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EDUCATION

Arizona State University *Expected May 2023*
Ph.D. in Finance

University of Michigan *2013*
MS in Financial Engineering

Sabanci University, Turkey *2012*
BS in Manufacturing Systems Engineering

PAST POSITIONS

Ozyegin University *2015-2017*
Research Assistant

Garanti BBVA *2014-2015*
Internal Auditor

Deutsche Bank Securities *Summer 2013*
Summer Analyst

WORKING PAPERS

Market Timing in Corporate Finance Decisions: Evidence From Stock Market Anomalies (Job Market Paper)

Presentations: Doctoral Student Consortium at FMA Annual Meeting (2022, Scheduled), ASU (2021)

Abstract: Using an equity mispricing score that incorporates 155 anomaly characteristics, I find that U.S. firms are 59% more likely to issue equity when overvalued and 28% more likely to repurchase shares when undervalued. Moreover, this relationship is more pronounced when executives own more equity in the firm. I also show that executives are more likely to use equity as currency in acquisitions when overvalued, and use cash when undervalued. I find consistent evidence using an international dataset that includes 33 countries. These findings provide new evidence about market timing and support the market timing hypothesis.

Monetary Policy Uncertainty and Asset Price Bubbles *with Sreedhar Bharath*

Presentations: AFA Annual Meeting (2023, Scheduled), FMA Annual Meeting (2022, Scheduled), SFA Annual Meeting (2022, Scheduled)

Abstract: We examine the impact of monetary policy uncertainty (MPU) in predicting asset price bubbles. Using US data from 1926-2019, we find that greater monetary policy uncertainty leads to a greater likelihood of bubbles in industry level returns. This relationship has weakened in magnitude over time, concomitant with the FED's increased transparency of its monetary policy. Machine learning models that incorporate MPU outperform ones that don't in their ability to predict bubbles in real time.

WORK IN PROGRESS

Implications of Equity Market Timing on Shareholders *with Ilona Babenko and Yuri Tserlukevich*

TEACHING EXPERIENCE

Instructor:

FIN 331 (Financial Markets/Institutions, Undergrad) 6.4/7.0 *Summer 2021*
Arizona State University

ACCT 201 (Financial Accounting) 4.5/5.0 *Summer 2016*
Ozyegin University, Turkey

PROFESSIONAL SERVICE

Referee:
Finance Research Letters, International Journal of Banking, Accounting and Finance

Invited Discussions:

- FMA 2021 (3 Sessions)
  - ▷ Cash Flow Expectations, Dividends Asset Pricing
  - ▷ Working Capital
  - ▷ Hedge Funds
- SFA 2022
  - ▷ Biases & Investment Flows

EARLIER PUBLICATIONS

Preferences for lottery stocks at Borsa Istanbul *with Biliana Guner*
Journal of International Financial Markets, Institutions and Money, 2018.

Abstract: We investigate the existence of lottery-like preferences of investors at Borsa Istanbul. Proxying these preferences with demand for stocks with extreme positive returns ("MAX"), we establish that high-MAX stocks' significantly underperform low-MAX stocks, controlling for a series of potential explanatory return characteristics. We find that the negative relationship between MAX and expected returns is driven by stocks strongly preferred by individual investors and strengthens following periods of high investor sentiment. A natural experiment suggests that the MAX discount increased during the period of temporary short-sale restrictions at Borsa Istanbul. Our findings suggest a limits-to-arbitrage explanation for the MAX anomaly.

HONORS, AWARDS, GRANTS AND FELLOWSHIPS

Graduate Associate Fellowship, Arizona State University *2017-2023*
High Honor Scholarship, Sabanci University *2007-2012*

PROGRAMMING SKILLS

Stata, SAS, Python, Matlab

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Market Timing in Corporate Finance Decisions: Evidence From Stock Market Anomalies

Ulas Alkan*

September 22, 2022

Abstract

Using an equity mispricing score that incorporates 155 anomaly characteristics, I find that U.S. firms are 59% more likely to issue equity when overvalued and 28% more likely to repurchase shares when undervalued. Moreover, this relationship is more pronounced when executives own more equity in the firm. I also show that executives are more likely to use equity as currency in acquisitions when overvalued and use cash when undervalued. I find consistent evidence using an international dataset that includes 33 countries. These findings provide new evidence about market timing and support the market timing hypothesis.

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1 Introduction

Stock prices can not perfectly reflect the available information because information is costly (Grossman and Stiglitz (1980)). Firm executives are likely to identify when stock prices deviate from the fundamental value. This information asymmetry can create an incentive for executives to maximize long term shareholders' wealth. Executives can maximize long term shareholders' wealth by conducting a seasoned equity offering (SEO) when the firm is overvalued and repurchasing shares when the firm is undervalued. These strategies are called market timing and lead to wealth transfers among investors (Baker and Wurgler (2002); Loughran and Ritter (1995)). However, despite the extensive literature, it is empirically hard to identify stock mispricing; hence, it remains a challenge to test whether executives engage in market timing (Baker, Ruback, and Wurgler (2007), Khan, Kogan, and Serafeim (2012), and Dong, Hirshleifer, and Teoh (2012)). To identify stock mispricing, earlier studies use both ex-ante and ex-post measures such as market-to-book (M/B) ratio, past abnormal returns, and future abnormal returns. However, these measures are still under debate. For example, M/B ratio and past returns might reflect growth opportunities that can also affect corporate finance decisions (Baker, Ruback, and Wurgler (2007)). In addition, future abnormal returns following firms' financial decisions might be a result of change in firm risk.[1] These studies show that we need a more reliable mispricing measure to test the market timing hypothesis.

I contribute to the literature by testing the market timing hypothesis using a mispricing score that incorporates 155 stock market anomalies. Using this measure, I show that firm mispricing impacts market timing behavior in issuances and repurchases. I also document that market timing behavior is related to executives' personal benefits. To further gain confidence in my findings regarding market timing, I test whether executives time the market in mergers and acquisitions (M&A). I find that executives use equity as currency in M&A transactions when the stock is overvalued and cash when the stock is undervalued.

[1] See, for example, Carlson, Fisher and Giammarino (2006); Carlson, Fisher, and Giammarino (2010), Eckbo, Masulis, and Norli (2000), Brav, Michaely, Roberts, and Zarutskie (2009).

A stock market anomaly is defined as a firm characteristic that shows return predictability in the cross-section. Existing literature documents that these firm characteristics are likely to reflect mispricing. For example, McLean and Pontiff (2016) show that the return predictability of a stock market anomaly becomes weaker after the anomaly is published in an academic journal. They argue that arbitrageurs become aware of anomaly characteristics in published articles and then correct any mispricing in the market. Moreover, Bowles, Reed, Ringgenberg, and Thornock (2020) show that after a short period of disclosure of anomaly characteristics, investors quickly react to the new information and correct most of the mispricing. This evidence also suggests that anomalies represent mispricing and arbitrageurs react to the financial disclosures.

These findings provide evidence that anomalies are likely to represent mispricing. However, using a single anomaly would be a noisy measure of mispricing. Therefore, I test the market timing hypothesis using a mispricing score that incorporates 155 continuous anomaly characteristics studied by Chen and Zimmermann (2021). My measure extends the Stambaugh, Yu, and Yuan's (2015) measure based on 11 anomaly characteristics that they use to study the idiosyncratic volatility (IVOL) puzzle.

Using this mispricing score, I first test whether executives use market timing strategies in their SEO decisions. In the sample period between 1980 and 2019, I find that a one standard deviation increase in the mispricing score (i.e., more overvaluation) leads to a 59% increase in the probability of an SEO in the next quarter, and a 16% increase in the total shares issued in an SEO to total shares outstanding ratio, relative to the unconditional means. I also investigate whether market timing has any impact on the fees paid to the investment banks. My hypothesis is that when executives issue equity when the stock is overvalued, investment banks would also identify overpricing at least partially. Therefore, they would ask higher fees since marketing overvalued equity would be more difficult. Executives are likely to accept these higher fees since the gain from market timing would outweigh the investment bank fees which are typically around 5%. In line with this hypothesis, I find that a one standard deviation increase in the mispricing score leads to a 7% increase in the investment bank fees relative to the mean.

Since market timing is selling overvalued equity and buying undervalued equity, I also investigate whether executives repurchase shares when the firm is undervalued in the stock market. I find that a one standard deviation decrease (i.e., more undervaluation) in the mispricing score leads to a 28% increase in the probability of a share repurchase in the next quarter; and with a 10% increase in the total shares repurchased to total shares outstanding ratio relative to the unconditional means.

To further validate my findings, I divide the 155 anomalies underlying my mispricing score into two groups corresponding to published and not yet published depending on whether the sample year is before or after the publication year of the anomaly. I then create two mispricing scores at the beginning of each quarter: $Mispricing\ Score_{published}$ and $Mispricing\ Score_{unpublished}$. For example, to calculate $Mispricing\ Score_{unpublished}$ ($Mispricing\ Score_{published}$) for a given stock in year 2006, I use the anomalies that are published after (before) 2006. This decomposition is motivated by the finding in McLean and Pontiff (2016) that an anomaly is likely to represent a stronger mispricing before it is published in an academic journal. Since the publication date is uncorrelated with firms' economic fundamentals, this decomposition allows for an exogenous change in the mispricing measure. I expect that anomalies have more explanatory power in SEO/repurchase decisions before the publication date because they are likely to represent stronger mispricing. Consistent with my hypothesis, I find that both measures significantly explain the SEO/repurchase decision, but that the mispricing score that is created using unpublished anomalies has a significantly larger effect. This finding strengthens the hypothesis that executives engage in market timing in their financial decisions.

While my results show that executives' mispricing signals are strongly correlated with anomaly characteristics, it is likely that such mispricing signals are more strongly correlated with some types of anomalies than with others. Executives are more likely to identify mispricing from a firm's financial statements. Therefore, executives' mispricing signals are more likely to be correlated with anomalies related to balance sheet or income statement items (i.e., accounting anomalies) than with other anomalies. To test this hypothesis, I classify anomalies as either an accounting anomaly or other anomaly based on the anomaly groups created by Chen and Zimmermann (2021). At the beginning of each quarter, I create two mispricing scores using the anomalies in each group and test the relationship between the SEO/repurchase decision and the two mispricing scores. Consistent with the hypothesis, I find that the mispricing score that is constructed using accounting anomaly characteristics has both economically and statistically significantly higher explanatory power than the mispricing score that is constructed using other types of anomalies in SEO/repurchase decisions.

I also investigate whether executives' incentives have any effect on market timing. Since existing shareholders benefit from market timing, executives would have more incentive to time the market when they own a large amount of equity in the firm. To examine this, I estimate the magnitude of the relationship between the SEO/repurchase decision and mispricing for different levels of equity ownership by executives. I find that when CEOs own more equity, they are more sensitive to mispricing in the SEO/repurchase decision; i.e., they are more sensitive to overpricing (underpricing) in issuing (repurchasing) equity when they hold a larger fraction of shares as a fraction of their total compensation. Specifically, following a one standard deviation increase (decrease) in the mispricing score, firms with CEOs in the top tercile of ownership are 55% (33%) more likely to issue (repurchase) equity than those in the bottom tercile of ownership. My results are robust to using the average ownership ratio of all executives, controlling for executives' unvested shares, and defining equity ownership as the sum of vested and unvested shares instead of using only vested shares.

Next, I investigate whether executives time the market in their mergers and acquisition (M&A) decisions. Shleifer and Vishny (2003) argue that rational managers rationally respond to less-than-rational markets by acquiring firms using overvalued equity. Motivated by this argument, I test the relation between mispricing score and two groups of M&A activities separately. The first group includes the transactions in which the acquiror uses equity as currency; the second group includes the transactions in which the acquiror uses cash as currency. I find that when firms are overvalued, they are more likely to use equity and when they are undervalued, they are more likely to use cash. These findings also support the hypothesis that executives time the market in corporate finance decisions.

My results show a robust relationship between the SEO/repurchase decision and the mispricing score for U.S. firms. In spirit of Fama and French (1998), I test the external validity of these results around the world. By using an international dataset that provides anomaly characteristics for each stock-month observation (Jensen, Kelly, and Pedersen (2022)), I extend my method and create a mispricing score using anomaly characteristics for each international firm. I also obtain firm-initiated issuances from the SDC database. Then, I examine the market timing hypothesis using the stocks from 33 countries. I find that executives are more likely to issue (repurchase) equity when the equity is overvalued (undervalued) in other countries as well. Moreover, the economic significance of this relationship is sizable. A one standard deviation increase (decrease) in the mispricing score leads to a statistically significant 7.5% (16.6%) increase in the likelihood of SEOs (share repurchases). These findings confirm that executives around the world use market timing strategies and these strategies are not confined to U.S. firms.

My study is related to McLean, Pontiff, and Reilly (2022) who examine how different types of stock market investors trade according to anomaly characteristics. Their paper finds that only insurance companies and firms are smart in that they sell more shares when stocks are overvalued. In their analysis, they use changes in number of shares outstanding to measure the trading activity of firms. However, a direct test of market timing hypothesis requires a refined measure. As shown by McKeon (2015), increases in the number of shares outstanding include many issuances initiated by employees that are not related to market timing. Indeed, using changes in number of shares outstanding, the evidence in McLean, Pontiff, and Reilly (2022) suggests that even undervalued firms issue equity, which casts doubt on the market timing hypothesis. If firms engage in market timing, I expect to find a relation between mispricing and the component of change in number of shares outstanding that is truly related to the SEO decisions of firm executives. Consistent with my hypothesis, I find that my mispricing measure explains SEO decisions but does not explain employee-initiated issuances. Furthermore, I show that market timing behavior is related to executives' incentives and extends to a firm's M&A decisions. These findings further support the market timing hypothesis.

My study is also related to recent studies that propose new mispricing measures to test the market timing hypothesis. For example, Khan, Kogan and Serafeim (2012) use mutual fund flow-driven purchases as an indicator of overvaluation and find that the probability of an SEO increases for the affected stocks in the following four quarters. Berger (2021) shows, however, that flow driven price increases might not capture mispricing. In another study, Dong, Hirshleifer and Teoh (2012) propose to identify mispriced stocks using the forward-looking residual income model of Ohlson (1995). However, a debate remains about the return predictability of this model and whether the model represents an omitted risk factor (Chen and Zimmermann (2021) and Hwang and Lee (2013)). Moreover, the cross-sectional predictability of future returns using a single variable may be unreliable since the anomaly literature documents more than 300 such variables. I build on these works by testing the market timing hypothesis using a new mispricing measure based on 155 anomaly characteristics. To further highlight my contribution to the market timing literature, I orthogonalize my mispricing measure with respect to the existing measures. I find that the orthogonalized version of my mispricing score still explains SEO and share repurchase decisions. Furthermore, the magnitudes of the estimated coefficients of the orthogonalized versions of my mispricing score are very similar to the magnitude of the unorthogonalized mispricing score. These findings characterize the novel feature of my mispricing measure and show that its predictive ability for SEO and share repurchase decisions improves upon that of existing measures.

2 Data and Variables

2.1 Sample Construction

My sample includes all common stocks (share code 10 or 11) that are listed in NYSE, Amex or Nasdaq between 1980-2019. I obtain SEO sample from Thomson Financial's SDC Platinum database. I exclude all private placements, right offerings, and unit offers from the sample similar to Eckbo, Masulis, and Norli (2000). I create my share repurchases sample by calculating the changes in the split-adjusted shares outstanding from CRSP database (Stephens and Weisbach (1998)). The share repurchase sample period starts in 1982 because there were no explicit rules directly regulating share repurchases in the United States until that time; therefore, there was a risk of SEC investigation of market manipulation for firms undertaking share repurchases before 1982 (Grullon and Michaely (2002)). I use CRSP dataset for market related data and Compustat for accounting variables. I create executive ownership variables by using Execucomps database. I obtain factor returns and risk-free rates from Kenneth French's website. My analysis is at quarter level; therefore, all frequencies reflect the relevant corporate decision in a quarter. The final sample includes 7,482 SEOs and 83,607 share repurchases.

2.2 Mispricing Measure

Empirical tests of the market timing hypothesis require a reliable measure of mispricing, therefore faces a significant challenge. The existing literature uses several mispricing measures, but each of them is still debated. The main potential issue with the existing measures is endogeneity. Existing measures are likely to be correlated with likelihood of firms' financial decisions, therefore it is not conclusive whether these measures represent mispricing or the correlation with the likelihood of financial decisions. The second issue is that existing mispricing measures are likely to be correlated with changes in risk, therefore it is hard to distinguish between risk and mispricing. By using an equity mispricing score that incorporates 155 anomaly characteristics, I aim to minimize endogeneity concerns and risk-based explanations. In this section, I first summarize the widely used mispricing measures and review the ongoing discussion about the need for a better mispricing measure to test the market timing hypothesis. Then, I introduce my mispricing measure and its advantages over the existing measures.

A strand of literature uses ex-ante mispricing measures to test the market timing hypothesis. For example, Eckbo and Masulis (1995) find evidence that new issues occur after a significant run-up in the issuer's stock price. The relation between price run-up and SEO decision would support the market timing hypothesis. Baker and Wurgler (2002) uses the Market to Book (M/B) ratio as a mispricing measure and explain how market timing affects firms' capital structure. This paper claims that using M/B ratio allows a comparison between the market price and a benchmark fundamental value, which is proxied by the book value of assets, and differences between market price and book value is attributed to mispricing. However, both past returns and M/B ratios are likely to be correlated with firm characteristics that are also correlated with SEO or share repurchase decision such as firm's investment opportunities. For example, a firm with valuable investment opportunities might experience a price run-up before the SEO decision and implement these investment opportunities by issuing equity. In addition, since book value is a backward-looking measure, any price run-up resulting from a future investment opportunity would increase the M/B ratio (Tobin (1969)). In this case, the documented relationship between mispricing measure and corporate financial decisions might not be due to market timing.

As an alternative to using prior returns, another strand of literature uses future abnormal returns to measure mispricing at the time of SEO or share repurchase (e.g., Ikenberry, Lakonishok, and Vermaelen (1995); Loughran and Ritter (1995)). These studies suggest that if a firm is overvalued (undervalued) at the time of a corporate financial decision (SEO or share repurchase), the future abnormal returns should be lower (higher) so that prices converge to the fundamental value. The underlying assumption in these studies is that firm risk remains constant after the SEO/repurchase decision. However, positive or negative future abnormal returns might be related to rational expectations about the firm's value rather than being related to deviations from the fundamental value. For example, if the firm risk is changing around SEO and share repurchase events, then future abnormal returns compared to an ex-ante benchmark might reflect changes in the firm risk. As argued by Eckbo, Masulis, and Norli (2000), equity issuance lowers systematic risk exposure by reducing leverage, thereby also reducing exposure to unexpected inflation and default risks. Thus, lower risk is likely to drive future lower returns rather than overvaluation at the time of an SEO. In addition, there is still an ongoing discussion about how to properly calculate and test future abnormal returns. For example, Mitchell and Stafford (2000) shows that although many papers use buy and hold returns to calculate future abnormal returns, this method is likely to be flawed.

