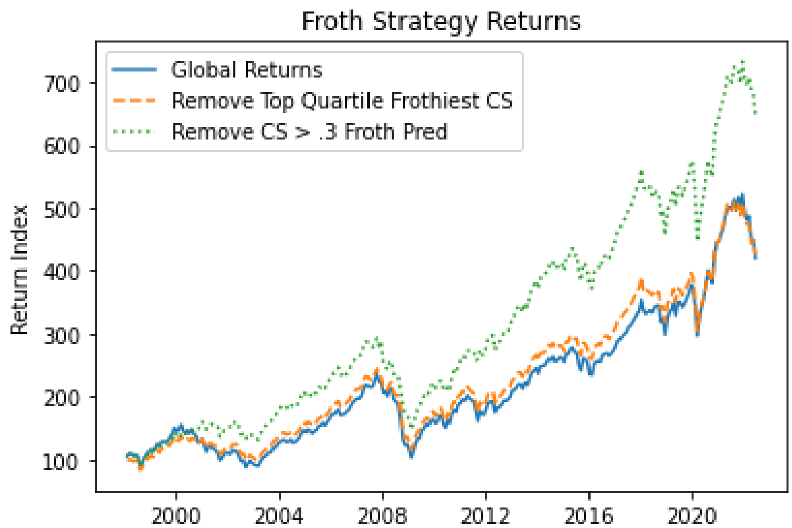

Figure 10: Comparison of Trading Strategies Built from Froth Metrics

VI. Conclusion

In this paper, we use simple panel regressions based on characteristics of over 80 countries and 400 country-sectors since 2000 to predict sector-level drawdowns. Consistent with other work that analyzes stock market bubbles, we show that several factors, including issuance, volatility, and the price path predict the potential for future declines. In addition, we add flow-based variables based on investor inflows and positioning, finding that these also help predict drawdowns. We interpret predicted values from these regressions as a measure of market froth.

Our findings add to a growing literature that periods of market froth concern more than simply high prices, or high valuation ratios, as suggested by Kindleberger, Minsky, and others. In fact, our data suggest that high past returns alone have at best only modest predictive power for future drawdowns; predictive power increases substantially based other measures such as volatility, the price path, trading volume, issuance, and investor behavior. An out-of-sample exercise based on the market drawdowns experienced in global markets during 2022 performs well, with large predicted drawdowns in 2021 leading larger realized drawdowns.

In performing our analysis, we have drawn upon a deliberately spare set of predictor variables from previous research that has studied bubbles. And, to limit data snooping, we have constrained our approach to simple linear specifications with a constant set of coefficients across all countries and all sectors. Future research is sure to add flexibility to this, potentially increasing predictive power. In addition, recent advances indicate that non-traditional data, such as information about media narratives (Goetzmann, Kim, and Shiller 2022; Bhargava, Lou, Ozik, Sadka, and Whitmore 2022) may be brought to bear on this question.

I. References

Baker, M., Wurgler, J., 2000. The equity share in new issues and aggregate stock returns. J. Finance 55, 2219-2257.

Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2019. Extrapolation and bubbles. J. Financ. Econ. 129, 203-227.

Brunnermeir, M., Nagel, S., 2004. Hedge funds and the technology bubble. J. Finance 59, 2013-2040.

Chen, J., Hong, H., Stein, J., 2001. Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. J. Financ. Econ. 61, 345-381.

Engle, R. F. and Ng, V. K. (1993). Measuring and testing the impact of news on volatility. Journal of Finance, 48:1749–1778.

Fama, E., 2014. Two pillars of asset pricing. Am. Econ. Rev. 104, 1467-1485.

Froot Bhargava, Cuipa, and Arabadjis, Multi-Asset Sentiment and Institutional Investor Behavior: A Cross-Asset Perspective, The Journal of Portfolio Management, Summer 2014. Available at https://www.iijournalseprint.com/JPM/SSGX/Sum14MultiAssetSentiment73j/index.html

Galbraith, J., 1954. The Great Crash 1929. Houghton Mifflin, New York.

Garber, P., 1989. Tulipmania. J. Polit. Econ. 97, 535-560.

Garber, P., 1990. Famous first bubbles. J. Econ. Perspect. 4, 35-54.

Goetzmann, W., 2016. Bubble investing: learning from history. CFA Res. Found. 3, 149-168.

Goetzmann, William N. and Kim, Dasol, Negative Bubbles: What Happens after a Crash (September 2017). NBER Working Paper No. w23830, Available at SSRN: https://ssrn.com/abstract=3038658

Goetzmann, William N. and Kim, Dasol and Shiller, Robert J., Crash Beliefs from Investor Surveys (March 19, 2016). Available at SSRN: https://ssrn.com/abstract=2750638 or http://dx.doi.org/10.2139/ssrn.2750638

Goetzmann, William N. and Kim, Dasol and Shiller, Robert J., Crash Narratives (July 2022). NBER Working Paper No. w30195, Available at SSRN: https://ssrn.com/abstract=4153089

Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. J. Financ. Econ. 93, 239-258.

Greenwood, Robin, Andrei Shleifer, and Yang You. "Bubbles for Fama." Journal of Financial Economics 131, no. 1 (January 2019): 20–43.

Griffin, J., Harris, J., Shu, T., Topaloglu, S., 2011. Who drove and burst the tech bubble? J. Finance 66, 1251-1290.

Kindleberger, C., 1978. Manias, Panics, and Crashes: A History of Financial Crises. Palgrave MacMillan, London, UK.

Lamont, O., Thaler, R., 2003. Can the market add and subtract? Mispricing in tech stock carveouts. J. Polit. Econ. 111, 227-268.

Mackay, C., 1841. Extraordinary Popular Delusions and the Madness of Crowds. Richard Bentley, London, UK.

Pontiff, J., Woodgate, A., 2008. Share issuance and cross-sectional returns. J. Finance 63, 921-945.

Scheinkman, J., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Polit. Econ. 111, 1183-1219.

Shiller, R., 2000. Irrational Exuberance. Princeton University Press, Princeton, NJ.

White, E., 1990. The stock market boom and crash of 1929 revisited. J. Econ. Perspect. 4, 67-83.

Table 1: Summary Statistics

Mean, standard deviation, and percentiles for predictor variables. The sample includes all country-sectors with two or more firms in that month. R denotes the value-weighted return; Fraction Large Issuance denotes the fraction of firms with split-adjusted common stock issuance in excess of 10%; Total Issuance is the equal-weighted split-adjusted common stock issuance; σ is the standard deviation of daily sector returns; tv[t-24,t] / tv[t-48,t-25] denotes scaled turnover; Peak Count is the number of times the sector return index has hit a monthly peak; Drawdown is the current 2 year drawdown of the country-sector, IB is the investor flow and positioning variable, BRS is the scaled global behavioral risk score, Max Drawdown is the target variable; the market-cap weighted 2YR future max drawdown.

	Variable Distributions									
	N	***Mean***	***Std.***	***Min***	***10%***	***25%***	***50%***	***75%***	***90%***	***Max***
$R_{[t-24,t]}$ (%)	105,430	0.227	0.629	-0.993	-0.402	-0.165	0.121	0.475	0.938	5.000
$R_{[t-24,t]} \geq 100\%$	112,052	0.084	0.278	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Fraction Large Issuance$_{[t-24,t]}$ (%)	112,052	0.109	0.175	0.000	0.000	0.000	0.000	0.167	0.333	1.000
Total Issuance (EW)$_{[t-24,t]}$ (%)	102,045	0.055	0.123	-0.671	-0.016	0.000	0.017	0.082	0.178	1.000
$\sigma_{[t-24,t]}$	108,899	0.018	0.007	0.005	0.010	0.013	0.017	0.022	0.028	0.080
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ (%)	104,585	1.280	0.796	0.000	0.538	0.770	1.036	1.506	3.000	3.000
Peak Count$_t$	108,883	2.683	4.018	0.000	0.000	0.000	0.000	5.000	9.000	22.000
Drawdown$_t$ (%)	111,480	0.191	0.202	0.000	0.000	0.022	0.126	0.299	0.498	0.994
IB_t	112,052	0.000	0.008	0.000	0.000	0.000	0.000	0.000	0.000	1.000
BRS_t	112,052	0.092	0.345	-0.849	-0.376	-0.118	0.097	0.322	0.534	1.000
Peak Count$_t$ x BRS_t	108,883	0.105	1.646	-16.971	-0.833	0.000	0.000	0.161	1.531	16.000
Max Drawdown$_{[t, t+24]}$ (%)	111,860	0.305	0.190	0.000	0.100	0.157	0.260	0.412	0.591	0.991
Firms in Country-Sector (Non-Input)	112,052	25.349	74.092	1.000	1.000	2.000	5.000	16.000	51.000	853.000