There are two more recent papers that propose new mispricing measures and test the market timing hypothesis. The first study is Khan, Kogan, and Serafeim (2012). This paper uses flow driven purchases by mutual funds as an indicator of overvaluation. The underlying assumption in this study is that prices reflect fundamental values before flow-driven purchases and that these purchases cause the stocks to be overvalued. The paper argues that a mispricing measure driven by investors is relatively exogenous to the firm characteristics and does not raise endogeneity concerns. In contrast, Berger (2021) shows that mispricing measures using mutual fund flows might not be capturing mispricing due to selection bias: Mutual funds select which stocks to buy (sell) following an inflow (outflow), therefore the criteria for the selection might be correlated with the SEO/repurchase decision. Berger (2021) argues that after accounting for this selection bias, the relation between market mispricing and a firms' financial decisions disappears.

The second study is Dong, Hirshleifer and Teoh (2012). This paper adopts an alternative fundamental value measure (V) and use the M/V ratio instead of the M/B ratio to identify mispriced stocks. More specifically, this paper uses the residual income model of Ohlson (1995), which uses analyst forecasts to derive a forward-looking measure of fundamental value. Therefore, the M/V ratio filters the effects of future investment opportunities from the market prices and is shown to predict future abnormal returns (Frankel and Lee (1998)). However, it is still empirically difficult to rule out concerns that the return predictability of Ohlson's (1995) model might be driven by omitted risk factors. For example, Hwang and Lee (2013) find supporting evidence that this measure is likely to capture risk rather than mispricing. In addition, Chen and Zimmermann (2021) find mixed results regarding the future return predictability of this model.

Overall, existing mispricing measures that are used to test the market timing hypothesis are still hotly debated, and there is no conclusive result yet. I contribute to this literature by using a mispricing score incorporating a large set of anomalies that show return predictability. My mispricing measure extends the Stambaugh, Yu and Yuan (2015) measure, which is based on 11 anomaly characteristics and is used to study IVOL puzzle. I use 155 continuous anomaly characteristics in Chen and Zimmermann (2021)[2] and create a single mispricing score for each stock-month observation. I list all the anomalies that I use to construct my mispricing score in Table A1

At the beginning of each quarter, I calculate the percentile ranking of each stock for each anomaly characteristic. Thus, each stock has a percentile ranking between 0 and 1 for each anomaly. If higher values of an anomaly characteristic represent undervaluation, I multiply the values for that characteristic by -1. This makes all anomalies consistent in the sense that high values represent overvaluation. If the stock has a missing value for a characteristic, then I replace the missing value with the median value of that characteristic in that month. After calculating percentile rankings, I calculate the equally weighted average of these percentile rankings for each stock-month to obtain a single mispricing score. This mispricing score has the advantage of using many characteristics, therefore is not dominated by a single anomaly. Since many mispricing signals are used together, this score is a more comprehensive measure of mispricing compared to any single anomaly characteristic.

[2]https://www.openassetpricing.com/

One might argue that anomalies might not represent mispricing and be a compensation for omitted risk factors. However, there is evidence in the literature that anomalies are likely to represent mispricing. For example, McLean and Pontiff (2016) show that many firm characteristics can predict future returns and most of the anomaly returns either vanish or has an alpha decay after the academic publication. This finding implies that anomalies represent mispricing and mispricing has been corrected after the anomalies are publicized broadly. Moreover, Bowles, Reed, Ringgenberg, and Thornock (2020) show that after a short period of anomaly characteristics disclosure, investors quickly react to the new information and correct most of the mispricing very quickly. If these returns were spurious, we would not expect to see any reaction to financial disclosures.

To show the return predictability of this mispricing measure, I sort firms into quintile portfolios according to mispricing score at the beginning of each month and observe the market value weighted returns of each portfolio in the following month. After obtaining time series of portfolio returns for each quintile, I regress portfolio returns on Fama French 3 factor returns and report the estimated coefficients from this regression in Table 1 1. This table shows that undervalued stocks deliver 0.21% monthly risk adjusted returns. In addition, overvalued stocks deliver -0.55% monthly risk adjusted returns. The spread portfolio, therefore, deliver 0.76% monthly risk adjusted returns. All these results are statistically significant at 1% level. These results confirm that a composite mispricing measure using anomaly characteristics predict future risk adjusted returns in the full sample period.

3 Results

3.1 SEO and Share Repurchase Decision

3.1.1 Main Specifications

I start my main analysis by testing the relation between probability of SEO/repurchase decision and the mispricing score. To investigate this relation, I estimate a linear probability model with high dimensional fixed effects. Linear probability models allow me to include industry by quarter fixed effects to control for unobservable variation across industries at each cross section and across time for a given industry. The estimated model is as follows:

$$\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{jt} + \epsilon_{it} \tag{1}$$

I estimate the model above for two different firm decision dependent variables. The first firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The second firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The "Controls" include the beginning of quarter values of B/M ratio, B/M, "Past 12m Net of Market Return", return on asset (ROA), "Cash by Asset", market capitalization, "Leverage","Dividend yield", "Volatility", "Change in the volatility (Δ Volatility), and "Firm Age" as explained in detail in the Appendix B. I also include industry by quarter fixed effects (γ_{jt}). I cluster the standard errors at the year level. In addition to SEO/repurchase decision, I also estimate the relation between mispricing score and shares issued (repurchased) to the total shares outstanding ratio. To estimate this relation, I replace the "Firm Decision" dependent variable with the associated ratio for SEOs and share repurchases separately.

For issuances, I conduct two more analyses. My first analysis tests the relation between mispricing and employee-initiated issuances. By using changes in number of shares outstanding as a measure of firm trade, McLean, Pontiff, and Reilly (2022) find that firms sell more shares when stocks are overvalued. However, changes in number of shares outstanding is a noisy measure of issuance because it includes many cases initiated by employees (McKeon (2015)). Since employee compensation decision is made years prior to issuance, only the firm-initiated component is related to market timing. For example, using the changes in number of shares outstanding measure, the evidence in McLean, Pontiff, and Reilly (2022) suggests that even undervalued firms issue equity, which casts doubt on market timing hypothesis. If firms engage in market timing, I expect to find a relation only between SEO decision and mispricing measure, and not between employee-initiated issuances and mispricing score. To test the relation between employee-initiated issuances and mispricing score, I follow McKeon (2015) and create an employee-initiated issuance indicator variable that is equal to 1 if number of shares outstanding increases less than 2% in a quarter and equal to 0 if there is no change. Then, I replace my dependent variable in Equation(1) with this indicator variable and estimate the equation. My second analysis investigates whether market timing has any implication on the fees paid to the investment banks. Since marketing overpriced shares would be more difficult, investment banks would ask higher fees from market timers. To estimate this relation, I replace the dependent variable with the logarithm of gross spread, calculated as the fees paid to the investment banks divided by total proceeds. The dataset does not include gross spread value for all SEOs, therefore my sample for this analysis includes 6,906 SEOs. I document all of the findings in Table 2.

In Panel A, I report the estimated coefficients and standard errors from Equation (1) by using "SEO" as "Firm Decision" variable. I find that a one standard deviation increase in mispricing score (more overvaluation) leads to 58.8% increase in the likelihood of SEOs relative to its unconditional probability. Moreover, one standard deviation increase in mispricing score leads to 15.6% increase in the shares issued to the total shares outstanding ratio relative to its mean. When I use employee-initiated issuance indicator as a dependent variable, I do not find a significant relation between mispricing and employee-initiated issuance. This finding supports the idea that mispricing explains only firm-initiated issuances consistent with the market timing hypothesis. Finally, I document the relation between mispricing score and gross spread and find that a one standard deviation increase in mispricing score leads to 6.4% increase in the total paid fees, relative to the mean.

In Panel B, I report the estimated coefficients and standard errors from Equation (1) by using "Share Repurchase" as "Firm Decision" variable. I find that a one standard deviation decrease in mispricing score (more undervaluation) leads to 27.9% increase in the likelihood of share repurchases relative to its unconditional probability. I also find that a one standard deviation decrease in mispricing score leads to 9.6% increase in the shares repurchased to the total shares outstanding ratio relative to its mean.

These results show that overvalued firms are more likely to issue equity and undervalued firms are more likely to repurchase shares. Moreover, the relation between mispricing score and the shares issued (repurchased) to total shares outstanding ratio is also positive (negative), further confirming that overvalued (undervalued) firms are more likely to issue (repurchase) more equity.

3.1.2 Decomposing Mispricing Score: Published vs Unpublished Anomalies

McLean and Pontiff (2016) document that most of the anomalies have alpha decay after the publication of these anomalies in the academic journals. This finding implies that return predictability of the anomalies is stronger before the publication date. Publication dates are exogenous to the firm decision variables, therefore the changes in mispricing score are exogenous to the firm decision variables. I exploit the variation in publication dates by creating two mispricing scores. I split anomalies into two groups as "Published" and "Unpublished" depending on the publication date at the beginning of each sample year. Then, I create two separate mispricing score using the anomalies in each group. For example, $MispricingScore_{unpublished}$ ($MispricingScore_{published}$) in January 2006 is created using the anomalies that are published after (before) 2006. By using these mispricing scores, I estimate Equation(1) again. Then, I add two mispricing scores together and repeat my estimation. I report the results in Table 3.

Panel A reports the estimated coefficients of mispricing scores when the firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In the first column, I use the mispricing score created by using published anomalies and in the second column, I use the mispricing score created by using unpublished anomalies. The third column reports the coefficients when I add both mispricing scores together. These result show that a one standard deviation increase in "Mispricing Score (Unpublished)" leads to higher likelihood of SEOs compared to "Mispricing Score (Published)" (0.51 vs 0.26). When I estimate the same model by including both mispricing scores together, the difference becomes larger (0.49 vs 0.10). Finally, I test the equality of the estimated coefficients of "Mispricing Score (Unpublished) and Mispricing Score (Published) and report the results in the last column. I find that I can reject the equality of these two mispricing scores at 1% statistical significance.

Panel B reports the estimated coefficients of mispricing scores when the firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Similar to Panel A, each column represents a model including "Mispricing score (Unpublished)", or "Mispricing score (Published)" or both of them together. I find that a one standard deviation decrease in "Mispricing Score (Unpublished)" leads to higher likelihood of share repurchases compared to "Mispricing Score (Published)" (3.23 vs 2.66). When I estimate the same model by including both mispricing scores together, the difference becomes larger (2.92 vs 1.48). Finally, I test the equality of the estimated coefficients of "Mispricing Score (Unpublished) and Mispricing Score (Published) and find that I can reject the equality of these two mispricing scores at 5% statistical significance.

These findings suggest that an anomaly based mispricing score explains firm decisions when the anomalies that are used to construct mispricing score represent stronger mispricing. These results further support the hypothesis that executives are more likely to issue equity when the firm is overvalued and repurchase shares when undervalued.

3.1.3 Decomposing Published Anomalies

In Section 3.1.2, I document that the mispricing score created by using unpublished anomalies has higher explanatory power in both SEO and share repurchase decisions compared to the mispricing score created by using published anomalies. To refine this test, I investigate whether it matters the publication date is near or far among published anomalies. Since anomalies represent weaker, if any, mispricing many years after the publication, a mispricing score using the anomalies that are published long before the sample date should have a very small explanatory power, if any, in SEO or share repurchase decision. In addition, I would also argue that the mispricing score using unpublished anomalies should have a similar or slightly higher explanatory power than a mispricing score using the anomalies that are published shortly before the sample date.

To empirically test these arguments, I create 3 different mispricing scores. The first mispricing score is created by using unpublished anomalies at each sample date. This measure is identical to the "Mispricing Score (Unpublished)" that is explained in Section 3.1.2. The second measure uses the anomalies that are published maximum 10 years before the sample date ("Mispricing Score ($Published < 10years$)"). The last mispricing score uses the anomalies that are published more than 10 years before the sample date ("Mispricing Score ($Published >= 10years$)"). I estimate the Equation(1) by using these three mispricing scores separately. I also augment the same model with all of the three mispricing scores together and estimate the relation between mispricing scores and SEO/repurchase decision. I report the estimated coefficients and standard errors in Table 4.

Panel A reports the estimation results when the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel B reports the estimation results when the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In each panel, I document that the relation between SEO/repurchase and the mispricing score is largest when I use Mispricing Score (Unpublished). This finding is consistent with McLean and Pontiff (2016) who show that anomalies represent stronger mispricing before the publication in academic journals. I also find that the relation between SEO/repurchase decision and "Mispricing Score

($Published >= 10 years$)" is not statistically significant. These findings are also consistent with the literature that shows that anomalies are corrected after the publication and do not represent a mispricing as strong as they do before the publication. Moreover, when I include all mispricing scores in the same model, I find that Mispricing Score (Unpublished) still has the largest explanatory power in SEO/repurchase decision with 1% statistical significance and "Mispricing Score ($Published >= 10 years$)" still does not retain statistical significance neither in SEOs nor in share repurchase decisions.

Finally, I test the equality of coefficients of i) "Mispricing Score (Unpublished)" and "Mispricing Score ($Published < 10 years$)" and ii) "Mispricing Score ($Published < 10 years$)" and "Mispricing Score ($Published >= 10 years$)". Consistent with my hypothesis, the equality of estimated coefficients of "Mispricing Score (Unpublished)" and "Mispricing Score ($Published < 10 years$)" can be rejected at 5% in Panel A and at 10% in Panel B. This result is likely to be due to alpha decay happening gradually. However, the equality of estimated coefficients of "Mispricing Score ($Published < 10 years$)" and "Mispricing Score ($Published >= 10 years$)" can be rejected at 5% statistical significance in Panel A and 1% statistical significance in Panel B. This result shows that explanatory power of anomaly based mispricing scores are different in SEO/ repurchase decisions depending on the strength of mispricing they represent.

These results further confirm that an anomaly based mispricing score explains SEO/repurchase decision consistent with the market timing hypothesis. Moreover, anomaly based mispricing score explains these corporate decisions only when the anomalies represent stronger mispricing and loses its explanatory power if anomalies that are published long before are used to create a mispricing score.

3.1.4 Decomposing Mispricing Score: Accounting Anomalies vs Other Anomalies

In the previous sections, I show that mispricing score significantly explains SEO and share repurchase decisions, confirming the market timing hypothesis. However, executives' mispricing signals might not be correlated with all types of anomalies. In this case, the relation between SEO/repurchase decision and the mispricing score that is created by using certain type of anomalies should be higher. Executives are likely to infer any mispricing from firm's financial statements, therefore anomaly characteristics that are calculated by using balance sheet or income statement items are potential candidates to be highly correlated with the executives' mispricing signals.

To test this hypothesis, I investigate whether a mispricing score using accounting anomalies has higher explanatory power in SEO/repurchase decisions compared to a mispricing score using all other anomalies. To study this, I split anomalies into two groups as "Accounting" and "Other" anomalies using the anomaly classification in Chen and Zimmermann (2021). Then, I create two mispricing scores using the anomalies in each group. I estimate Equation (1) by including "Mispricing Score (Accounting)" and "Mispricing Score (Others)" separately and then both of them together. I report the estimated coefficients and standard errors in Table 5. Panel A reports the estimated coefficients of mispricing scores when the firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel B reports the estimated coefficients of mispricing scores when the firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In each panel, first two columns report the estimation results when each mispricing score is included in the model one at a time and the last column reports the estimation results when both mispricing scores are included in the model together.

Consistent with my hypothesis, I document that the magnitude of the estimated coefficients of "Mispricing Score (Accounting)" are larger compared to the that of "Mispricing

Score (Others)" for both SEO and share repurchase decisions. For SEOs, the estimated coefficient of Mispricing Score (Accounting) is equal to 0.71 and the estimated coefficient of Mispricing Score (Others) is equal to 0.30. For share repurchases, the estimated coefficient of Mispricing Score (Accounting) is equal to -3.72 and the estimated coefficient of Mispricing Score (Others) is equal to -2.29. Both coefficients are statistically significant at 1% level in each model. In the last column of each Panel, I add two mispricing score together and test the relation between SEO/repurchase decision and these mispricing scores. I find that coefficients of "Mispricing Score (Accounting)" retain statistical significance at 1% level but "Mispricing Score (Other)" retains statistical significance only in Panel B. has a larger coefficient than "Mispricing Score (Others)". Even in Panel B, "Mispricing Score (Accounting)" has a larger explanatory power in share repurchase decision compared to "Mispricing Score (Other)". I can reject the equality of coefficients of "Mispricing Score (Accounting)" and "Mispricing Score (Other)" at 1% statistical significance level. Overall, these findings also support the hypothesis that executives respond to mispricing signals and their signals have higher correlation with the mispricing score that is created by using Accounting anomalies than the mispricing score that is created by using all other anomalies.

3.2 The Effect of Executives' Equity Ownership on Market Timing

Market timing benefits long term existing shareholders because a market timer firm sells overpriced equity to the new shareholders or repurchase underpriced equity from short term shareholders. However, if executives do not have any personal benefit, then there would be very limited or no motivation for them to use market timing strategies. Therefore, we can argue that as executives gain more personal benefit from market timing, they would become more sensitive to the mispricing signals in their SEO and share repurchase decisions.