Table 2: Baseline Specification

Panel regressions of the maximum 2-year drawdown on predictor variables, *t*-statistics based on standard errors clustered at the year level shown in brackets. Regression data from January 2000-December 2020. Coefficients are shown with *t*-statistics in brackets.

Panel A: Global Full sample

	Dependent Variable: Maximum 2-year Forward Looking Drawdown (%)											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant	0.295	0.294	0.288	0.283	0.175	0.258	0.237	0.286	0.303	0.294	0.295	0.149
	[15.979]	[15.721]	[15.101]	[15.709]	[6.108]	[14.277]	[10.816]	[18.774]	[16.623]	[19.946]	[15.983]	[5.545]
$R_{[t-24,t]}$ *(%)*	0.025	0.005	0.026	0.027	0.037	0.023	0.073	0.014	0.020	0.010	0.025	0.034
	[0.965]	[0.159]	[0.986]	[1.058]	[1.407]	[0.893]	[2.9]	[0.728]	[0.796]	[0.558]	[0.965]	[2.086]
$R_{[t-24,t]} \geq 100\%$		0.063										-0.014
		[3.032]										[-1.321]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.060									-0.006
			[4.613]									[-0.332]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				0.149								0.111
				[8.680]								[3.449]
$\sigma_{[t-24,t]}$					6.474							5.762
					[6.084]							[5.589]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.029						0.014
						[4.026]						[1.742]
Drawdown$_t$ *(%)*							0.246					0.066
							[5.676]					[1.287]
Peak Count$_t$								0.004		0.004		0.005
								[1.132]		[1.199]		[1.323]
BRS_t									-0.073	-0.056		-0.071
									[-2.556]	[-2.465]		[-2.969]
Peak Count$_t$ *x* BRS_t										-0.006		-0.005
										[-1.195]		[-1.042]
IB_t											0.231	0.173
											[3.490]	[2.992]
N	105,263	105,263	105,263	101,897	105,252	104,428	105,263	105,252	105,263	105,252	105,263	101447
R^2	0.007	0.012	0.010	0.018	0.071	0.023	0.052	0.014	0.025	0.032	0.007	0.116

Panel B: US Full sample

	Dependent Variable: Maximum 2-year Forward Looking Drawdown (%)											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant Term	0.182	0.186	0.130	0.132	0.108	0.065	0.118	0.159	0.192	0.171	0.182	0.034
	[7.794]	[7.956]	[3.882]	[4.68]	[1.932]	[2.23]	[4.199]	[7.872]	[8.356]	[8.099]	[7.793]	[0.827]
$R_{[t-24,t]}$ *(%)*	0.021	-0.008	0.029	0.026	0.069	0.041	0.153	-0.022	0.012	-0.028	0.021	0.028
	[0.335]	[-0.152]	[0.471]	[0.463]	[1.034]	[0.804]	[2.077]	[-0.359]	[0.195]	[-0.466]	[0.335]	[0.693]
$R_{[t-24,t]} \geq 100\%$		0.218										0.104
		[1.415]										[1.366]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.284									-0.322
			[2.324]									[-1.813]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				0.688								0.962
				[2.903]								[3.422]
$\sigma_{[t-24,t]}$					5.016							0.502
					[1.536]							[0.222]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.095						0.072
						[4.28]						[3.61]
Drawdown$_t$ *(%)*							0.433					0.184
							[2.74]					[1.986]
Peak Count$_t$								0.006		0.005		0.006
								[2.644]		[2.511]		[3.468]
BRS$_t$									-0.091	-0.094		-0.096
									[-2.333]	[-2.633]		[-3.264]
Peak Count$_t$ *x BRS*$_t$										0.002		0.001
										[0.315]		[0.239]
N	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416
$\boldsymbol{R^2}$	0.002	0.022	0.027	0.069	0.031	0.113	0.081	0.038	0.048	0.079	0.002	0.283

Panel C: G10 Countries Full sample

	Dependent Variable: Maximum 2-year Forward Looking Drawdown (%)										
	(US)	**(BE)**	**(CA)**	**(FR)**	**(DE)**	**(IT)**	**(JP)**	**(NL)**	**(SE)**	**(CH)**	**(GB)**
Constant Term	0.034	0.082	0.125	0.137	0.165	0.144	0.038	0.159	0.114	0.074	0.084
	[0.626]	[1.279]	[1.871]	[2.068]	[3.278]	[1.647]	[1.135]	[2.72]	[2.878]	[1.082]	[1.273]
$R_{[t-24,t]}$ *(%)*	0.028	-0.033	0.055	0.077	0.101	0.042	0.07	0.064	0.008	0.191	0.143
	[0.512]	[-0.983]	[1.734]	[1.029]	[1.445]	[0.736]	[1.133]	[1.398]	[0.216]	[2.196]	[1.616]
$R_{[t-24,t]} \geq 100\%$	0.104	-0.008	-0.022	-0.095	0.016	-0.055	0.058	-0.012	-0.029	-0.068	0.000
	[1.827]	[-0.133]	[-0.383]	[-1.813]	[0.261]	[-0.861]	[0.789]	[-0.156]	[-0.635]	[-1.088]	[0.001]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*	-0.322	-0.129	-0.255	-0.363	-0.193	-0.072	0.219	0.123	-0.242	0.185	-0.170
	[-1.578]	[-1.461]	[-1.559]	[-1.762]	[-1.065]	[-0.639]	[0.777]	[1.623]	[-2.065]	[1.32]	[-0.868]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*	0.962	0.361	0.764	0.378	0.292	0.147	0.359	-0.127	0.259	-0.231	0.577
	[2.845]	[2.318]	[4.83]	[1.158]	[1.27]	[1.044]	[1.127]	[-0.824]	[1.481]	[-1.297]	[1.897]
$\sigma_{[t-24,t]}$	0.502	9.084	2.284	5.275	-0.149	5.284	4.61	0.163	7.168	0.789	0.292
	[0.165]	[1.824]	[1.241]	[1.785]	[-0.045]	[1.422]	[1.983]	[0.046]	[2.99]	[0.14]	[0.129]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*	0.072	0.043	0.015	0.003	0.038	0.046	0.043	0.061	0.008	0.034	0.034
	[3.325]	[2.98]	[1.040]	[0.084]	[1.167]	[1.71]	[1.908]	[5.288]	[0.396]	[1.056]	[1.869]
$Drawdown_t$ *(%)*	0.184	-0.170	0.123	0.149	0.273	0.033	0.136	0.171	-0.042	0.487	0.368
	[1.449]	[-1.448]	[1.412]	[1.097]	[1.831]	[0.292]	[1.132]	[1.855]	[-0.311]	[2.565]	[2.031]
Peak Count$_t$	0.006	0.015	0.005	0.013	0.006	0.005	0.012	0.004	0.014	0.001	0.007
	[2.714]	[1.960]	[1.162]	[2.849]	[1.087]	[0.736]	[2.178]	[0.531]	[2.399]	[0.365]	[1.557]
BRS_t	-0.096	-0.107	-0.070	-0.092	-0.051	-0.075	-0.085	-0.052	-0.096	-0.036	-0.089
	[-3.55]	[-4.764]	[-2.026]	[-2.936]	[-2.185]	[-3.294]	[-3.091]	[-2.194]	[-3.227]	[-0.880]	[-2.712]
Peak Count$_t$ *x* BRS_t	0.001	-0.004	-0.004	0.001	-0.008	-0.001	0.012	-0.006	0.003	-0.005	-0.000
	[0.249]	[-0.465]	[-0.774]	[0.153]	[-1.486]	[-0.147]	[2.486]	[-1.252]	[0.275]	[-1.007]	[-0.036]
N	2,416	2,218	2,416	2,386	2,150	2,242	2,203	1,949	2,106	2,105	2,386
$\boldsymbol{R^2}$	0.283	0.176	0.192	0.226	0.141	0.09	0.372	0.152	0.173	0.148	0.209