Existing literature shows that executives' personal benefits would affect corporate decisions. For example, Bergstresser and Philippon (2004) show that accruals management increases as the CEO's compensation becomes more sensitive to current share prices. A similar argument can be made in the market timing context. Executives' SEO and share repurchase decisions can be affected by their personal benefits. To investigate this, I study whether the executives are more sensitive to mispricing signals when they have more equity in the firm. A simple formulation of a CEO's personal benefits from issuing equity (share repurchase) when the stock price is above (below) the fundamental value is as follows:

The number of shares outstanding is equal to N1 and the current price is equal to either P1 or P2. Fair price of the stock, P0, which is less than P1 and greater than P2. Market value of the firm is the multiplication of price and total shares outstanding, N1*P0. If CEO owns α fraction of total shares, her total ownership is equal to α*N1. CEO can either do nothing, issue equity if price is equal to P1, or repurchase shares if price is equal to P2. I calculate the final total ownership for each case:

i) Do Nothing:

$$TotalOwnership = P_0 * \alpha * N_1 \tag{2}$$

ii) Issue β fraction of total shares outstanding, N1*β:

$$\begin{aligned} TotalOwnership &= \frac{\alpha * N1}{N1(1+\beta)} * [N1 * P0 + P1 * N1 * \beta] \\ &= \frac{\alpha * N1}{1+\beta} * [P0 + P1 * \beta] \end{aligned} \tag{3}$$

$$\frac{\partial TotalOwnership}{\partial \beta} = \frac{\alpha * N1 * (P1 - P0)}{(1+\beta)^2} > 0 \tag{4}$$

iii) Repurchase β fraction of total shares outstanding, N1*β:

$$
\begin{aligned}
TotalOwnership &= \frac{\alpha * N1}{N1(1-\beta)} * [N1 * P0 - P1 * N1 * \beta] \\
&= \frac{\alpha * N1}{1-\beta} * [P0 - P1 * \beta]
\end{aligned} \tag{5}
$$

$$
\frac{\partial TotalOwnership}{\partial \beta} = \frac{\alpha * N1 * (P0 - P1)}{(1-\beta)^2} > 0 \tag{6}
$$

I start my analysis by calculating firm executives' ownership in the firm. I obtain equity ownership data from Execucomp and increase my sample period back to 1980 by using the dataset of Frydman and Saks (2010). I sum total dollar value of equity and vested option ownership to calculate total ownership. When the option ownership data is missing, I replace the total ownership value with equity ownership only. However, using total ownership value to study incentives would be misleading because a similar dollar gain from market timing for a very large firm executive would be very different from that for a very small firm executive. Therefore, I scale total ownership value by total executive compensation in the end of the most recent fiscal year. The most ideal denominator to scale total ownership would be executives' total wealth. However, we do not directly observe executives' wealth. Therefore, I use total compensation in the most recent fiscal year as a proxy for total wealth. This scaling allows me to compare incentives of executives of firms with different market capitalizations. After obtaining total equity ownership to total compensation ratio, I sort firms into terciles based on this ratio at the beginning of each quarter. Then, I add "Equity Ownership" tercile dummy variables and interaction of these tercile dummy variables with the mispricing score into the Equation (1). I hypothesize that interaction of the mispricing score with the highest tercile dummy variable should be positive for SEOs and negative for share repurchases, suggesting that higher equity ownership makes executives more sensitive to the mispricing signals in their SEO and share repurchase decisions. The estimated equation is as follows:

$$
\begin{aligned}
\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \beta_2 \times \mathbb{1}_{EquityOwnership_{i,t}=2} \\
+\beta_3 \times \mathbb{1}_{EquityOwnership_{i,t}=3} + \beta_4 \times \mathbb{1}_{EquityOwnership_{i,t}=2} \times \text{Mispricing Score}_{it} \\
+\beta_5 \times \mathbb{1}_{EquityOwnership_{i,t}=3} \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{ijt} + \epsilon_{it}
\end{aligned} \tag{7}
$$

I report estimated coefficients and associated standard errors in Table 6. Panel A shows that a one standard deviation increase (decrease) in mispricing score makes the firms with CEOs in the highest equity ownership tercile 55% (33%) more likely to issue shares (repurchase shares) compared to the firms with CEOs in the lowest equity ownership tercile. The results are statistically significant at 1% level and confirm that executives use market timing strategies even more heavily when they own more equity in the firm.

Although CEO is the top executive in the firm, one might argue that he/she does not make all the decisions on his/her own. Instead, other executives would affect these decisions or CEO might delegate some decision-making responsibilities to the other executives. Therefore, other executives' ownership levels may also affect the sensitivity of SEO/repurchase decision to firm mispricing. To investigate whether including other top executives' ownership in the firm affects market timing strategies, I first calculate equally weighted average of equity ownership to total compensation ratios across all executives. Then, I sort firms into terciles based on this measure at the beginning of each quarter. Finally, I repeat the same analysis that I conduct for CEOs by replacing "Equity Ownership (CEO)" variable with "Equity Ownership (All)" variable. I report the results in Panel B of Table 6.

I find that a one standard deviation increase (decrease) in mispricing score makes the firms with executives in the highest average equity ownership to compensation tercile 75% (57%) more likely to issue shares (repurchase shares) compared to the firms with executives in the lowest tercile. These findings confirm that SEO and share repurchase decisions are more sensitive to mispricing when the top executives on aggregate own more equity in the firm.

4 The Effect of Market Timing on Mergers and Acquisitions

I also investigate whether executives time the market in their mergers and acquisition (M&A) decisions. In an acquisition, acquiring firm can use equity, cash, or combination of these two payment methods. Firm executives can time the market by using overvalued equity as a currency in their acquisitions (Shleifer and Vishny (2003)). Using overvalued equity as currency would create a wealth transfer from target firm's shareholders to acquiring firm's shareholders. Similarly, if a firm is undervalued, then executives would use cash as currency instead of equity. Motivated by this argument, I test the relation between mispricing score and two types of acquisitions separately. First type of acquisitions include the transactions in which acquiror uses equity as a payment method. Second type of acquisitions include the transactions in which acquiror uses cash as a payment method. I hypothesize that when acquiring firm is overvalued, executives would prefer to pay with overvalued equity. Similarly, when the acquiring firm is undervalued, executives would prefer to pay with cash instead. I report the estimated coefficients and standard errors in Table 7.

My analysis documents that acquiring firm is 34% more likely to make a stock-based acquisition following a one standard deviation increase in the mispricing score, relative to the unconditional mean. In addition, I also show that acquiring firm is 10% more likely to make a cash-based acquisition following a one standard deviation decrease in the mispricing score. I can reject the equality of these results at 1% significance level. These findings further support the hypothesis that executives time the market in corporate financial decisions.

5 International Evidence

In the previous sections, I documented supporting evidence for the market timing hypothesis for U.S. firms. However, there might a potential concern about the external validity of these results. In spirit of Fama and French (1998), I test the external validity of these results around the world.

I study market timing hypothesis for 33 countries that are listed in Table A2. Jensen, Kelly, and Pedersen (2022)[3] documents international evidence for the return predictability of anomaly characteristics. Motivated by this predictability, I extend my method and create a mispricing score for each international firm using 144 continuous anomaly characteristics in their dataset.

I start my sample construction by including all the stocks between 1990 and 2019. My sample starts in 1990 because SDC has very limited coverage for non-U.S. shares in that period (McLean, Zhang, and Zhao (2011)). Then, I apply suggested screening by Jensen, Kelly, and Pedersen (2022) such as including only common stocks that are listed in the main exchanges, main observations, and primary listings. I obtain anomaly characteristics, along with market variables such as return, industry, and split-adjusted number of shares outstanding from this dataset. To remove the potential biases from low number of observations, I removed each country cross section that has fewer than 100 observations. I also exclude the countries that have fewer than 50 SEO or share repurchases in the full sample period. The construction of mispricing score is identical to the mispricing score constructed for the U.S. sample and explained in detail in Section 2.2.

I use SDC dataset to obtain SEO sample and use the quarterly difference in split-adjusted shares to identify share repurchases, i.e., a decrease in split-adjusted shares represents a share repurchase. International sample has a similar frequency of SEOs. 0.98% of the total observations has an SEO in a given quarter. However, only 2.17% of the total observations has a share repurchase in a given quarter, which is much lower than the U.S. sample.

Similar to the main analysis for the U.S. firms, I estimate the relation between mispricing and two firm decision variables as represented in Equation (8). The first firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if

[3]https://jkpfactors.com/

there is no SEO or share repurchase. The second firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The firm level control variables are same as in Equation (1) and explained in detail in the Appendix B. I include Country × Industry × Quarter fixed effects instead of including Industry × Quarter fixed effects to also control for any unobservable variation across countries. I cluster my standard errors at Country × Year level. I report the estimated coefficients and associated standard errors in Panel A of Table 8 for both SEOs and share repurchases.

$$\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{jkt} + \epsilon_{it} \tag{8}$$

The coefficient of Mispricing Score in each regression confirms that executives are more likely to issue (repurchase) shares when the firm is overvalued (undervalued) in the stock market. This result is statistically significant at 1% level. The economic significance of the relation between mispricing and SEO/repurchase decision is lower than the US sample but still sizable. A one standard deviation increase (decrease) in mispricing score leads to a 7.5% (16.6%) increase in the likelihood of SEOs (share repurchases) relative to the unconditional mean. These findings show that market timing strategies are not limited to the U.S. firms and are confirmed when I use a large set of countries as a sample.

I further investigate whether there is any difference in using market timing strategies across countries. I argue that investor protection should have an effect on the relation between mispricing and corporate finance decisions. This argument is motivated by McLean, Pontiff, and Watanabe (2009), who find that the return predictability of ISSUE variable, changes in shares outstanding, is higher in countries with stronger investor protection. If investor protection is low, investors would be reluctant to participate in SEOs or sell shares when a firm announces a share repurchase. For example, investors would be willing to participate in an SEO in a high investor protection country but be afraid of doing so in a very low investor protection country because the cost of information asymmetry would be very large for them. In that case, since there will be no counter party for firms in a stock trade, executives can not use market timing strategies. This is not the case for high investor protection countries since market timing strategies are not fully revealing.

I use World Bank's "Strength of investor protection" data[4] for 33 countries in my sample and augment Equation (8) by including a "High Investor Protection" indicator variable that is equal to 1 if a country is above median in terms of investor protection for a given year and 0 otherwise. I also interact "High Investor Protection" variable with "Mispricing Score" to observe the effect of mispricing on firm decision for countries with different levels of investor protection. Investor protection data is available for the sample period between 2008-2018, therefore my sample period includes the firm-quarter observations in this period. The estimated model is as follows:

$$\begin{aligned}\text{Firm Decision}_{i,t+1} &= \beta_0 + \beta_1 \times \text{High Investor Protection} + \beta_2 \times \text{Mispricing Score} \\ &+ \beta_3 \times \text{Mispricing Score}_{it} \times \text{High Investor Protection} + \text{Controls}_{it} + \gamma_{jkt} + \epsilon_{it}\end{aligned} \tag{9}$$

I report the estimated coefficients and standard errors in Panel B of Table 8. My estimation results show that the documented evidence for market timing in Panel A is fully driven by the countries with high investor protection. The estimated coefficient of "Mispricing Score" is statistically insignificant for both SEOs and share repurchases, documenting that firms in low investor protection countries do not respond to mispricing in their SEO and share repurchase decisions. These results highlight the importance of country level characteristics in market timing and confirm my hypothesis that market timing is more likely to exist in high investor protection countries.

[4] https://govdata360.worldbank.org

6 Robustness Tests

6.1 Orthogonalized Mispricing Measure

In Section 2.2, I discuss the potential drawbacks of using existing mispricing measures to test market timing hypothesis. However, it is still useful to show that the mispricing measure I use is different than the existing measures. To isolate and characterize the novel feature of my measure, I orthogonalize my mispricing measure with respect to the existing measures. I obtain orthogonalized mispricing score by regressing my mispricing measure on each of the existing measures separately, and then obtaining the residual series from each regression. Existing mispricing measures include Book to Market ratio (BM), Past 12-month net of market return (Past Return), Residual Income Model (RIM), and Mutual Fund buy pressure (Buy Pressure) and explained below:

BM: Total book value of equity divided by market capitalization, calculated as market price of the stock times total shares outstanding

Past Return: Buy and hold stock return minus value weighted CRSP market return in the past 12 months.

RIM: Total book value of equity plus discounted value of analyst forecasts of future earnings.

Buy Pressure: Overvalued stocks are those heavily purchased by mutual funds with large capital inflows, but not subject to widespread buying pressure by other mutual funds.

I estimate Equation(1) by using each orthogonalized mispricing measure. I argue that my mispricing score explains the SEO/repurchase decision even after removing the effects of the existing mispricing measures. In Table 9, I report estimated coefficients and associated standard errors of each orthogonalized Mispricing Score. First four columns represent the models including an orthogonalized mispricing score with respect to an existing measure. The parenthesis next to "Mispricing Score" denotes which variable I use as an existing measure to estimate orthogonalized version of my mispricing score. I also orthogonalize my mispricing measure with respect to all of the existing measures together and include Orthogonalized Mispricing Score (All) in the model. I report the estimated coefficient of Orthogonalized Mispricing Score (All) in the last column of each panel. In each specification in Panel A, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Panel B, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase.

The estimated coefficients of "Orthogonalized Mispricing Score" in each panel confirm that my mispricing measure explains SEO and share repurchase decisions even after removing the effect of the existing measures, supporting the novel feature of my measure. Moreover, the magnitude of the estimated coefficient of each orthogonalized versions of my mispricing score is comparable to that of mispricing score reported in Table 2. My findings show that even orthogonalizing with respect to all of the existing variables do not change the results and the relation between mispricing score and SEO/repurchase decision remains both statistically and economically significant. These results confirm that my mispricing measure has more explanatory power in explaining SEO/repurchase decision and this relation can not be explained by the existing mispricing measures that are used to test market timing hypothesis.

6.1.1 The Relation Between Mispricing Score and SEO/Repurchase Decision by Market Capitalization

In the previous sections, I show evidence that executives use market timing strategies. However, there might be a potential concern that the total effect of these results on the economy would be limited if only the executives of small firms are using market timing strategies. This concern can be due to two reasons. First, large firm executives would incur higher reputation costs if they use market timing strategies since market timing leads to wealth loss for new shareholders in SEOs and for short term shareholders in share repurchases. Second, arbitrageurs would allocate less attention to the small firms, thereby leading to any mispricing lasts longer for small firms. Although I use market capitalization as a firm level control, small firms would still affect the estimation results if a high fraction of small firm executives use market timing strategies.

To alleviate this concern, I sort stocks into terciles on market capitalization at the beginning of each quarter and then estimate Equation (1) for the firms in each tercile separately. I report estimation results in Table 10. Panel A reports the coefficients when the "Firm Decision" variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. I document that the effect of mispricing score on SEO decision is smallest for the smallest stocks, and largest for the largest stocks. A one standard deviation increase in mispricing score makes the largest firms 1.04% more likely to issue shares, and the result is statistically significant at 1% level.

Panel B reports the coefficients when the "Firm Decision" variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. I document that the effect of mispricing score on share repurchase decision is smallest for the smallest stocks, and largest for the largest stocks. A one standard deviation increase in mispricing score makes the largest firms 5.33% more likely to repurchase shares, and the result is statistically significant at 1% level. These findings show that the sensitivity of executives to mispricing score in SEO/repurchase decisions is not fully driven by small firms, therefore impacts a large portion of the total economy.

6.2 Controlling for Unvested Shares

When I study the effect of mispricing on SEO/repurchase decision for different levels of executive equity ownership, I only include vested shares and options to the calculation. Since unvested shares have not been earned yet, their effect on the executives' incentives would be limited. However, if managers own unvested shares and plan to stay in the firm for a long period, then unvested shares might also create an incentive for market timing.

To investigate the robustness of my previous results to taking unvested shares into account, I first calculate unvested stock to total compensation ratio and sort firms into terciles at the beginning of each quarter. Then, I include tercile dummy variables as additional control variables in Equation (7). This analysis answers the question that controlling for executives' total unvested shares, how much existing equity ownership affects firm's SEO/repurchase decision. I report the estimation results in Panel A of Table 11. Moreover, I also create a new executive ownership variable that combines vested and unvested equity ownership as a measure of total executive ownership to examine the total incentives. I report these results in Panel B of Table 11.

I find that controlling for unvested shares, managers who own more equity in the firm are still more sensitive to the mispricing in SEO and share repurchase decisions. The estimated coefficients are comparable to the ones in Table 6 and retain statistical significance at 1% level. I also find that the combined executive ownership variable that includes both vested and unvested shares still explains SEO and share repurchase decisions, and the economic effect is comparable in each model with 1% statistical significance.

7 Conclusion

Stock prices can not always reflect fundamental value and firm executives would identify the times when the stock price deviates from the fundamental value. Market timing hypothesis claims that firm executives can maximize long term shareholder value by issuing equity when the firm is overvalued and repurchase shares when the firm is undervalued.

The challenge to test the market timing hypothesis is to identify mispriced (overvalued and undervalued) stocks. Past studies use both ex-ante and ex-post measures of mispricing. However, there is still a debate on using these variables as a measure of mispricing in testing market timing hypothesis. Moreover, more recent papers that propose new mispricing measures to solve this issue are also debated, therefore we do not have a conclusive result yet.

To contribute to market timing literature, I create a mispricing measure by using 155 anomaly characteristics that predict future returns. I test the market timing hypothesis using this mispricing measure and document that executives are more likely to issue (repurchase) equity when the equity is overvalued (undervalued) in the stock market. I also show that the explanatory power of mispricing score becomes larger if I only include anomalies that are published after the sample date. This finding confirms that anomalies that are likely to represent stronger mispricing have more explanatory power in SEO/repurchase decisions and further supports market timing hypothesis.

I also document that when executives own more equity in the firm, they are more sensitive to mispricing in their SEO and share repurchase decisions because they would gain more personal benefits from market timing. To further gain confidence in my findings regarding market timing, I test whether executives time the market in mergers and acquisitions. I find that executives use equity as currency in M&A transactions when the stock is overvalued and cash when the stock is undervalued. Finally, I also document international evidence for market timing by studying 33 countries. The economic significance for international evidence is still sizable and related to investor protection in a country. Overall, these findings support the market timing hypothesis for an international sample and show external validity of the market timing hypothesis.

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Table 1: Mispricing Score vs Future Returns

At the beginning of each month between January 1980 and December 2019, I sort stocks into quintile portfolios based on mispricing score that is constructed using 155 anomaly characteristics. The construction of mispricing score is explained in detail in Section 2.2. I report estimated coefficients and associated standard errors from regressing quintile portfolio returns on Fama French 3 factors. Portfolio returns are calculated as the value weighted average of stock returns within each portfolio. Last column reports the results when the dependent variable is spread portfolio return, which is the return difference between the first quintile portfolio ("Undervalued") and last quintile portfolio ("Overvalued"). Significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

	Undervalued	2	3	4	Overvalued	Spread
Mkt	0.91***	1.00***	1.09***	1.06***	0.93***	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
SMB	-0.05***	-0.08***	0.08***	0.28***	0.40***	-0.45***
	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)
HML	0.18***	0.05***	-0.14***	-0.15***	-0.30***	0.48***
	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.05)
Constant	0.21***	0.01	-0.31***	-0.35***	-0.55***	0.76***
	(0.05)	(0.04)	(0.06)	(0.09)	(0.10)	(0.13)
Observations	480	480	480	480	480	480

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: The Relation Between Mispricing Score and Financial Decisions of Firms

Panel A of this table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision (Column 1), between mispricing score and shares issued to total shares outstanding ratio (Column 2), between mispricing score and employee-initiated issuances, and between mispricing score and total fees (gross spread) paid to the underwriters of the SEO (Column 4). Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In Column 1, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I replace the dependent variable with $\log(1+\frac{\text{shares issued}}{\text{shares outstanding}})$ value. In Column 3, the dependent variable is an employee-initiated issuance indicator that is equal to 1 if number of shares outstanding increases less than 2% and 0 if number of shares outstanding remains the same. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. In Column 4, the dependent variable is logarithm of total gross spread paid to the underwriters of the SEO. Panel B of this table reports linear probability estimates of the relation between mispricing score and share repurchase decision (Column 1) and the relation between mispricing score and shares repurchased to total shares outstanding ratio (Column 2). In Column 1, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I replace the dependent variable with $\log(1+\frac{\text{shares repurchased}}{\text{shares outstanding}})$ value. Each specification includes industry×quarter fixed effects along with firm level characteristics. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	Shares Issued/Shrout	Employee Initiated Issuances (Δ Shrout<2%)	Gross Spread
Mispricing Score	0.73***	0.15***	-0.28	6.39***
	(0.06)	(0.01)	(0.37)	(0.75)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	58.8	15.6		6.6
Industry × Quarter FE	✓	✓	✓	
Controls	✓	✓	✓	
Observations	440,357	440,357	378,907	6,906
Adjusted R^2	0.02	0.01	0.28	0.02

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Shares Repurchased/Shrout
Mispricing Score	-4.07***	-0.09***
	(0.38)	(0.01)
% change in DV from +s/2 to -s/2 of Mispricing Score relative to unconditonal (%)	27.9	9.6
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	495,503	495,503
Adjusted R^2	0.08	0.01

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Decomposing Mispricing Score by Publication Date of the Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and two different anomaly based mispricing scores. The dependent variable in Panel A is SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are published in the academic journals after the sample date (Unpublished) and the second mispricing score uses the anomalies that are published in the academic journals before the sample date (Published). The construction of each mispricing score is explained in detail in Section 3.1.2. The first two columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when both mispricing scores are included in the model. I test the equality of the coefficients for the two mispricing scores and report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO
Mispricing Score (Published)	0.26***		0.10*
	(0.06)		(0.05)
Mispricing Score (Unpublished)		0.51***	0.49***
		(0.09)	(0.09)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	440,357	418,390	418,390
Adjusted R^2	0.02	0.02	0.02
χ^2(β_Misp. Score (Unpub.) = β_Misp Score (Pub.))			8.72
p-value			0.01

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase
Mispricing Score (Published)	-2.66***		-1.48***
	(0.62)		(0.49)
Mispricing Score (Unpublished)		-3.23***	-2.92***
		(0.36)	(0.33)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	495,503	465,899	465,899
Adjusted R^2	0.07	0.07	0.07
χ^2(β_Misp. Score (Unpub.) = β_Misp Score (Pub.))			4.26
p-value			0.05

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Decomposing Published Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and three different anomaly based mispricing scores. The dependent variable in Panel A is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are published in the academic journals after the sample date (Mispricing Score (Unpublished)), second mispricing score uses the anomalies that are published in the academic journals within 10 years before the sample date ($MispricingScore(Published < 10years)$), and the third mispricing score uses the anomalies that are published in the academic journals at least 10 years before the sample date ($MispricingScore(Published >= 10years)$). The construction of each mispricing score is explained in detail in Section 3.1.3. The first three columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when all of the mispricing scores are included in the model. I test the equality of the coefficients for the Mispricing Score (Unpublished) and Mispricing Score (Published<10 years), and Mispricing Score (Published<10 years) and Mispricing Score (Published>=10 years). I report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO	SEO
Mispricing Score (Unpublished)	0.43***			0.45***
	(0.07)			(0.09)
Mispricing Score (Published<10 years)		0.18***		0.15**
		(0.04)		(0.06)
Mispricing Score (Published>=10 years)			0.05	0.00
			(0.05)	(0.04)
Industry × Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	418,390	440,357	408,322	386,355
Adjusted R^2	0.02	0.02	0.02	0.02
$\chi^2(\beta_{\text{Misp. Score Unpub.}} = \beta_{\text{Misp Score Pub<10 yrs}})$				5.18
p-value				0.03
$\chi^2(\beta_{\text{Misp Score Pub<10 yrs}} = \beta_{\text{Misp Score Pub>=10 yrs}})$				4.70
p-value				0.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase	Repurchase
Mispricing Score (Unpublished)	-3.08***			-2.74***
	(0.32)			(0.30)
Mispricing Score (Published<10 years)		-2.36***		-1.51***
		(0.51)		(0.45)
Mispricing Score (Published>=10 years)			-0.37	0.02
			(0.23)	(0.17)
Industry × Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	465,899	495,503	481,270	451,666
Adjusted R^2	0.07	0.07	0.07	0.07
$\chi^2(\beta_{\text{Misp. Score Unpub.}} = \beta_{\text{Misp Score Pub<10 yrs}})$				3.66
p-value				0.06
$\chi^2(\beta_{\text{Misp Score Pub<10 yrs}} = \beta_{\text{Misp Score Pub>=10 yrs}})$				12.94
p-value				0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Decomposing Mispricing Score by Accounting Anomalies vs Other Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and two different anomaly based mispricing scores. The dependent variable in Panel A is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are classified as "Accounting" anomalies based on Chen and Zimmermann's (2021) classification and the second mispricing score uses other anomalies. The construction of each mispricing score is explained in detail in Section 3.1.4. The first two columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when both mispricing scores are included in the model. I test the equality of the coefficients for the two mispricing scores and report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO
Mispricing Score (Accounting)	0.71***		0.72***
	(0.05)		(0.05)
Mispricing Score (Others)		0.30***	-0.04
		(0.05)	(0.04)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	440,357	440,357	440,357
Adjusted R^2	0.02	0.02	0.02
χ^2(β_Misp. Score (Account.) = β_Misp Score Pub (Others))			117.15
p-value			0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchases	Repurchases	Repurchases
Mispricing Score (Accounting)	-3.72***		-3.50***
	(0.34)		(0.33)
Mispricing Score (Others)		-2.29***	-0.65***
		(0.28)	(0.23)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	495,503	495,503	495,503
Adjusted R^2	0.08	0.07	0.08
χ^2(β_Misp. Score (Account.) = β_Misp Score Pub (Others))			51.83
p-value			0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The Effect of Executives' Equity Ownership on the Relation Between Mispricing Score and SEO/Repurchase Decision

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between mispricing score and SEO/ share repurchase decision depending on the executives' equity ownership in the firm. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each panel, Column 1 represents the estimated results from the model where the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Column 2 represents the estimated results from the model where the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel A reports the estimated relation between mispricing score and SEO/repurchase decision depending on the CEO ownership to total compensation ratio and Panel B reports the estimated relation between mispricing score and SEO/repurchase decision depending on the equally weighted average of all executive ownership to total compensation ratios. Executive ownership includes vested equity and options when available. If option ownership is missing due data availability, I only use equity ownership. Total compensation is the total payments to the executive in the previous fiscal year. After calculating the ownership by compensation ratios, I split firms into terciles based on the value of these ratios at the beginning of each quarter. I add tercile indicator variables along with the interaction of these variables with the mispricing score. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) Only CEOs

	SEO	Repurchase
Mispricing Score	0.78***	-5.80***
	(0.10)	(0.41)
Equity Ownership Tercile=3 × Mispricing Score	0.08	-2.00***
	(0.15)	(0.27)
Equity Ownership Tercile=3 × Mispricing Score	0.43***	-1.89***
	(0.11)	(0.40)
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	84,109	116,499
Adjusted R^2	0.03	0.13

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) All Executives

	SEO	Repurchase
Mispricing Score	0.56***	-4.21***
	(0.08)	(0.37)
Equity Ownership Tercile=3 × Mispricing Score	0.19*	-1.83***
	(0.10)	(0.36)
Equity Ownership Tercile=3 × Mispricing Score	0.42***	-2.38***
	(0.10)	(0.42)
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	91,541	128,670
Adjusted R^2	0.03	0.12

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Market Timing in Mergers and Acquisitions

This table reports linear probability estimates of the relation between mispricing score and mergers and acquisitions activity. I split mergers and acquisitions into two groups by the payment method. In the first column, I report estimated coefficients of mispricing score when dependent variable is equal to 1 if acquiring firm uses equity as a payment method and 0 otherwise. In the second column, I report estimated coefficients of mispricing score when dependent variable is equal to 1 if acquiring firm uses cash as a payment method and 0 otherwise. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. Each specification includes industry×year fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

	Payment Method	
	Stock Only	Cash Only
Mispricing Score	0.08***	-0.03**
	(0.02)	(0.01)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	34.2	-9.8
Industry × Year FE	✓	✓
Controls	✓	✓
Observations	529,869	529,869
Adjusted R^2	0.00	0.01
Coefficient: Mispricing Score		
$\chi^2(\beta_{StockOnly} = \beta_{Cashonly})$	37.96	
p-value	0.00	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: International Evidence

This table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision (Column 1), and between mispricing score and share repurchase (Column 2) decision for a sample of firms from 33 countries. The construction of mispricing score is identical to the mispricing score constructed for the US sample and explained in detail in Section 2.2. I obtain the anomaly variables and stock characteristics from Jensen, Kelly, and Pedersen (Forthcoming). I only include countries that have at least 50 SEOs or share repurchases and exclude the cross-section of firms that have fewer than 100 firms for a given country. In Column 1, I report the estimated results when the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I report the estimated results when the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes country×industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at country×year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) All Firms

	SEO	Repurchase
Mispricing Score	0.07**	-0.36***
	(0.04)	(0.07)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	7.5	16.6
Industry × Country × Quarter FE	✓	✓
Controls	✓	✓
Observations	1,721,974	1,721,974
Adjusted R^2	0.01	0.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) The Effect of Investor Protection on Market Timing

	SEO	Repurchase
Mispricing Score	-0.07	-0.02
	(0.07)	(0.06)
High Investor Protection Country × Mispricing Score	0.30***	-0.42***
	(0.08)	(0.15)
Industry × Country × Quarter FE	✓	✓
Controls	✓	✓
Observations	866,313	866,313
Adjusted R^2	0.01	0.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Orthogonalized Mispricing Measure

This table reports linear probability estimates of the relation between orthogonalized versions of mispricing score and SEO (Panel A) or share repurchase decision (Panel B). Each orthogonalized mispricing score is constructed by regressing the anomaly based mispricing score, explained in detail in Section 2.2, on the existing measures of mispricing separately and then taking the residual series from this regression. I explain each orthogonalized mispricing scores in Section 6.1. In the first four columns of each panel, I report estimated results when I include each orthogonalized mispricing score in the model. Finally, I regress anomaly based mispricing score on the existing mispricing measures together and create "Orthogonalized Mispricing Score (All)" variable using the residual series from this regression. In the last column, I report estimated results when I include "Orthogonalized Mispricing Score (All)" in the model. In each specification in Panel A, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Panel B, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO	SEO	SEO
Orthogonalized Mispricing Score (BM)	0.78***				
	(0.05)				
Orthogonalized Mispricing Score (Past Return)		0.75***			
		(0.05)			
Orthogonalized Mispricing Score (RIM)			0.69***		
			(0.10)		
Orthogonalized Mispricing Score (Buy Pressure)				0.62***	
				(0.06)	
Orthogonalized Mispricing Score (All)					1.00***
					(0.11)
Industry × Quarter FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	527,017	527,017	37,474	151,443	27,683
Adjusted R^2	0.02	0.02	0.02	0.02	0.03

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase	Repurchase	Repurchase
Orthogonalized Mispricing Score (BM)	-4.41***				
	(0.35)				
Orthogonalized Mispricing Score (Past Return)		-4.13***			
		(0.36)			
Orthogonalized Mispricing Score (RIM)			-5.71***		
			(0.47)		
Orthogonalized Mispricing Score (Buy Pressure)				-5.05***	
				(0.34)	
Orthogonalized Mispricing Score (All)					-6.98***
					(0.53)
Industry $\times$ Quarter FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	499,448	499,448	37,428	150,052	27,662
Adjusted R^2	0.08	0.08	0.17	0.13	0.17

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The Relation Between Mispricing Score and SEO/Repurchase Decision by Market Capitalization

Panel A of this table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision. Each column represents the estimated results for small, medium, and large firms separately. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each column, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. To identify small, medium, and large firms, I first calculate firm size by multiplying share price with number of shares outstanding at the beginning of each quarter. Then, I sort firms into tercile portfolios based on firm size. Panel B of this table reports linear probability estimates of the relation between mispricing score and share repurchase decision. Each column represents the estimated results for small, medium, and large firms separately. In each column, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	Small	2	Large
Mispricing Score	0.21***	0.78***	1.04***
	(0.04)	(0.07)	(0.09)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	149,241	147,023	143,031
Adjusted R^2	0.01	0.02	0.03

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Small	2	Large
Mispricing Score	-2.27***	-3.49***	-5.33***
	(0.21)	(0.32)	(0.53)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	158,283	162,531	173,839
Adjusted R^2	0.03	0.05	0.13

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: The Effect of Executives' Unvested Equity Ownership on the Relation Between Mispricing Score and SEO/Repurchase Decision

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between mispricing score and SEO/ share repurchase decision depending on the executives' equity ownership in the firm by taking unvested shares into account. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each panel, Column 1 represents the estimated results from the model where the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Column 2 represents the estimated results from the model where the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel A reports the estimated relation between mispricing score and SEO/repurchase decision depending on the CEO's ownership in the firm to total compensation ratio. CEO's Ownership includes vested equity and options when available. If option ownership is missing due data availability, I only use equity ownership. Total compensation is the total payments to the executive in the previous fiscal year. After calculating the ownership by compensation ratios, I split firms into terciles based on the value of these ratios at the beginning of each quarter. I add tercile indicator variables along with the interaction of these variables with the mispricing score. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. In addition to these controls, I also control for the ownership of unvested shares. I add a control variable that is the ratio of total value of unvested shares to the CEO compensation. In Panel B, instead of adding unvested share ownership as a control variable, I define ownership in the firm as a sum of vested and unvested equity and options. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) Equity Ownership and SEO & Repurchase Decision

	SEO	Repurchase
Mispricing Score	0.82***	-9.50***
	(0.09)	(0.39)
Equity Ownership = 2 × Mispricing Score	0.05	-2.39***
	(0.10)	(0.40)
Equity Ownership = 3 × Mispricing Score	0.30***	-2.61***
	(0.10)	(0.37)
Firm Controls	Yes	Yes
CEO Controls (Unvested Shares)	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Equity Ownership and SEO & Repurchase Decision

	SEO	Repurchase
Mispricing Score	0.83***	-9.73***
	(0.09)	(0.37)
Equity Ownership (Vested+Unvested) = 2 × Mispricing Score	0.01	-1.98***
	(0.10)	(0.41)
Equity Ownership (Vested+Unvested) = 3 × Mispricing Score	0.32***	-2.37***
	(0.10)	(0.37)
Firm Controls	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A Tables

Table A1: List of Anomalies that are Used to Calculate Mispricing Score

This table documents the stock market anomalies used in constructing mispricing score.

Acronym	Long Description	Paper	Journal	Category
Abnormalaccruals	Abnormal Accruals	Xie (2001)	AR	Accounting
Accruals	Accruals	Sloan (1996)	AR	Accounting
Activism1	Takeover vulnerability	Cremers and Nair (2005)	JF	13F
Activism2	Active shareholders	Cremers and Nair (2005)	JF	13F
Adexp	Advertising Expense	Chan, Lakonishok and Sougiannis (2001)	JF	Accounting
Ageipo	IPO and age	Ritter (1991)	JF	Event
Am	Total assets to market	Fama and French (1992)	JF	Accounting
Analystrevision	EPS forecast revision	Hawkins, Chamberlin, Daniel (1984)	FAJ	Analyst
Analystvalue	Analyst Value	Frankel and Lee (1998)	JAE	Analyst
Announcementreturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok (1996)	JF	Price
Aop	Analyst Optimism	Frankel and Lee (1998)	JAE	Analyst
Beta	CAPM beta	Fama and MacBeth (1973)	JPE	Price
Betafp	Frazzini-Pedersen Beta	Frazzini and Pedersen (2014)	JFE	Price
Betaliquidityps	Pastor-Stambaugh liquidity beta	Pastor and Stambaugh (2003)	JPE	Price
Betatailrisk	Tail risk beta	Kelly and Jiang (2014)	RFS	Price
Betavix	Systematic volatility	Ang et al. (2006)	JF	Price
Bidaskspread	Bid-ask spread	Amihud and Mendelsohn (1986)	JFE	Trading
Brandinvest	Brand capital investment	Belo, Lin and Vitorino (2014)	RED	Accounting
Cashprod	Cash Productivity	Chandrashekar and Rao (2009)	WP	Accounting
Cboperprof	Cash-based operating profitability	Ball et al. (2016)	JFE	Accounting
Cf	Cash flow to market	Lakonishok, Shleifer, Vishny (1994)	JF	Accounting

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam (2004)	AR	Accounting
Changeinrecommendation	Change in recommendation	Jegadeesh et al. (2004)	JF	Analyst
Chassetturnover	Change in Asset Turnover	Soliman (2008)	AR	Accounting
Cheq	Growth in book equity	Lockwood and Prombutr (2010)	JFR	Accounting
Chinv	Inventory Growth	Thomas and Zhang (2002)	RAS	Accounting
Chinvia	Change in capital inv (ind adj)	Abarbanell and Bushee (1998)	AR	Accounting
Chnncoa	Change in Net Noncurrent Op Assets	Soliman (2008)	AR	Accounting
Chnwc	Change in Net Working Capital	Soliman (2008)	AR	Accounting
Chtax	Change in Taxes	Thomas and Zhang (2011)	JAR	Accounting
Compequiss	Composite equity issuance	Daniel and Titman (2006)	JF	Accounting
Compositedebtissuance	Composite debt issuance	Lyandres, Sun and Zhang (2008)	RFS	Accounting
Coskewacx	Coskewness using daily returns	Ang, Chen and Xing (2006)	RFS	Price
Coskewness	Coskewness	Harvey and Siddique (2000)	JF	Price
Customermomentum	Customer momentum	Cohen and Frazzini (2008)	JF	Other
Delbreadth	Breadth of ownership	Chen, Hong and Stein (2002)	JFE	13F
Delcoa	Change in current operating assets	Richardson et al. (2005)	JAE	Accounting
Delcol	Change in current operating liabilities	Richardson et al. (2005)	JAE	Accounting
Deldrc	Deferred Revenue	Prakash and Sinha (2012)	CAR	Accounting
Delequ	Change in equity to assets	Richardson et al. (2005)	JAE	Accounting
Delfinl	Change in financial liabilities	Richardson et al. (2005)	JAE	Accounting
Dellti	Change in long-term investment	Richardson et al. (2005)	JAE	Accounting
Delnetfin	Change in net financial assets	Richardson et al. (2005)	JAE	Accounting
Dnoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang (2004)	JAE	Accounting
Dolvol	Past trading volume	Brennan, Chordia, Subra (1998)	JFE	Trading
Earningsconsistency	Earnings consistency	Alwathainani (2009)	BAR	Accounting
Earningsforecastdisparity	Long-vs-short EPS forecasts	Da and Warachka (2011)	JFE	Analyst
Earningsstreak	Earnings surprise streak	Loh and Warachka (2012)	MS	Accounting
Earningssurprise	Earnings Surprise	Foster, Olsen and Shevlin (1984)	AR	Analyst