Table 3: Predicting Large Drawdown Probability

Panel regressions of the binary flag of maximum 2-year drawdown > 40% on predictor variables, *t*-statistics based on standard errors two-way clustered at the country-sector and year-level shown in brackets. Input data from January 2000-December 2020. Coefficients displayed with t-statistics in brackets.

Panel A: Global Full sample

	Dependent Variable: Binary Flag of Maximum 2-year Forward Looking Drawdown > 40%											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant Term	0.244	0.243	0.230	0.222	0.051	0.172	0.145	0.224	0.261	0.239	0.244	-0.015
	[6.774]	[6.651]	[6.164]	[6.373]	[0.895]	[4.959]	[3.329]	[7.979]	[7.193]	[8.643]	[6.776]	[-0.322]
$R_{[t-24,t]}$ *(%)*	0.047	0.019	0.048	0.052	0.065	0.043	0.128	0.019	0.036	0.011	0.047	0.063
	[0.931]	[0.336]	[0.953]	[1.029]	[1.306]	[0.857]	[2.635]	[0.529]	[0.752]	[0.339]	[0.931]	[1.986]
$R_{[t-24,t]} \geq 100\%$		0.087										-0.044
		[1.852]										[-1.975]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.121									-0.005
			[4.445]									[-0.136]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				0.289								0.218
				[6.600]								[2.950]
$\sigma_{[t-24,t]}$					10.455							9.223
					[4.475]							[4.720]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.056						0.032
						[5.275]						[2.709]
$Drawdown_t$ *(%)*							0.422					0.127
							[4.256]					[1.228]
$Peak\ Count_t$								0.010		0.010		0.011
								[1.319]		[1.415]		[1.452]
BRS_t									-0.152	-0.112		-0.137
									[-2.505]	[-2.529]		[-2.938]
$Peak\ Count_t \times BRS_t$										-0.013		-0.012
										[-1.239]		[-1.146]
IB_t											0.366	0.243
											[3.587]	[2.775]
N	105,430	105,430	105,430	102,045	105,419	104,585	105,430	105,419	105,430	105,419	105,430	101,587
R^2	0.005	0.006	0.007	0.012	0.035	0.015	0.029	0.012	0.019	0.026	0.005	0.073

Panel B: US Full sample

	Dependent Variable: Binary Flag of Maximum 2-year Forward Looking Drawdown > 40%											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant Term	0.089	0.094	0.041	0.004	0.004	-0.063	-0.025	0.073	0.103	0.094	0.089	0.041
	[2.457]	[2.648]	[0.606]	[0.067]	[0.045]	[-1.933]	[-0.503]	[2.138]	[2.759]	[2.473]	[2.457]	[0.605]
$R_{[t-24,t]}$ *(%)*	0.054	0.016	0.061	0.063	0.109	0.08	0.288	0.025	0.042	0.015	0.054	0.165
	[0.467]	[0.148]	[0.537]	[0.596]	[0.866]	[0.778]	[1.967]	[0.216]	[0.36]	[0.13]	[0.467]	[1.481]
$R_{[t-24,t]} \geq 100\%$		0.284										0.056
		[0.944]										[0.301]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.261									-1.499
			[0.996]									[-3.102]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				1.171								2.778
				[2.291]								[3.878]
$\sigma_{[t-24,t]}$					5.735							-5.679
					[0.926]							[-1.704]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.123						0.096
						[3.384]						[2.077]
Drawdown$_t$ *(%)*							0.762					0.640
							[2.243]					[2.779]
Peak Count$_t$								0.004		0.003		0.001
								[0.904]		[0.638]		[0.328]
BRS$_t$									-0.132	-0.158		-0.135
									[-1.925]	[-2.300]		[-2.185]
Peak Count$_t$ *x BRS*$_t$										0.005		0.002
										[0.569]		[0.302]
N	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416	2,416
R^2	0.003	0.011	0.008	0.048	0.012	0.046	0.059	0.007	0.025	0.029	0.003	0.177