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Earnsupbig	Earnings surprise of big firms	Hou (2007)	RFS	Accounting
Ebm	Enterprise component of BM	Penman, Richardson and Tuna (2007)	JAR	Accounting
Entmult	Enterprise Multiple	Loughran and Wellman (2011)	JFQA	Accounting
Ep	Earnings-to-Price Ratio	Basu (1977)	JF	Price
Equityduration	Equity Duration	Dechow, Sloan and Soliman (2004)	RAS	Price
Exclexp	Excluded Expenses	Doyle, Lundholm and Soliman (2003)	RAS	Analyst
Feps	Analyst earnings per share	Cen, Wei, and Zhang (2006)	WP	Analyst
Fgr5Yrlag	Long-term EPS forecast	La Porta (1996)	JF	Analyst
Firmage	Firm age based on CRSP	Barry and Brown (1984)	JFE	Other
Firmagemom	Firm Age - Momentum	Zhang (2004)	JF	Price
Forecastdispersion	EPS Forecast Dispersion	Diether, Malloy and Scherbina (2002)	JF	Analyst
Fr	Pension Funding Status	Franzoni and Marin (2006)	JF	Accounting
Frontier	Efficient frontier index	Nguyen and Swanson (2009)	JFQA	Accounting
Gp	gross profits / total assets	Novy-Marx (2013)	JFE	Accounting
Gradexp	Growth in advertising expenses	Lou (2014)	RFS	Accounting
Grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo (2006)	JF	Accounting
Grcapx3Y	Change in capex (three years)	Anderson and Garcia-Feijoo (2006)	JF	Accounting
Grltnoa	Growth in long term operating assets	Fairfield, Whisenant and Yohn (2003)	AR	Accounting
Grsaletogrinv	Sales growth over inventory growth	Abarbanell and Bushee (1998)	AR	Accounting
Grsaletogroverhead	Sales growth over overhead growth	Abarbanell and Bushee (1998)	AR	Accounting
Herf	Industry concentration (sales)	Hou and Robinson (2006)	JF	Other
Herfasset	Industry concentration (assets)	Hou and Robinson (2006)	JF	Other
Herfbe	Industry concentration (equity)	Hou and Robinson (2006)	JF	Other
High52	52 week high	George and Hwang (2004)	JF	Price
Hire	Employment growth	Bazdresch, Belo and Lin (2014)	JPE	Other
Idiovol3F	Idiosyncratic risk (3 factor)	Ang et al. (2006)	JF	Price
Idiovolaht	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley (2003)	JFE	Price
Illiquidity	Amihud's illiquidity	Amihud (2002)	JFM	Trading

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Indmom	Industry Momentum	Grinblatt and Moskowitz (1999)	JFE	Price
Indretbig	Industry return of big firms	Hou (2007)	RFS	Price
Intanbm	Intangible return using BM	Daniel and Titman (2006)	JF	Accounting
Intancfp	Intangible return using CFtoP	Daniel and Titman (2006)	JF	Accounting
Intanep	Intangible return using EP	Daniel and Titman (2006)	JF	Accounting
Intansp	Intangible return using Sale2P	Daniel and Titman (2006)	JF	Accounting
Intmom	Intermediate Momentum	Novy-Marx (2012)	JFE	Price
Investment	Investment to revenue	Titman, Wei and Xie (2004)	JFQA	Accounting
Investppeinv	change in ppe and inv/assets	Lyandres, Sun and Zhang (2008)	RFS	Accounting
Invgrowth	Inventory Growth	Belo and Lin (2012)	RFS	Accounting
Io_Shortinterest	Inst own among high short interest	Asquith Pathak and Ritter (2005)	JFE	13F
Lrreversal	Long-run reversal	De Bondt and Thaler (1985)	JF	Price
Maxret	Maximum return over month	Bali, Cakici, and Whitelaw (2010)	JF	Price
Meanrankrevgrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny (1994)	JF	Accounting
Mom12M	Momentum (12 month)	Jegadeesh and Titman (1993)	JF	Price
Mom12Moffseason	Momentum without the seasonal part	Heston and Sadka (2008)	JFE	Price
Mom6M	Momentum (6 month)	Jegadeesh and Titman (1993)	JF	Price
Mom6Mjunk	Junk Stock Momentum	Avramov et al (2007)	JF	Price
Momoffseason	Off season long-term reversal	Heston and Sadka (2008)	JFE	Price
Momoffseason06Yrplus	Off season reversal years 6 to 10	Heston and Sadka (2008)	JFE	Price
Momoffseason11Yrplus	Off season reversal years 11 to 15	Heston and Sadka (2008)	JFE	Price
Momoffseason16Yrplus	Off season reversal years 16 to 20	Heston and Sadka (2008)	JFE	Price
Momseason	Return seasonality years 2 to 5	Heston and Sadka (2008)	JFE	Price
Momseason06Yrplus	Return seasonality years 6 to 10	Heston and Sadka (2008)	JFE	Price
Momseason11Yrplus	Return seasonality years 11 to 15	Heston and Sadka (2008)	JFE	Price
Momseason16Yrplus	Return seasonality years 16 to 20	Heston and Sadka (2008)	JFE	Price
Momseasonshort	Return seasonality last year	Heston and Sadka (2008)	JFE	Price
Mrreversal	Medium-run reversal	De Bondt and Thaler (1985)	JF	Price

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Netdebtfinance	Net debt financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Netdebtprice	Net debt to price	Penman, Richardson and Tuna (2007)	JAR	Accounting
Netequityfinance	Net equity financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Noa	Net Operating Assets	Hirshleifer et al. (2004)	JAE	Accounting
Numearnincrease	Earnings streak length	Loh and Warachka (2012)	MS	Accounting
Operprof	operating profits / book equity	Fama and French (2006)	JFE	Accounting
Operprofrd	Operating profitability R&D adjusted	Ball et al. (2016)	JFE	Accounting
Opleverage	Operating leverage	Novy-Marx (2010)	ROF	Accounting
Optionvolume1	Option to stock volume	Johnson and So (2012)	JFE	Trading
Optionvolume2	Option volume to average	Johnson and So (2012)	JFE	Trading
Orderbacklog	Order backlog	Rajgopal, Shevlin, Venkatachalam (2003)	RAS	Accounting
Orderbacklogchg	Change in order backlog	Baik and Ahn (2007)	Other	Accounting
Orgcap	Organizational capital	Eisfeldt and Papanikolaou (2013)	JF	Accounting
Pctacc	Percent Operating Accruals	Hafzalla, Lundholm, Van Winkle (2011)	AR	Accounting
Pcttotacc	Percent Total Accruals	Hafzalla, Lundholm, Van Winkle (2011)	AR	Accounting
Predictedfe	Predicted Analyst forecast error	Frankel and Lee (1998)	JAE	Accounting
Pricedelayrsq	Price delay r square	Hou and Moskowitz (2005)	RFS	Price
Pricedelayslope	Price delay coeff	Hou and Moskowitz (2005)	RFS	Price
Pricedelaytstat	Price delay SE adjusted	Hou and Moskowitz (2005)	RFS	Price
Probinformedtrading	Probability of Informed Trading	Easley, Hvidkjaer and O'Hara (2002)	JF	Trading
Ps	Piotroski F-score	Piotroski (2000)	AR	Accounting
Rd	R&D over market cap	Chan, Lakonishok and Sougiannis (2001)	JF	Accounting
Rdability	R&D ability	Cohen, Diether and Malloy (2013)	RFS	Accounting
Rdcap	R&D capital-to-assets	Li (2011)	RFS	Accounting
Rds	Real dirty surplus	Landsman et al. (2011)	AR	Accounting
Realestate	Real estate holdings	Tuzel (2010)	RFS	Accounting
Residualmomentum	Momentum based on FF3 residuals	Blitz, Huij and Martens (2011)	JEmpFin	Price
Retconglomerate	Conglomerate return	Cohen and Lou (2012)	JFE	Price

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Returnskew	Return skewness	Bali, Engle and Murray (2015)	Book	Price
Returnskew3F	Idiosyncratic skewness (3F model)	Bali, Engle and Murray (2015)	Book	Price
Rev6	Earnings forecast revisions	Chan, Jegadeesh and Lakonishok (1996)	JF	Analyst
Revenuesurprise	Revenue Surprise	Jegadeesh and Livnat (2006)	JFE	Accounting
Roe	net income / book equity	Haugen and Baker (1996)	JFE	Accounting
Sfe	Earnings Forecast to price	Elgers, Lo and Pfeiffer (2001)	AR	Analyst
Shareiss1Y	Share issuance (1 year)	Pontiff and Woodgate (2008)	JF	Accounting
Shareiss5Y	Share issuance (5 year)	Daniel and Titman (2006)	JF	Accounting
Shortinterest	Short Interest	Dechow et al. (2001)	JFE	Other
Skew1	Volatility smirk near the money	Xing, Zhang and Zhao (2010)	JFQA	Options
Smileslope	Put volatility minus call volatility	Yan (2011)	JFE	Options
Sp	Sales-to-price	Barbee, Mukherji and Raines (1996)	FAJ	Accounting
Std_Turn	Share turnover volatility	Chordia, Subra, Anshuman (2001)	JFE	Trading
Tang	Tangibility	Hahn and Lee (2009)	JF	Accounting
Tax	Taxable income to income	Lev and Nissim (2004)	AR	Accounting
Totalaccruals	Total accruals	Richardson et al. (2005)	JAE	Accounting
Varcf	Cash-flow to price variance	Haugen and Baker (1996)	JFE	Accounting
Volmkt	Volume to market equity	Haugen and Baker (1996)	JFE	Trading
Volsd	Volume Variance	Chordia, Subra, Anshuman (2001)	JFE	Trading
Volumetrend	Volume Trend	Haugen and Baker (1996)	JFE	Trading
Xfin	Net external financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Zerotrade	Days with zero trades	Liu (2006)	JFE	Trading

Table A2: List of Countries that are Used in the International Analysis

This table documents the list of countries that are used in the international analysis.

Australia	India	Turkey
Belgium	Israel	Vietnam
Brazil	Italy	South Africa
Canada	Japan	
Switzerland	Korea, Republic	
Chile	Malaysia	
China	Netherlands	
Germany	Norway	
Denmark	New Zealand	
Spain	Philippines	
Finland	Poland	
France	Russian Federation	
United Kingdom	Singapore	
Hong Kong SAR, China	Sweden	
Indonesia	Thailand	

B Control Variables

Return on Asset: The most recent annual value of "Operating Income Before Depreciation" (OIBDP) variable scaled by lag "Total Asset" (AT).

Cash by Asset: The most recent quarterly value of "Cash and Cash Equivalents" (CHEQ) variable scaled by "Total Asset" (ATQ). If quarterly value is missing, I replace variable value with the most recent ratio from annual data.

Market Capitalization: The value of stock price multiplied by total shares outstanding at the beginning of quarter .

Leverage: The most recent quarterly value of "Total Liabilities" (LTQ) variable scaled by "Total Asset" (ATQ). If quarterly value is missing, I replace variable value with the most recent ratio from annual data.

Dividend Yield: The most recent annual value of "Dividends" (DVC) variable scaled by end of year market value, calculated as the product of stock price and total shares outstanding.

Volatility: Daily volatility of returns in the previous quarter.

Δ ***Volatility:*** Year over year change in the daily volatility of returns in the previous quarter.

Firm Age: Number of months since first listed in CRSP database.

Monetary Policy Uncertainty and Asset Price Bubbles

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Abstract

We examine the impact of monetary policy uncertainty (MPU) in predicting asset price bubbles. Using US data from 1926-2019, we find that greater monetary policy uncertainty leads to a greater likelihood of bubbles in industry level returns. The result is robust to criticisms on the ex-ante identification of bubbles. The evolution of this relationship over time is concomitant with the FED's increased transparency of its monetary policy. Machine learning models that incorporate MPU outperform models that don't in their ability to predict bubbles in real time.

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1 Introduction

In this paper we study the impact of monetary policy uncertainty (MPU) in predicting future asset price bubbles. Using US data from 1926-2019, we find that greater monetary policy uncertainty leads to a greater likelihood of bubbles in industry level returns. Including MPU in machine learning models improves their ability to predict bubbles in real time.

Concerns about the adverse impact of MPU on the economy have increased in the wake of the global financial crisis and serial crises in the Eurozone. For example, the International Monetary Fund (IMF) (2012, 2013) suggests that uncertainty about U.S. and European monetary policies (among other factors) contributed to a steep economic decline in 2008–2009 and slow recoveries afterward. In contrast, in July 2012, during the eurozone debt crisis, the European Central Bank (ECB) chairman Mario Draghi, said the ECB would do "whatever it takes" to preserve the euro - adding "And believe me, it will be enough". [1] Draghi's prompt and unequivocal resolution of MPU (by asserting that ECB would print euros to buy the government bonds of the struggling countries) was widely credited by economic experts as the key reason for stemming the eurozone debt crisis (Mordfin (2014)).

Expansionary monetary policy where the level of government interest rates are effectively zero have long been recognized to create bubbles in the valuation of risky assets (Woodford (2012)). These bubbles might then burst if interest rates start to move back up again, producing economic declines. The 2000 - 2008 housing bubble followed by the financial crisis in the US was considered a prime example of this phenomenon of low level of interest rates producing asset price bubbles. However, empirical analysis of the second moment i.e., MPU, in generating asset price bubbles has received far less attention in the literature. We organize our hypothesis around the theoretical insights from the models of Allen and Gale (2000, 2004). These models account for financial market imperfections (agency problems between lenders and borrowers) and suggest that greater uncertainty about the future monetary policy would

[1] During this time, there were credit downgrades across Europe and deep financial problems in many countries including Greece, Portugal and Ireland.

generate and amplify asset price bubbles through the credit dynamics.

We first investigate the relationship between MPU this period and industry level asset price bubbles next period, between January 1985 and June 2019 when the "MPU Index" of Baker, Bloom and Davis (2016) (BBD, hereafter) is available [2]. We find that a one standard deviation increase in the "MPU Index" leads to a statistically significant 73% increase in the likelihood of an industry level asset price bubble relative to its unconditional mean. We also find that a one standard deviation decrease in the interest rate change (a declining interest rate environment) leads to a statistically significant 205% increase in the likelihood of an industry level asset price bubble relative to its unconditional mean.

To investigate the relationship between MPU and industry level asset price bubbles in a longer sample period, we construct an alternative "MPU Index" between January 1931 and October 2014. During this longer sample period, we find a much more pronounced relationship between the MPU Index and asset price bubbles. We find that a one standard deviation increase in the "MPU Index" leads to a statistically significant 327% increase in the likelihood of an industry level asset price bubble relative to its unconditional mean. However, the relationship between MPU and asset price bubbles becomes stronger in a declining interest rate environment, consistent with the idea that lower cost of borrowing coupled with MPU is more likely to produce a bubble.

The difference in the strength of the relationship between MPU and asset price bubbles between the short sample period (Jan 1985-Jun 2019) and the long sample period (Jan 1931-Oct 2014) can be explained by the Federal Reserve Board's (FED) disclosure policy, defined as the elapsed time lag between the Federal Open Market Committee (FOMC) meetings and the publication of the official minutes of the meeting. Until 1967, the minutes of the FOMC meetings were published once a year. In June 1967, the FED announced that the Records of Policy Actions would be released around ninety days after the meeting. In 1975, the Committee decreased the ninety days lag to forty-five days, and in 2004, further decreased

[2] We identify bubbles by adapting Greenwood, Shleifer and You (2019)'s definition of an asset price bubble at the industry level

the lag to twenty-one days. Theories of disclosure (Easley and O'Hara (2004), Pastor and Veronesi (2003)) suggest that timely communications from the FED are likely to decrease MPU in the financial markets in the short sample period relative to the long sample period, potentially leading to the weakening relationship between MPU and asset price bubbles. However, the relationship remains economically and statistically significant even in the short sample period.[3]

We also conduct a battery of robustness tests. First, we use the Husted Rogers and Sun (2020, HRS hereafter) "MPU Index" instead of the BBD's "MPU Index" and confirm our earlier results. We also use the first principal component of BBD's "MPU Index" and HRS' "MPU Index" to capture the common variation between these two measures and find similar results. To alleviate any potential concerns that the price run-ups and the subsequent crashes in industry returns might be an artifact of rational expectations about the real economy, we follow HRS and explicitly include their additional explanatory variables related to expected economic conditions. Our results continue to remain economically and statistically significant.

Our empirical procedure adapts Greenwood, Shleifer and You (2019, GSY hereafter)'s method and identifies bubbles as price run-ups followed by crashes, defined as at least a 30% drawdown (lowest cumulative return) within the 12 months after a price run-up. However, Kim and Richardson (2022, KR hereafter) criticize the GSY's identification of bubbles by pointing out such a run-up and a crash would be expected even in a world without bubbles having a high level of volatility and a random walk model of stock prices. We employ extensive simulation evidence to examine this issue and conclude that our findings are not driven by the KR criticism about the GSY procedure to define a bubble.

Motivated by the relationship between MPU and industry level asset price bubbles in the full sample period, we investigate whether the bubbles are predictable in real time. To do so, we employ an array of 135 machine learning models. First, we specify the time period

[3]We discuss this issue in detail in Section 5.2

between January 1931 and December 1989 as the training (in-sample) period for the machine learning models. Then, we predict asset price bubbles between January 1990 and June 2019 (out-of-sample period). For each machine learning model, we estimate two specifications: one specification with the "MPU Index" included with all other control variables and a second specification with the "MPU Index" excluded but all other control variables included in the estimation. Finally, we calculate the average performance improvement in the F2 score after the inclusion of the "MPU Index".[4] The average F2 score of the models improves by 1.2% in the in-sample period. More importantly, the average F2 score improves by an impressive 9.7% in the out-of-sample period. This result suggests that machine learning models generalize very well in making predictions during the out of sample period. Our previous results underscore the importance of Wolpert's (1996) "no free lunch theorem" in machine learning. Using prior domain specific knowledge of economic theory about how MPU causes asset price bubbles produces predictions vastly superior to a purely data driven machine learning approach incorporating other economic variables. While the prediction improvement on the training data is small, the real value of this Economics driven machine learning approach can be seen in the dramatic prediction improvement on a yet-unseen test dataset.

2 Theoretical Predictions

As noted in the introduction, MPU and its resolution are very important for financial markets. However, understanding the dynamics between MPU and stock market bubbles requires an economic model.

We use the three-period model in Allen and Gale (2000) that documents the relation between MPU and asset price bubbles. In this model, investors borrow from intermediaries (banks) and invest in a fixed supply risky asset such as a stock or real estate at period 0.

[4]The F2 score is a measure of model accuracy in machine learning. It is calculated from the precision (related to type 1 error) and recall (related to type 2 error) of a test. See section 6.2 for details.

Central banks determine the credit supply in the economy and the contemporaneous level of credit supply is observable to the investors. However, investors know only the potential levels of credit supply at period 1 with their associated probabilities. In addition, investors also know the risky asset's payoffs and probabilities for each state in period 2. By using this information, it is possible to derive the price of the risky asset at time 0 which depends on the potential credit supply levels at period 1. In this model, the only variable is the total credit supply at period 1, and there are no changes in the real economy.

The key friction in the model is an agency problem between investors and banks. If investors invest with their own money, they would be willing to pay up to the fundamental value of the asset. However, when investors borrow from the banks, the limited liability constraint produces an agency problem between the investors and the banks. Since the banks can not observe how the funds are used by the investors, the investors can indulge in risk shifting and invest more in the riskier asset to benefit from the upside but walk away from the downside due to the limited liability constraint. This agency problem gives investors an incentive to bid up the asset prices more than the fundamental values because their return on investment will be higher when they use external funds.

Figure 1 illustrates the model. The price of the risky asset in the future is denoted by P_{tj} where t denotes the time period and j denotes the state of the economy. The total credit supply in the future is denoted by B_{tj}. The total credit supply at time 0 is equal to B_0. The investor pays P_0 for the risky asset and invests the remaining amount x (the difference between the credit supply B_0 and P_0) in the safe asset at time 0. The interest rate on the bank loans is denoted by r and determined by the marginal product of capital in the economy.

$$x = B - P$$

And the economy's productive technology produces f(x) in the next period:

$$f(x) = 3(B - P)^{0.5}$$

Therefore, the first derivative of this function will be equal to the interest rate on bank loans given that market for loans is competitive.

$$f'(B-P) = r = 1.5(B-P)^{-0.5}$$

Risk neutral investors will be indifferent between borrowing and investing in the risky asset or the safe asset. Therefore, borrowing and investing in the risky asset should not yield any profits for the investors in equilibrium. Using the equations above, the price of the risky asset can be calculated as follows:

$$0.25(\frac{1}{P} \times 6 - r) + 0.75 \times 0 = 0$$

The first term corresponds to good outcome in which case the borrower repays the loan. The second term corresponds to bad outcome in which case the borrower walks away due to the limited liability. Using the value of $r = 1.5(B-P)^{-0.5}$ in the above equation, we obtain

$$P = 4(B-P)^{0.5}$$

Solving for P gives

$$P = 8(-1 + \sqrt{1 + 0.25B})$$

By using the price equation above, P_{11} and P_{12} can be calculated by substituting the credit supply values for each state (B_{11} and B_{12}). Then, P_0 can be derived by repeating the same procedure with B_0, P_{11} and P_{12}.

The model has two main predictions. First, credit supply uncertainty leads to asset price bubbles and the bubbles get stronger when the credit supply uncertainty increases. We note that the fundamental value of the asset (no borrowing) is the expected payoff at date 2 which is \$2.25. However, if we assume borrowing and that $B_{11} = 7$ and $B_{12} = 5$, then P_0 is equal to \$4.42. Thus, the size of the asset price bubble is \$4.42-\$2.25 = \$2.17. Moreover, increasing the spread between B_{11} and B_{12} by preserving their mean leads to a stronger bubble. When $B_{11} = 8$ and $B_{12} = 4$, P_0 is equal to \$4.62 and the size of the bubble increases to \$4.62-\$2.25 = \$2.37. We observe stronger bubbles when the credit supply uncertainty increases although the expected credit supply remains the same. Second, lower interest rates exacerbates the agency problem and lead to stronger bubbles. Therefore, central banks can not determine a higher credit supply (lower interest rates) to avoid a financial crisis.

3 From Theory to Empirical Tests

Empirical tests of the theoretical predictions require two main variables. The first variable is the fundamental value of the assets to identify the asset price bubbles. However, fundamental values are not observable. Being unable to observe the fundamental value gives rise to the view that bubbles do not exist in financial markets. The main criticism about the existence of the bubbles is that a price run-up and a crash going forward is defined as a bubble. However, this pattern might not necessarily mean that the market prices deviate from the fundamental value. As Fama[5] points out, if bubbles exist, then they must be predictable. He argues that without finding statistical ways to identify the bubbles, one can not argue that the asset price bubbles exist in financial markets.

In response to this argument, Greenwood, Shleifer and You (2019, GSY hereafter) documents that a sharp price increase predicts a substantially heightened probability of a crash. By using the past industry returns up to 5 years, this paper finds that the probability of a crash increases as the magnitude of the price run-up increases. This result shows that probability of a crash can be systematically predicted after a price run-up although we do not observe the fundamental values. Motivated by this finding, we adapt GSY's procedure to identify the bubbles.

The second variable that we need for our empirical tests is a measure for the monetary

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

policy uncertainty. However, monetary policy uncertainty is not observable either, and we do not have a direct way to measure it. To overcome this issue, we use two news based MPU indexes that are widely used in the literature. The first MPU Index is created by Baker, Bloom and Davis (2016, BBD hereafter) and the second MPU Index is created by Husted, Rogers and Sun (2020, HRS hereafter). They both use the newspaper articles to create an MPU index but with slightly different techniques. We describe each MPU Index in detail in the Section 4.3.1. We use the BBD's MPU Index to measure monetary policy uncertainty in our main specifications but we also estimate our model and show that our results are similar by using the HRS' MPU index.

4 Data and Variables

4.1 Sample Construction

Our sample includes all the U.S. common stocks (share code 10 or 11) in the CRSP database from January 1926 through June 2019. By using these stocks, we form industry portfolios based on the Fama-French 49 industry definitions excluding "Other". We assign each stock to an industry portfolio by using Compustat historical SIC codes when available, and, if not, using CRSP SIC codes. Unlike the Fama-French industry portfolios that are updated annually, we update our portfolios monthly similar to GSY. This modification allows us to include the recently listed companies that might be the drivers of the asset price bubbles. We calculate the monthly industry returns as the value weighted average of the monthly returns of all the stocks in each industry.

4.2 Price Run-ups and Bubbles

We classify each industry-month in our sample period into three groups by adapting the procedure followed by GSY: "No Price Run-up", "Bubble" or "No Bubble". If the monthly industry return is below a certain threshold (percentile) of the entire historical return distribution, we define this industry-month as "No Price Run-up". We use 3 different thresholds to define a price run-up, 95th, 90th, and 75th percentile of the historical returns. "Bubbles" are defined as the price run-ups followed by at least 30% drawdown (crash) at any point within the next 12 months. Price run-ups that are not followed by a crash are defined as "No Bubble". Since we need the historical distribution of the industry returns to classify monthly observations, we include each industry in our sample after it has amassed five years of return data. Therefore, our sample period starts in January 1931, five years after the first observation in the CRSP database.

Figure 2 shows the equally weighted average of the cumulative industry returns around the "No Bubble" and "Bubble" events, which are defined based on the 95th percentile threshold during our sample period. For each industry level event ("No Bubble" or "Bubble"), we calculate the subsequent 12 month cumulative returns when there is a price run up in that month. Finally, we plot the equally weighted average of the cumulative industry returns in event time for each event.

In Figure 2, we observe that for the "No Bubble" events, a price run-up is followed by a further increase in the asset prices over the next 12 months. In contrast, for the "Bubble" events, a price run-up is followed by a crash on average within the next seven months, and then returns remain relatively stable.

In Figure 3, we plot the dates of all "No Bubble" and "Bubble" events on the x-axis for each industry represented on the y-axis. "Bubble" events are rare and tend to cluster around similar dates, i.e., beginning of 1930s, mid 1970s, and beginning of 2000s. "No Bubble" events are far more in number but there is no discernable pattern for the time periods in which they occur. This finding accords with the hypothesis that the "Bubble" events are perhaps related to a macroeconomic variable (such as MPU) and "No Bubble" events are perhaps related to fundamentals.

Next, we investigate if the number of "Bubble" events is concentrated in some specific industries. In particular, there might be a potential concern that industries with high return volatility are more likely to have extreme returns and thus over-represented in the "Bubble" events sample.

To examine this issue, we report the number of "Bubble" events in each industry over our sample period in Panel A of Table 1. Five industries have experienced 0-1 "Bubble" events and three industries have experienced more than 10 "Bubble" events between January 1931 and June 2019. For the remaining industries, the number of "Bubble" events is between 2 and 9. These numbers show that the "Bubble" events while infrequent occur across all industries.

Panel B of Table 1 documents the frequencies of the three events that make up our sample: "Bubble", "No Bubble", and "No Price Run-up" across all industry-months. For the period spanning from January 1931 to June 2019, only 0.5% of the industry-months are "Bubble" events, and 2.9% are "No Bubble" events. This table shows that asset price bubbles are indeed very rare events and any approach to detect them in real-time would be very difficult.

In Panel C of Table 1, we investigate whether "Bubble" events are different than "No Bubble" events in terms of change in industry volatility, change in share turnover, industry age (value weighted age of the stocks in the industry), age tilt (difference between equally weighted and age-weighted monthly industry returns), and issuance (percentage of the firms in the industry that has increased the adjusted total shares outstanding at least by 5% in the last year). We find that all the variables except for age tilt are different across "No Bubble" and "Bubble" events, supporting the idea that these two events are fundamentally different from each other. Detailed variable definitions are outlined in Section 4.4.

4.3 Uncertainty Measures

4.3.1 Monetary Policy Uncertainty

The first monetary policy uncertainty measure that we use in our analysis is BBD's MPU Index, which incorporates hundreds of U.S. newspapers covered by Access World News. This index is constructed by calculating the ratio of number of articles discussing monetary policy uncertainty to the total number of articles. BBD normalize this index so that it has a mean of 100 from 1985 to 2010. We use the BBD MPU Index between January 1985 and June 2019 in our tests. We further standardize this measure to have a mean zero and a standard deviation of 1 over our sample period. Since the MPU Index data is available only in the recent period, it does not allow us to the identify the relationship between MPU and asset price bubbles in the long run.

To address this issue and increase our sample period, we construct a MPU Index between January 1931 and October 2014. We construct this longer time series of MPU Index by regressing BBD's MPU Index on their "US Historical News-Based Economic Policy Uncertainty Index" and Lukas Püttmann's (2018) "Financial Stress Indicator" series between January 1985 and October 2014. We then use the estimated coefficients from this regression to obtain a fitted MPU series between January 1931 and October 2014. While "US Historical News-Based Economic Policy Uncertainty Index" and "Financial Stress Indicator" are available from the beginning of our sample period, the former measure is available only until October 2014, thereby limiting our constructed MPU series until October 2014.

Panel A of Figure 4 presents the BBD's MPU Index between January 1985 and June 2019 and labels some major events that coincide with the spikes in this index. Panel B of Figure 4 presents the longer MPU Index between January 1931 and October 2014 and labels some major events that coincide with the spikes in this index. These figures show that the spikes in both of the MPU Indexes successfully capture heightened uncertainty around major political and economical events. Panel C of Figure 4 presents the two series together in the overlapping period, which is between January 1985 and October 2014. The striking similarity between the two indexes shows that our procedure for extending the MPU time series over a longer period is successful in capturing the relevant information in the MPU Index.

We also assess the stability of our results by using two alternative MPU measures. The first alternative is HRS' MPU Index. This index is broadly constructed in a similar way to BBD's index but with some important differences. HRS state that the difference between two indexes is driven by differences in newspaper coverage, keywords, and the scaling procedure employed. HRS use major newspapers such as Wall Street Journal, New York Times and Washington Post whereas the BBD's MPU Index uses more than 2,000 newspapers. In addition, HRS' selection of keywords allows them to capture the monetary policy uncertainty only in the U.S., while BBD's MPU Index captures both domestic and foreign sources of MPU. Finally, the two indexes differ in scaling the number of articles that contain MPU. To scale the number of MPU related articles, BBD uses the total number of articles in the newspapers whereas HRS uses the number of articles that mention the word "Federal Reserve". The reported correlation between the two MPU series is 0.49 and both of them are available after 1985. The second alternative measure we use is the first principal component of BBD's and HRS' MPU indexes to capture the common variation between the two indexes.

4.3.2 Economic Policy Uncertainty

It is important in the theory to distinguish between economic policy uncertainty (EPU) and MPU. However, EPU and MPU are highly positively correlated and this might cause mistaken inferences. To alleviate this concern, we explicitly include EPU as a control variable in our estimations. We use two EPU measures depending on the sample period. For the period between January 1985 and June 2019, we use BBD's EPU Index. Similar to BBD's MPU Index, this index is also only available after January 1985. For the period between January 1931 and October 2014, we use BBD's "US Historical News-Based Policy Index". This measure has been used by Gulen and Ion (2016) to study corporate investments and Bonaime, Gulen and Ion (2018) to study mergers and acquisitions.

4.4 Industry Level Control Variables

In addition to MPU and EPU, industry conditions are also likely to affect the likelihood of asset price bubbles. To control for this possibility, we use five industry characteristics as constructed by GSY in our tests.

Our first control variable is Δ *Volatility*, which is the change in the value weighted percentile ranked volatility measure over the previous 12 months. At the beginning of each month, we calculate each stock's daily volatility in the previous month and then percentile rank all stocks based on these volatility measures. Finally, we take the value weighted average of the percentile ranks of all stocks in each industry-month and calculate its change over the previous 12 months.

Δ *Turnover* is the change in the value weighted percentile ranked turnover measure over the previous 12 months. Turnover for each stock is defined as the ratio of number of shares traded to the number of shares outstanding in any given month. At the beginning of each month, we calculate each stock's monthly turnover in the previous month and then percentile rank all the stocks based on the turnover measure. Finally, we calculate the value weighted average of the percentile ranks of all stocks in each industry-month and calculate its change over the previous 12 months.

Industry Age: At the beginning of each month, we calculate each stock's age in years (from the time of its first appearance in the CRSP database) and then percentile rank all stocks based on the age. Finally, we calculate the value weighted average of the percentile ranks of all stocks in each industry-month.

Age tilt is the difference between the equally weighted and age-weighted monthly industry returns of all stocks in that industry.

Issuance is the percentage of the firms in an industry that has increased their adjusted total shares outstanding at least by 5% over the previous 12 months.

4.5 Interest Rates

It is widely believed that a declining interest rate environment is one of the most important drivers of asset price bubbles. Therefore, we also include changes in interest rates as an explanatory variable in our estimations. By controlling for changes in the interest rates, we argue that the second moment of the monetary policy has an incremental effect on the likelihood of asset price bubbles. We measure changes in the interest rates ($\Delta Interest\ Rate$) as the monthly change in the Effective Federal Funds Rate[6] when available (during the time period between July 1954 and June 2019), or the 3-Month Treasury Bill rate in the secondary market[7] (during the time period between January 1934 and June 1954), or the yield on short term securities[8] (during the time period between January 1931 and December 1933), depending on the data availability.

5 Methodology and Results

5.1 The Relation Between Asset Price Bubbles and Monetary Policy Uncertainty

5.1.1 Analysis of the January 1985 - June 2019 Period

We begin our analysis by estimating the relationship between MPU and likelihood of asset price bubbles between January 1985 and June 2019. We use a multinomial logistic model as follows:

$$\begin{aligned} log\left(\frac{P(\mathrm{y}_{i,t+1} = \text{No Bubble})}{P(\mathrm{y}_{i,t+1} = \text{No Price Run-up})}\right) &= \beta_{10} + \beta_{11} \times \text{MPU Index}_t + \beta_{12} \times \text{EPU Index}_t \\ &+ \beta_{13} \times \Delta\text{Interest Rate}_t + \gamma_i + \text{Controls}_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} log\left(\frac{P(\mathrm{y}_{i,t+1} = \text{Bubble})}{P(\mathrm{y}_{i,t+1} = \text{No Price Run-up})}\right) &= \beta_{20} + \beta_{21} \times \text{MPU Index}_t + \beta_{22} \times \text{EPU Index}_t \\ &+ \beta_{23} \times \Delta\text{Interest Rate}_t + \gamma_i + \text{Controls}_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

Our outcome variable, $y_{i,t+1}$, takes three values for industry i in month t+1: ”No Price

[6] https://fred.stlouisfed.org/series/FEDFUNDS
[7] https://fred.stlouisfed.org/series/TB3MS
[8] https://fred.stlouisfed.org/series/M1329AUSM193NNBR

Run-up", "No Bubble", or "Bubble" as defined in Section 4.2. We use BBD's MPU Index and EPU Index. ΔInterest Rate is the monthly change in the interest rate as described in Section 4.5. *Controls* are industry level features that are defined in Section 4.4. γ_i denotes industry fixed effects. The standard errors of the estimated coefficients are clustered at the industry level.

We report our estimation results in Table 2. As explained in Section 4.2, we use three different industry return thresholds to define a price run-up (95th, 90th, or 75th). For all these three thresholds, we report the estimated coefficients in the multinomial logistic regression for the "No Bubble" and "Bubble" events (all the coefficients are relative to the "No Price Run-up" event). We also report the χ^2 statistic and the associated p-values for the null hypothesis that the estimated coefficients (MPU Index, $\Delta Int.Rate$ and EPU Index) are equal across the "No Bubble" and "Bubble" events.