Panel C: G10 Countries Full sample

	Dependent Variable: Binary Flag of Maximum 2-year Forward Looking Drawdown > 40%										
	(US)	**(BE)**	**(CA)**	**(FR)**	**(DE)**	**(IT)**	**(JP)**	**(NL)**	**(SE)**	**(CH)**	**(GB)**
Constant Term	0.041	-0.239	0.007	-0.032	-0.077	0.040	-0.133	0.010	-0.102	-0.153	0.038
	[0.442]	[-1.773]	[0.052]	[-0.277]	[-1.019]	[0.195]	[-1.607]	[0.078]	[-1.04]	[-1.324]	[0.500]
$R_{[t-24,t]}$ *(%)*	0.165	-0.049	0.153	0.088	0.294	0.115	0.193	0.053	-0.010	0.376	0.211
	[1.255]	[-0.617]	[2.507]	[0.717]	[2.855]	[1.142]	[1.333]	[0.63]	[-0.119]	[2.374]	[1.507]
$R_{[t-24,t]} \geq 100\%$	0.056	-0.045	-0.125	-0.105	-0.163	-0.075	0.097	0.003	-0.032	-0.156	-0.052
	[0.346]	[-0.326]	[-1.088]	[-0.939]	[-1.452]	[-0.654]	[0.644]	[0.018]	[-0.382]	[-1.207]	[-0.664]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*	-1.499	-0.345	-0.627	-0.259	-0.315	-0.215	-0.145	0.300	-0.317	0.264	-0.730
	[-3.204]	[-1.826]	[-1.94]	[-0.647]	[-0.673]	[-0.939]	[-0.366]	[1.586]	[-1.571]	[0.762]	[-1.602]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*	2.778	0.978	1.341	-0.03	0.648	0.315	2.087	-0.097	0.125	-0.168	1.455
	[3.723]	[3.131]	[5.917]	[-0.053]	[1.243]	[1.151]	[2.809]	[-0.26]	[0.353]	[-0.415]	[2.145]
$\sigma_{[t-24,t]}$	-5.679	23.165	1.239	6.548	-3.515	2.908	2.856	-0.62	14.273	-2.953	-7.187
	[-1.622]	[1.916]	[0.199]	[1.28]	[-0.645]	[0.317]	[0.376]	[-0.075]	[3.38]	[-0.295]	[-2.933]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*	0.096	0.097	0.032	0.028	0.132	0.133	0.078	0.112	0.025	0.098	0.058
	[2.133]	[2.796]	[1.051]	[0.475]	[2.043]	[2.726]	[2.162]	[3.312]	[0.566]	[2.183]	[3.850]
Drawdown$_t$ *(%)*	0.640	-0.469	0.433	0.253	0.468	0.117	0.256	0.225	-0.228	1.037	0.554
	[2.689]	[-1.924]	[2.783]	[1.08]	[1.73]	[0.389]	[0.741]	[1.022]	[-0.859]	[3.157]	[2.187]
Peak Count$_t$	0.001	0.026	0.008	0.029	0.015	0.008	0.020	0.019	0.025	0.002	0.014
	[0.297]	[1.630]	[0.942]	[2.633]	[1.554]	[0.582]	[1.546]	[1.801]	[2.329]	[0.333]	[1.582]
BRS$_t$	-0.135	-0.229	-0.124	-0.173	-0.031	-0.162	-0.106	-0.086	-0.143	-0.060	-0.107
	[-2.172]	[-4.595]	[-1.635]	[-2.549]	[-0.624]	[-2.783]	[-1.686]	[-1.729]	[-1.965]	[-1.012]	[-1.883]
Peak Count$_t$ *x BRS*$_t$	0.002	-0.007	-0.006	-0.007	-0.027	-0.004	0.041	-0.011	-0.004	-0.005	-0.007
	[0.290]	[-0.432]	[-0.436]	[-0.519]	[-2.405]	[-0.198]	[2.441]	[-1.119]	[-0.202]	[-0.664]	[-0.531]
N	2,416	2,218	2,416	2,386	2,150	2,242	2,203	1,949	2,106	2,107	2,386
$\boldsymbol{R^2}$	0.177	0.151	0.127	0.145	0.166	0.074	0.259	0.110	0.112	0.149	0.148