We document that the estimated coefficients of the MPU Index for the "Bubble" event are positive and statistically significant at the 1% level regardless of the price run-up threshold used to define a bubble. At the same time, we also find that the estimated coefficients of the MPU Index for the "No Bubble" event are negative and sometimes statistically significant at the 1% level. The equality of the coefficients for MPU Index between the "No Bubble" and "Bubble" events in the regressions is strongly rejected across all the three specifications at the 1% level of statistical significance. This result suggests that MPU is strongly associated with the formation of asset price bubbles as predicted by the theory in Section 2.

The estimated coefficients are economically significant as well. For example, in the specification that uses the 95th percentile threshold to define a price run-up, a one standard deviation increase in the MPU Index is associated with a 71% increase in the probability of an asset price bubble relative to the unconditional probability. The economic magnitudes of the MPU Index coefficient are comparable for the other two specifications with the alternate price run-up thresholds.

We also test whether EPU and $\Delta Int.Rate$ have differential effects on the likelihood of a "Bubble" and a "No Bubble" event. Our results show that the sign of the estimated coefficient on the EPU Index is positive and statistically significant for the "No Bubble" event. In sharp contrast, we find that the sign of the estimated coefficient on the EPU Index is negative and statistically significant for the "Bubble" event across all specifications. A formal χ^2 test shows that we can reject the equality of the two coefficients at the 1% statistical significance level across all specifications.

These results are consistent with the argument that increasing EPU is associated with higher values of real options for firms and industries, thereby making a "No Bubble" (an extended price run-up) more likely. We also find that higher levels of EPU is negatively associated with "Bubble" events in contrast to the earlier result that higher levels of MPU is positively associated with "Bubble" events. These results further strengthen the notion that MPU is not simply a subset of EPU, and measures a phenomenon orthogonal to the underlying EPU in the economy.

We also report the estimated coefficients of $\Delta Int.Rate$. We document that in a declining interest rate environment, the likelihood of a "Bubble" event is greater than the likelihood of a "No Bubble" event. We can reject the equality of the estimated coefficients across the two events in the regression at a very high level of statistical significance (5% or 1% level depending on the regression specification).

5.1.2 Analysis of the January 1931 - October 2014 Period

Our results show a robust positive relationship between MPU and asset price bubbles as predicted by theory, for the post 1985 time period. We now investigate whether the documented relationship exists over a longer sample period. We estimate the Equation (1) and Equation (2) (the multinomial logistic model) for the period spanning from January 1931 to October 2014. Since we don't have an existing MPU measure in the literature for the period before 1985, we construct a longer time series of the MPU Index as explained in Section 4.3.1. Among control variables, we also use BBD's "News Based Economic Policy Uncertainty Index" (instead of the EPU Index, which is not available before 1985). We construct $\Delta Int.Rate$ using alternative measures of interest rates for this time period as described in Section 4.5.

We now describe our regression results for the period between January 1931 and October 2014. In panel A of Table 3, we show that the relationship between MPU and asset price bubbles is even stronger in the longer sample period. All the estimated coefficients of the MPU Index are positive and statistically significant at the 1% level for the "Bubble" event and much greater than the estimated coefficients of the MPU Index in Table 2 (the shorter sample period between Jan 1985-Jun 2019). The coefficients for the longer sample period (Jan 1931-Oct 2014) are 3.6x to 5x bigger than the coefficients for the shorter sample period. A one standard deviation increase in the MPU Index is associated with a 327% increase in the probability of an asset price bubble relative to its unconditional probability (for the specification that uses the 95th percentile return threshold to define a price run-up). Thus, the economic impact of MPU on asset price bubbles seems to be declining over time. We investigate this issue in greater detail in Section 5.2

There is one notable difference in the long sample period results compared to the short sample period results. The estimated coefficients of the MPU Index for the "No Bubble" events in the regression are also positive and statistically significant in the specifications that use 95th and 90th percentile return thresholds to define a price run-up. However, we can still reject the equality of the estimated coefficients of the MPU Index between "Bubble" and "No Bubble" events at the 1% statistical significance level. This result confirms that the effect of MPU on the likelihood of a "Bubble" vs a "No Bubble" event is different in the long sample period as well.

We also augment the model in Panel A of Table 3 with two interaction terms to better understand the effects of MPU in different economic conditions. We include an interaction between MPU and $\Delta Int.Rate$ (MPU Index*$\Delta Int.Rate$) as well as an interaction between MPU and EPU (MPU Index*EPU Index) into our model. The first interaction is designed to capture the differential effect of MPU on asset price bubbles in low and high interest rate environments. The second interaction is designed to capture the differential effect of MPU in an environment with low and high values of real options that are available to firms in an industry. We report the coefficients of these augmented estimations in Panel B of Table 3. The estimated coefficient of the MPU Index*$\Delta Int.Rate$ is negative and statistically significant at the 1% level for the "Bubble" event. This result suggests that there is a more pronounced likelihood of an asset price bubble when MPU is high in a declining interest rate environment. This is consistent with the idea that lower borrowing costs in a declining interest rate environment incentivizes investors to borrow more and bid up the prices, producing an asset price bubble.

The estimated coefficient of the MPU Index*EPU Index is negative and statistically significant at the 1% level for the "Bubble" event. This result indicates that in a high EPU environment, high MPU is less likely to produce an asset price bubble. This result is consistent with the idea that increasing EPU in the economy makes real options available to firms in any industry more valuable, and thus the existence of an asset price bubble even in a high MPU environment is less likely. Finally, we test the equality of these two estimated interaction coefficients between the "Bubble" and "No Bubble" events in the regression and can reject the null hypothesis mostly at the 1% level of statistical significance.

5.2 FED's Disclosure Policy and the Relationship between MPU and Asset Price Bubbles

The economic significance of MPU on the likelihood of asset price bubbles is much greater in the long sample period compared to the short sample period by comparing the results in Table 3 and Table 2 respectively. This suggests that the impact of MPU on the formation of asset price bubbles seems to be declining over time. We investigate the reasons for this phenomenon.

Monetary policy in the U.S. comprises the Federal Reserve's (FED) actions and communications to promote maximum employment, stable prices and moderate long term interest rates. The U.S. congress has instructed the FED to pursue these economic goals since its creation in 1913. Thus, it is reasonable to conjecture that the FED's stance on how it communicates its economic policy is likely to have a big impact on MPU.

Lack of timely communications from the FED are likely to increase MPU while clear and timely disclosures are likely to decrease MPU in the financial markets. This conjecture is consistent with the theories of disclosure that suggest that timely and high quality information reduces information asymmetries, affect the uncertainty about the future of a company and thus reduce its stock return volatility (Easley and O'Hara (2004), Pastor and Veronesi (2003)).

The Federal Open Market Committee (FOMC) is the key monetary policy setting body of the FED. The FOMC holds eight regularly scheduled meeting every year to determine the appropriate stance of the monetary policy. For most of its existence, the publicly available reports from the FOMC meetings were the Records of Policy Actions, which were published once a year. The FOMC however maintained detailed confidential minutes which recorded attendance, discussions, and decisions at each meeting. Thus, it is quite likely that the markets experienced greater MPU until 1967 with scant and delayed information was made available to the public (Danker and Luecke (2005)). [9] In June 1967, the FED announced that the Records of Policy Actions would be released around ninety days after the meeting. In 1975, the Committee decreased the ninety days lag to forty-five days, and in 2004, further decreased the lag to twenty-one days. These changes in the FED disclosure policy are expected to have an effect on our results because MPU would decrease on timely release of information.

The above arguments suggest that MPU is likely to be lower in the US financial markets in the later part of our sample time period compared to the earlier time period. However, as explained in Section 4.3.1, we construct the longer time series of the MPU Index by regressing

[9] Initially, the Records of Policy Actions included only a paragraph or two of background or reasoning behind each FED action. These records grew over time and had reached an average of about five pages per meeting by the mid-1960s, when the Committee reviewed its information-disclosure practices. In 1964, the FOMC made the minutes for the years 1936-1960 available to the public through the National Archives.

BBD's MPU Index on their "US Historical News-Based Economic Policy Uncertainty Index" and Lukas Püttmann's (2018) "Financial Stress Indicator" series between January 1985 and October 2014, a time period when the FED's disclosure was timely and of a higher quality as explained above. This means our MPU index used in the estimations is likely to understate the true level of MPU in the earlier time periods, thus leading to higher estimates of the regression coefficients.[10]

To examine whether the relationship between MPU and likelihood of asset price bubbles changes during our sample period, we estimate the multinomial logistic model in the Equation (1) and the Equation (2) for the January 1931 to December 1935 period and store the estimated coefficient of the MPU Index for the "Bubble" event from this regression. We then increase the sample period by one month and next estimate the same model for the time period January 1931 to January 1936 and store the estimated coefficient of the MPU Index for the "Bubble" event from this regression. We repeat this exercise until the end of the sample period October 2014, successively increasing the sample size one month at a time. This procedure produces a time series of the estimated coefficients of MPU Index on the "Bubble" event between December 1935 and October 2014. We produce three such time series of coefficients from three exercises. Each exercise corresponds to a different threshold that we use to define a price run-up (75th, 90th and 95th percentile) of industry returns. We use an expanding window of data (rather than a rolling window procedure) in order to estimate the regressions because asset price bubbles are by their nature very rare events and we would like to include all such events in our estimations.

In Figure 5, we plot the estimated coefficients of the MPU Index for the "Bubble" event for the three time series on the y axis. On the x axis, we plot the last date of the sample period of the regression that produced the corresponding estimated coefficient. All the three graphs produce identical inferences. Consistent with our conjecture, we observe a declining trend in the coefficient of MPU around 1975, when FED adopts a more timely disclosure

[10] The intuition is as follows: Our regression model is $Y = a + bX + \epsilon$. In the earlier time periods our measured $X^{'} = \frac{X}{\nu}$, where $\nu > 1$. Therefore our estimated $b^{'} = b\,\nu > b$

policy and the amount of data in the high disclosure regime steadily increases over time. The effect of the change in disclosure around 1967 presumably affects the coefficients of MPU once sufficient data points have been accumulated in the high and timely transparency regime. We observe another declining trend in the estimated coefficient of the MPU Index for the Bubble event after December 2004. This is again consistent with our conjecture because the FED decreased the information release lag from 45 days to 21 days in December 2004.

Interestingly, we observe a steady increase in the estimated coefficients of the MPU Index for the "Bubble" event from 1935 to 1975. Friedman (1968) argues that Keynes offered simultaneously an explanation for the presumed impotence of monetary policy to stem the great depression, a nonmonetary interpretation of the depression, and an alternative to monetary policy for meeting the depression. Friedman (1968) further notes that wide acceptance of Keynes' theories in the economics profession meant that for two decades monetary policy was believed by almost all to have been rendered obsolete. Friedman's development of monetarism that rejected Keynesianism gradually took hold in the profession during the 1950s to the 1970s. These developments probably are consistent with the increasing impact of the MPU on asset price bubbles as market participants thinking about the importance of monetary policy evolved over time. Our observed pattern of the increase in the estimated coefficients of the MPU Index for the "Bubble" events in the regression from 1935 to 1975 is indeed consistent with this phenomenon.

5.3 Robustness Tests

5.3.1 Estimation Results by Using Alternative MPU Measures for the Post 1985 Time Period

We estimate the Equation (1) and the Equation (2) (the multinomial logistic model) by using two alternative MPU Indexes instead of the BBD's MPU Index for the period after 1985. For brevity, we only report the regression specification that uses the 95th percentile of monthly industry return as the threshold to define a price run-up and an asset price bubble. We report the estimated coefficients and associated z-scores of the regressions in Table 4.

5.3.1.1 Husted, Rogers, and Sun's (2020) MPU Index

The first alternative MPU measure is the MPU Index introduced by Husted, Rogers, and Sun (2020, HRS hereafter), which is available between January 1985 and June 2019. HRS argue that their text based MPU measure captures a significant degree of monetary policy uncertainty beyond interest rate fluctuations, the latter calculated using derivative prices in financial markets. This text based MPU series of HRS is also constructed by using newspaper data. The construction of HRS' MPU Index and its comparison with BBD's MPU Index are discussed in detail in Section 4.3.1.

We report our regression estimations using $MPUIndex_{HRS}$ in columns 1-2 of Table 4. We document a positive relationship between $MPUIndex_{HRS}$ and asset price bubbles, which mirrors the evidence developed in Table 2 using the BBD's MPU Index. The estimated coefficient of the $MPUIndex_{HRS}$ for the "Bubble" event is statistically significant at the 5% level while the estimated coefficient of $MPUIndex_{HRS}$ for the "No Bubble" event is negative and significant at the 10% level.

The economic significance of the above results are sizable. A one standard deviation increase in $MPUIndex_{HRS}$ is associated with a 22% increase in the likelihood of asset price bubbles relative to its unconditional mean. This compares with a 71% increase in the likelihood of asset price bubbles relative to the unconditional mean in the regression specification using BBD's MPU Index in Table 2. We hypothesize difference in magnitudes of economic significance is likely due to differences in the construction of the two indexes. These differences were discussed in detail in Section 4.3.1.

We also test the equality of the estimated coefficients of $MPUIndex_{HRS}$, *EPU Index*, and $\Delta Int.Rate$ between "Bubble" and "No Bubble" events in the regression. We can reject the equality of each of these coefficients between the two events at the 1% level of statistical significance. In sum, although the correlation of 0.49 between BBD's and HRS' MPU Indexes is not very high, we find similar results for the relationship between MPU and the likelihood of asset price bubbles using the two indexes.

5.3.1.2 First Principal Component of the BBD's MPU Index and HRS' MPU Index

The second alternative MPU measure we use is the first principal component of the BBD's MPU Index and HRS' MPU Index. Given the described differences in the construction of these two MPU Indexes, the first principal component would allow us to capture the common variation of MPU between the two indexes. We construct the first principal component between January 1985 and June 2019, during which both series are available.

We report our regression estimations that use "MPU Index (1st Principal Component)" in columns 3-4 of Table 4. Similar to the estimation results in Table 2 and the first two columns of Table 4, we document a positive relationship between "MPU Index (1st Principal Component)" and asset price bubbles. The estimated coefficient of the "MPU Index (1st Principal Component)" for the "Bubble" event is statistically significant at the 1% level while the estimated coefficient of "MPU Index (1st Principal Component)" for the "No Bubble" event is negative and significant at the 5% level. The results are economically significant as well. A one standard deviation increase in the "MPU Index (1st Principal Component)" is associated with a 35% increase in the likelihood of asset price bubbles relative to its unconditional mean.

As before, we also test the equality of the estimated coefficients of "MPU Index (1st Principal Component)", *EPU Index*, and $\Delta Int.Rate$ between "Bubble" and "No Bubble" events in the regression. We can reject the equality of each of these coefficients between the two events at the 1% level of statistical significance. In sum, we conclude that our results are robust to alternate measures of MPU.

5.3.2 Expected Economic Conditions

An important potential concern is that MPU and future economic conditions are likely highly positively correlated. This would lead to a false positive identification of the asset price bubbles using our procedure because the price run-ups followed by crashes might be due to rational expectations about the real economy, and not related to MPU.

While this concern seems valid, it does not explain why we observe significantly different estimated coefficients of the MPU Index for the "Bubble" and "No Bubble" events in the regressions as predicted by Allen and Gale (2000). If all price run-ups and subsequent returns are results of rational expectations about the real economy, then we would expect to observe similar coefficients of the MPU Index for the "Bubble" and "No Bubble" events.

Nevertheless, to further alleviate this concern, we augment our model by using three real economy variables in HRS that capture expected economic conditions. The first two real economy variables are "The Index of Consumer Sentiment" and "Business Conditions Expected During the Next Year" from the University of Michigan's Survey of Consumers data. These two series are 96% correlated, so we use only one of them at a time in the models we estimate. The last real economy variable is the GDP growth forecast in the next quarter from the Federal Reserve Bank of Philadelphia's "Survey of Professional Forecasters' GDP estimates". Since this data is updated quarterly, we use the same values for all the months in a given quarter.

We report the estimated coefficients and associated z-scores in Table 5. In each model, the estimated coefficients of the MPU Index are virtually unchanged compared to the results in our main specification as reported in Table 2.

In the first model (Column 1-2), we include "GDP Growth Forecast" and "Expected Business Conditions Index" as control variables. The estimated coefficient of the MPU Index for "Bubble" event is 0.73 in the regression and is identical to the value of 0.73 in our main specification in Table 2. In the second model (Column 3-4), we include "GDP Growth Forecast" and "Consumer Sentiment Index" as control variables. The estimated coefficient of the MPU Index for "Bubble" event in the regression is virtually unchanged and statistically significant at the 5% level of significance. We can reject the equality of the coefficients of *MPU Index*, *EPU Index*, and $\Delta Int.Rate$ between "Bubble" and "No Bubble" events in the regression at the 1% or 5% statistical significance levels. Overall, the results of the two models suggest that MPU is an economically and statistically significant determinant of asset price bubbles even after controlling for the expected economic conditions in the future.

5.3.3 Classification Procedure for Industry Bubbles

Greenwood, Shleifer and You (2019, GSY hereafter) identifies bubbles as price run-ups followed by crashes, defined as at least a 40% drawdown within the 24 months after a price run-up. Drawdown is defined as the lowest cumulative return within the 24 month period. GSY shows that these bubbles are ex-ante predictable. We adapt GSY's definition in our paper to identify bubbles as at least a 30% drawdown in the next 12 months after a price run-up. We also use alternative cutoffs of a 40% and a 50% drawdown to identify bubbles in our robustness tests.

However, Kim and Richardson (2022, KR hereafter) argues that GSY's identification of bubbles using this methodology is questionable. In particular KR take issue with GSY's definition of the drawdown. They suggest a 40% drawdown over a 24 month period would be expected after a price run-up even in a world without bubbles. Such a world is characterized by KR with a moderate level of volatility and a random walk model of stock prices. Using their model and simulation evidence, KR conclude that the episodes identified by the GSY methodology should not be classified as bubbles. If the conclusions of KR are accurate, they pose a direct threat to the empirical design in this paper, which uses the GSY methodology. Therefore, we reexamine this issue in detail below.

KR show that if stock prices follow a geometric Brownian motion with no drift and annualized volatility σ, then the expected maximum drawdown over a T-year period is $\sigma\sqrt{\frac{\pi\ T}{2}}$. Over the 24 month period identified by GSY, the expected maximum drawdown will be approximately 1.77σ. To produce GSY type 40% drawdown over a 2 year period, an annualized volatility of just 22.5% is sufficient. Thus, GSY type bubbles and crashes are possible in a world truly without bubbles.