Table 4: Predicting Drawdown from Large Return Subsample

Panel regressions of the maximum 2-year drawdown on predictor variables, *t*-statistics based on standard errors two-way clustered at the country-sector and year-level shown in brackets. Sample restricted to observations where 2 Year contemporaneous return of the Country-Sector is greater than 50%. Input data from January 2000 to December 2020. Coefficients displayed with t-statistics in brackets.

	Dependent Variable: Maximum 2-year Forward Looking Drawdown (%)											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant Term	0.304	0.306	0.299	0.295	0.185	0.273	0.281	0.285	0.304	0.286	0.304	0.120
	[7.386]	[7.287]	[7.087]	[6.935]	[2.613]	[6.646]	[5.809]	[11.167]	[7.54]	[11.357]	[7.386]	[2.724]
$R_{[t-24,t]}$ *(%)*	0.034	0.027	0.034	0.032	0.006	0.027	0.036	0.027	0.035	0.028	0.034	-0.013
	[2.969]	[3.118]	[2.957]	[2.795]	[0.4]	[2.788]	[3.344]	[2.508]	[3.102]	[2.754]	[2.969]	[-1.202]
$R_{[t-24,t]} \geq 100\%$		0.014										-0.002
		[1.473]										[-0.297]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.048									-0.078
			[2.137]									[-2.467]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				0.191								0.228
				[5.642]								[4.058]
$\sigma_{[t-24,t]}$					8.465							10.189
					[3.472]							[6.426]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.027						0.011
						[3.003]						[1.701]
Drawdown$_t$ *(%)*							0.381					-0.004
							[2.506]					[-0.028]
Peak Count$_t$								0.005		0.005		0.007
								[1.158]		[1.131]		[1.835]
BRS_t									-0.066	-0.05		-0.075
									[-1.524]	[-1.673]		[-2.353]
Peak Count$_t$ *x* BRS_t										-0.002		0.000
										[-0.381]		[0.003]
IB_t											0.386	0.277
											[7.991]	[3.876]
N	24,968	24,968	24,968	24,070	24,967	24,797	24,968	24,968	24,968	24,968	24,968	24,002
$\boldsymbol{R^2}$	0.011	0.012	0.013	0.025	0.065	0.022	0.037	0.026	0.022	0.035	0.012	0.127

Table 5: Predicting Probability of Large Drawdown from Large Return Subsample

Panel regressions of the binary flag of maximum 2-year drawdown > 40% on predictor variables, *t*-statistics based on standard errors two-way clustered at the country-sector and year-level shown in brackets. Sample restricted to observations where 2 Year contemporaneous return of the Country-Sector is greater than 50%. Input data from January 2000-December 2022. Coefficients displayed with t-statistics in brackets.

	Dependent Variable: Binary Flag of Maximum 2-year Forward Looking Drawdown > 40%											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant Term	0.293	0.296	0.283	0.272	0.108	0.233	0.248	0.244	0.294	0.247	0.293	-0.037
	[3.409]	[3.384]	[3.244]	[3.135]	[0.749]	[2.700]	[2.483]	[4.831]	[3.487]	[4.953]	[3.408]	[-0.486]
$R_{[t-24,t]}$ *(%)*	0.037	0.027	0.036	0.036	-0.006	0.026	0.041	0.019	0.039	0.022	0.037	-0.040
	[1.465]	[1.523]	[1.438]	[1.302]	[-0.196]	[1.131]	[1.691]	[0.71]	[1.562]	[0.825]	[1.465]	[-1.674]
$R_{[t-24,t]} \geq 100\%$		0.020										-0.008
		[0.898]										[-0.430]
Fraction Large Issuance$_{[t-24,t]}$ *(%)*			0.103									-0.143
			[2.203]									[-2.303]
Total Issuance (EW)$_{[t-24,t]}$ *(%)*				0.379								0.450
				[4.481]								[3.667]
$\sigma_{[t-24,t]}$					13.181							16.18
					[2.653]							[6.201]
$tv_{[t-24,t]} / tv_{[t-48,t-25]}$ *(%)*						0.052						0.023
						[3.107]						[1.645]
Drawdown$_t$ *(%)*							0.751					0.108
							[2.385]					[0.361]
Peak Count$_t$								0.012		0.012		0.016
								[1.382]		[1.368]		[1.885]
BRS$_t$									-0.143	-0.103		-0.142
									[-1.550]	[-1.651]		[-2.262]
Peak Count$_t$ *x BRS*$_t$										-0.005		-0.002
										[-0.451]		[-0.168]
IB$_t$											0.666	0.457
											[7.052]	[3.032]
N	24,985	24,985	24,985	24,085	24,984	24,812	24,985	24,985	24,985	24,985	24,985	24,015
$\boldsymbol{R^2}$	0.003	0.003	0.004	0.014	0.029	0.011	0.023	0.022	0.013	0.030	0.003	0.089

Table 6: Analysis of Prediction Errors

Panel A summarizes true and false positive rates. The left-column shows the number of events that we identify conditional on a prediction cutoff of X% predicted drawdown or greater. The three right columns then show the fraction of the time that such predicted drawdowns are met by a drawdown in that sector of a given size. In parentheses below each fraction, we show the average number of months prior to the event that we first predicted the event. Panel B analyzes true and false negative rates. Here we first identify all drawdowns of a certain magnitude (20%, 40% or 50%), and reports what fraction of the time our model was able to flag such a drawdown occurring within a two-year window prior to such event.

Panel A: % Predictions Succeeded by a Large Drawdown Event

	Size of Drawdown Event		
Drawdown Prediction Cutoff (*N Prediction Events*)	**≥ 20%**	**≥ 40%**	**≥ 50%**
.25	26.4%	17.8%	12.6%
(N = 9339)	(16.2)	(16.0)	(15.7)
.30	27.2%	19.8%	14.6%
(N = 6329)	(14.3)	(14.2)	(14.0)
.35	26.3%	21.2%	16.1%
(N = 3145)	(12.6)	(12.8)	(12.7)
.40	27.4%	23.3%	18.9%
(N = 1220)	(12.0)	(11.4)	(11.1)
.45	28.1%	25.5%	22.9%
(N = 459)	(10.4)	(10.4)	(9.7)
.50	24.5%	22.7%	20.2%
(N = 163)	(9.7)	(9.8)	(8.9)

Panel B: % Events Preceded By Large Prediction

	Size of Drawdown Event		
Drawdown Prediction Cutoff	**≥ 20% *(N = 1350)***	**≥ 40% *(N = 900)***	**≥ 50% *(N = 637)***
.25	99.0%	99.2%	99.5%
.30	79.3%	85.0%	87.6%
.35	44.2%	52.0%	55.6%
.40	19.8%	25.0%	28.7%
.45	08.4%	11.4%	14.4%
.50	02.8%	03.9%	04.9%

Table 7: Performance Implications of Avoiding Frothy Sectors

Using our computed global market-cap weighted return index as a benchmark, we analyze the returns of strategies that remove frothy country-sectors using varied froth conditions for removal. The right column reports average monthly returns; the two left columns report alphas and market betas of monthly returns based on a time-series regression of returns over the full sample.

Return Index	***α***	***β***	***Avg. Monthly Return***
Remove Frothiest Decile	-.0004 [-.123]	.959 [140.004]	.006
Remove Frothiest Quartile	.0005 [.976]	.896 [79.753]	.006
Remove > .2 Predictions	-.003 [-.960]	.673 [9.478]	.001
Remove > .3 Predictions	.002 [2.853]	.794 [42.377]	.007
Remove >.4 Predictions	.001 [2.726]	.943 [121.453]	.007