However, as KR themselves note, the formula for the maximum expected drawdown suffers from various issues. First, the formula assumes the drift term (expected return) of the stock is 0 while in reality the expected return is positive. However, a positive expected return serves to lower the maximum drawdown and no closed form solution for the drawdown is available. Second, the analysis assumes that the stock market volatility is constant. However, as Schwert (1989) shows, financial leverage, interest rate volatility and corporate bond return volatility are some of the many factors that affect stock return volatility over time. As such, constant volatility is not a tenable assumption in this analysis. Therefore, we examine this issue by resorting to simulations in Appendix B to simultaneously account for a positive expected return and time varying stock market volatility.

Figure 6 documents the results of our simulations. We plot the expected drawdown from the simulation for each level of initial volatility ranging from 5% to 80% with 2.5% increments. The figure also plots three horizontal lines corresponding to the three expected drawdown values of 30%, 40% and 50% respectively, which are the values used in our analysis to classify bubbles. The figure also plots the unconditional volatilities of each 48 Fama French industries over the sample period (Jan 1926-June 2019) on the 30% expected drawdown line.

The figure clearly shows that even at 30% expected drawdown, the unconditional volatilities of all the industries lie well above the simulated curve. Given the unconditional industry volatilities, a 30% drawdown is very unlikely since we need a $\sim$60% initial volatility to reach 30% expected drawdown. The annualized industry volatilities of the 48 FF industries range from 16% to 54%, with a mean (median) of 26% (25%). Furthermore, if we require a 40% expected drawdown in the same period, annualized industry volatilities should exceed $\sim$75%, which is even above the maximum value of the unconditional annualized industry volatilities. This suggests that even a high level of volatility and a random walk model of stock prices is unlikely to produce the patterns that we classify as bubbles in the data.

The above exercise used unconditional industry level volatilities to assess the criticism of KR. However, it is quite possible that volatilities are highly elevated during periods of stock price bubbles (Hong and Sraer (2013)). We find that at an annualized volatility level of 60% and 75% in an industry-month, it is quite possible to produce spurious bubbles as they correspond to 30% and 40% expected drawdowns in our simulations. Therefore, we examine what proportion of industry-months in our sample have annualized volatilities greater than 60% and 75% respectively. We find that only 2.7% (1.4%) of the industry-months has annualized volatility greater than 60% (75%) in our sample. At an expected drawdown of 50%, no level of annualized volatility produces a spurious bubble in our simulations. Thus, even at a level of 2x to 3x unconditional volatility, we are unlikely to classify a spurious bubble with our methodology.[11]

Nevertheless, as a matter of abundant caution, we redo all of our main analyses in Table 2 and Table 3 by redefining a bubble using drawdowns of 40% and 50% respectively. We use 95th percentile of historical returns as the threshold to define a price run-up for these estimations. It is important to note from Figure 6 that at a drawdown of 50%, our simulations produce no spurious bubbles of the type identified by KR. We repeat our estimations by using these redefined bubbles.

We report our results of these estimations in Table 6. In Panel A, we report the estimation results for the period between January 1985 and June 2019. At both 40% and 50% levels of drawdown, our results are statistically significant at the 1% level, qualitatively similar to, and sometimes quantitatively stronger than our main specification in Table 2: the coefficient of the "MPU Index" for the "Bubble" event is even higher than the coefficient reported in Table 2 when we require a 40% maximum drawdown to define a bubble. The coefficient

[11] We obtain the distribution of monthly industry volatilities by using daily industry returns. We estimate monthly volatilities for each industry-month and check the occurrences where the annualized monthly volatility is greater than 60% or 75%. We follow French, Schwert, and Stambaugh (1987) and estimate monthly industry variance as follows:

$$\sigma_{it}^2 = \sum_{j=1}^{N_t} r_{ijt}^2 + 2\sum_{j=1}^{N_t-1} r_{ijt} r_{i+1,j,t}$$

where r_{ijt} is the day j return of industry i in month t and N_t is the total number of trading days in month t. We multiply monthly industry variance with 12 to annualize the variance and then take square root of it to obtain annualized industry volatilities.

of the "MPU Index" for the "Bubble" event is almost the same as the coefficient reported in Table 2 when we require a 50% maximum drawdown to define a bubble. These results suggest that our findings are robust to much more stringent definitions of a bubble in order to circumvent the criticisms of KR. The equality of coefficients for "MPU Index" between "No Bubble" and "Bubble" events in the regression is rejected at least at 3%. The results are economically significant as well. For the specification with 40% drawdown, a one standard deviation increase in MPU Index is associated with a 97% increase in the probability of a bubble relative to the unconditional probabilities.

In Panel B, we repeat the same analysis as above for the period spanning from January 1931 to October 2014. At both 40% and 50% levels of drawdown, our results are statistically significant at the 1% level, and uniformly quantitatively stronger than our main specification in Table 3: the coefficients of the "MPU Index" for the "Bubble" event are even higher than the coefficient reported in Table 3.

In conclusion, the results of this section show that our findings are not driven by the KR criticism about the GSY procedure to define a bubble.

5.4 Relationship between Monetary Policy Uncertainty and Industry Returns

Our results show that an increase in MPU is associated with a higher likelihood of industry asset price bubbles. Asset price bubbles are characterized by extreme industry returns followed by a crash. In this section, we investigate how MPU affects industry returns across the various quantiles of the return distribution. Therefore, we estimate a quantile regression model of monthly industry returns on MPU and other control variables for the sample period between January 1931 and October 2014 as follows:

$$
\begin{aligned}
Q_\tau(R_{i,t+1}) = \beta_0(\tau) + \beta_1(\tau) \times MPUIndex_t + \beta_2(\tau) \times MPUIndex_t \times \mathbb{1}_{NB,i,t+1} \\
+ \beta_3(\tau) \times MPUIndex \times \mathbb{1}_{B,i,t+1} + \beta_4(\tau) \times \text{EPU Index} \\
+ \beta_5(\tau) \times \Delta\text{Interest Rate} + \gamma_i(\tau) + \text{Controls}_{it} + \epsilon_{it}(\tau)
\end{aligned}
$$

Unlike our main specification in Table 2, the dependent variable is the monthly industry return instead of a categorical variable that classifies each industry-month as a "No Price Run-up", "No Bubble" or "Bubble" event. $Q_\tau(R_{i,t+1})$ represents the τth quantile of industry i's return distribution in month t+1, which is estimated using a quantile regression. τ denotes the quantile of the monthly industry returns and range from 10% to 90% in increments of 10%. We therefore obtain an estimated set of β coefficients, of all variables in the regression, for each level of τ. To examine the differential effect of MPU on industry return quantiles for the "Bubble" and "No Bubble" events, we interact the MPU Index with two indicator variables, $\mathbb{1}_{NB,i,t+1}$ and $\mathbb{1}_{B,i,t+1}$. $\mathbb{1}_{NB,i,t+1}$ assumes the value of 1 if the industry i in month $t+1$ is a "No Bubble" event and 0 otherwise. Similarly, $\mathbb{1}_{B,i,t+1}$ assumes the value of 1 if the industry i in month $t+1$ is a "Bubble" event and 0 otherwise. The omitted group corresponds to the "No Price Run-up" event.

The estimated coefficients of the $MPUIndex_t \times \mathbb{1}_{NB,i,t+1}$ and $MPUIndex_t \times \mathbb{1}_{B,i,t+1}$ variables show the relationship between MPU and industry returns for the "No Bubble" and "Bubble" events respectively. *EPU Index*, Δ*Interest Rate* and additional control variables are identical to the regression specifications in Panel A of Table 3.

We report the estimated coefficients in Table 7. Bootstrapped standard errors (with 100 replications) are clustered at the industry level and the associated t statistics are reported in parentheses. We document that an increase in MPU is associated with an increase in all quantile estimates (except the 10th percentile) of the expected industry returns for the

"Bubble" events. This relationship is monotonically increasing as we move towards the right tail of the return distribution. A similar pattern is observed for the quantiles of the expected industry returns for the "No Bubble" events as well. A formal test for the equality of the coefficients $MPUIndex_t \times \mathbb{1}_{B,i,t+1}$ and $MPUIndex_t \times \mathbb{1}_{NB,i,t+1}$ is rejected at the 5% significance level or higher for all quantiles beyond the median. This result suggests that the effect of MPU on industry returns is more pronounced during "Bubble" events.

6 Machine Learning Techniques to Predict Asset Price Bubbles

The documented positive relationship between MPU in this period and the likelihood of asset price bubbles in the next period still might not guarantee that MPU helps predict asset price bubbles in real time. However, Greenwood, Shleifer, and You (2016) and Greenwood, Hanson, Shleifer, and Sørensen (2022) show that industry wide asset price bubbles and post-war worldwide financial crises are substantially predictable. Motivated by this evidence, in this section we examine whether including MPU Index as an explanatory variable substantially improves the ability to predict asset price bubbles.

However, "Bubble" events are very rare, so predicting them in real time would be very difficult. Since prediction is the main concern, we utilize a battery of techniques available in the machine learning (ML) literature to examine this issue. We use machine learning techniques to compare the predictions of two otherwise identical models that use the same control variables but one model includes MPU Index as an additional explanatory variable. We then examine the performance of these two models in predicting asset price bubbles.

We use the period spanning from January 1931 to December 1989 as an in-sample (training) period for all the ML models, and predict the asset price bubbles from 1990 to June 2019, out-of-sample (validation) period. Thus, we avoid look-ahead bias in our prediction exercise by using the information only until the end of the training period to fit our models.

As Table 1 Panel B shows, "Bubble" and "No Bubble" events comprise a very small portion of our sample, accounting for just 0.5% and 2.9% of the total monthly observations respectively. Most of the monthly observations (96.6%) fall into the "No Price Run-up" event. Thus, any machine learning model with no skill would predict a "No Price Run-up" event very often in order to increase its prediction performance. To address this issue, we employ two steps: First, we redefine our dependent variable, a categorical variable with three groups (No Price Run-up, Bubble or No Bubble), to an indicator variable. Our indicator variable assumes the value of 1 if there is a "Bubble" event for a given industry-month and 0 if there is a "No Bubble" event. Therefore, our sample only includes price run-ups (either a "Bubble" or a "No Bubble"). The ML models estimate if there will be a crash ("Bubble") or not ("No Bubble") in the next 12 months conditional on observing a price run-up. Our training sample thus includes 174 "Bubble" events and 906 "No Bubble" events, therefore "Bubble" events comprises 16% of the training sample. Our validation sample includes 67 "Bubble" events and 473 "No Bubble" events, therefore "Bubble" events comprises 12% of the validation sample. Second, we use techniques of resampling in ML in order to achieve a balanced sample of "Bubble" and "No Bubble" events while estimating the ML models.

We use beginning of month values of *MPU Index*, *EPU Index*, and Δ*Interest Rate* and contemporaneous values of all other explanatory variables in Equation (1) and Equation (2) relative to the dependent variable. We use the constructed MPU Index described in Section 4.3.1 from January 1931 to January 1985 and splice it with BBD's MPU Index from February 1985 until June 2019 in order to form one consistent time series for our tests. We also construct a spliced EPU Index in a similar manner.

6.1 Machine Learning Algorithms

6.1.1 Models and Resampling Techniques

It is difficult to know a priori, which machine learning model will have the best performance in predicting asset price bubbles. Therefore, our analysis is agnostic about the correct machine learning model and uses nine different models described in Brownlee (2020). Although we remove the "No Price Run-up" events in our sample, we still have an imbalance between the "Bubble" (16%) and the "No Bubble" (84%) events in the training sample. This might also lead to overprediction of "No Bubble" events since conditional on a price run-up, "Bubble" events comprise only 16% of the total observations in the training period. To overcome this potential issue, we use 15 resampling techniques described in the ML literature to balance the two outcome events in our training sample. To do so, we either oversample the minority class ("Bubbles") or undersample the majority class ("No Bubbles") or do both together. Thus, we have either equal number of observations in majority and minority classes or create a sample that is less ambiguous along the class boundary between the two events. We therefore combine each of the 9 ML models with the 15 resampling techniques and thus have a total of 135 machine learning model-resampling technique pairs. We report all the models and resampling techniques in Table 8 and explain them in detail in Appendix A.

6.1.2 Cost Sensitive Models

Additionally, we also use cost sensitive ML models that are suitable for the imbalanced data problem. Instead of resampling the data, cost sensitive models impose a penalty vector as an input to the ML algorithm. The penalty vector decreases the performance metric of the model much more for wrong predictions of the minority class compared to the wrong predictions of the majority class. In particular, we penalize a model more heavily if it classified a "Bubble" event as a "No Bubble" event rather than vice versa. We follow Brownlee (2020) and use the inverse of the frequency of the two groups as our penalty vector. So, if majority class is 10 times more than the minority class (10:1 data), any wrong prediction of the minority class will affect the performance metric 10 times more negatively than the wrong prediction of the majority class.

6.2 Performance Measure

We use a widely used performance metric in the machine learning literature, F_β score, to measure the performance of each ML model. This measure uses *Precision* and *Recall* scores and weigh them based on the value of the β. The definitions of F_β, *Precision*, and *Recall* are as follows:

$$\text{Precision} = \text{True Positives}/(\text{True Positives} + \text{False Positives})$$

$$\text{Recall} = \text{True Positives}/(\text{True Positives} + \text{False Negatives})$$

$$F_\beta = \frac{(1+\beta^2) * Precision * Recall}{\beta^2 * Precision + Recall}$$

Thus, precision is related to type I error and recall is related to type II error. "True Positive" prediction in our setup is defined as a correct prediction of a "Bubble" event. "False Positive" prediction is defined as an incorrect prediction of a "No Bubble" event as a "Bubble" event. "False Negative" prediction is defined as an incorrect prediction of a "Bubble" event as a "No Bubble" event. The only difference between Precision and Recall stems from the value that is used to scale the number of true positive predictions. The former uses the sum of the true positive and false positive predictions whereas the latter uses the sum of the true positive and false negative predictions to scale the number of true positive predictions.

The calculation of the F_β score can be customized by changing the β value. The most common β values in the literature are 0.5, 1, and 2. Higher β values put more weight on the recall score which is analogous to minimizing false negatives. Since asset price bubbles are too costly to the economy to be missed out, we aim to minimize the number of predictions that predict a "Bubble" event as a "No Bubble" event. Therefore, we use F2 score, a form of F_β score where β assumes a value of 2, in all our performance measures to assign more weight to the recall score.

6.3 Results

6.3.1 Analysis Using Machine Learning Model - Resampling Technique Pairs

We first estimate the relationship between asset price bubbles and the explanatory variables (Equation (1) and Equation (2)) using the in-sample period (training period). For each of the 135 ML model-resampling technique pair, we obtain two estimations from two otherwise identical models which differ by the inclusion of MPU Index as an explanatory variable. Then, using each estimated model, we predict asset price bubbles in both the in-sample (training) and out of sample (validation) period. We calculate the F2 score for the model that includes MPU as an explanatory variable and the F2 score for the model that excludes MPU as an explanatory variable. If MPU has additional explanatory power in predicting asset price bubbles, we would expect to see an improvement in the F2 score of the model that includes the MPU Index over the model that excludes the MPU Index.

In Panel A of Table 9, we document the results. We report the mean and median F2 scores of all the models that include MPU as an explanatory variable ("With MPU") and all the models that exclude MPU as an explanatory variable ("Without MPU"). We report the statistics for both in-sample and out-of-sample periods along with standard errors in parentheses. The in-sample results indicate that including the MPU Index in the prediction model results in an improved fit in the training period. We find that the model fit improves by 1.2% on average and we can also reject the equality of both the mean and median F2 scores between "With MPU" and "Without MPU" groups at the 1% level of statistical significance. However, this result might not carry through to the out-of-sample period. If the models suffer from overfitting, then adding MPU might not improve our predictions in the out-of-sample period. To examine this issue, we repeat the same mean and median tests on the F2 statistics for the out-of-sample period predictions.

The out-of-sample results show that our estimated models do not suffer from the over-fitting problem. Instead, we find that our models that include MPU, generalize very well in making predictions during the out of sample period. This is because the performance improvement in F2 scores by including MPU in our models is much higher in the out of sample period compared to the performance improvement in the in-sample period. We observe a 9.7% improvement in the average F2 scores when we include MPU. We can reject the equality of both the mean and median F2 scores between "With MPU" and "Without MPU" groups at the 1% level of statistical significance. Overall, the results in this section are consistent with the view that adding MPU as an explanatory variable in ML models substantially improves our ability to predict asset price bubbles in real time.

6.3.2 Analysis Using Cost Sensitive Models

An alternative way to resolve the imbalanced data problem ("Bubble" and "No Bubble" events account for just 0.5% and 2.9% of the total monthly observations respectively) is to use cost sensitive ML models as described in the Section 6.1.2. However, not all the nine ML methods described in Section 6.1.1 admit a penalty vector as an input to the algorithm. We therefore utilize four out of the nine ML methods that explicitly consider the costs of prediction errors into account when training a machine learning model. We report our results in Panel B of Table 9.

Similar to Panel A of Table 9, we compare the average F2 scores of two groups of models: all the models that include MPU as an explanatory variable ("With MPU") and all the models that exclude MPU as an explanatory variable ("Without MPU"). The in-sample period results show that the average F2 scores are not statistically different between the two groups, presumably because we have only four models to evaluate. However, even with this limited set, the out-of-sample differences between the two groups are statistically significant at the 10% level. The performance improvement in F2 scores by including MPU in our models is much higher in the out of sample period compared to the performance improvement in the in-sample period. We observe a 8.9% improvement in the average F2 scores when we include MPU for the out of sample period while recording only a 1.0% improvement in the in-sample period. These results also support the hypothesis that adding MPU improves the

ML model performance in predicting asset price bubbles in real time and this improvement is more pronounced in the out-of-sample period.

6.3.3 Prediction Performance by Types of Machine Learning Algorithms

In this section, we compare the prediction performance (using the average F2 scores) of different types of ML algorithms. We first group the nine machine learning models into six categories: Regression Algorithms, Ensemble Algorithms, Instance-based Algorithms, Decision Tree Algorithms, Dimensionality Reduction Algorithms, and Bayesian Algorithms. We also group the fifteen resampling techniques into three categories: Oversampling, Undersampling, and Mixed methods. Then, we investigate whether our improved results are driven by a specific set of models and resampling techniques. For each model category-resampling category pair, we calculate the improvement in the F2 score in predicting asset price bubbles when we add MPU as an explanatory variable to the ML model.

We report the average percentage improvement in the F2 score by each category pair in Table 10. We also calculate the average percentage improvement in the F2 score by each model and resampling category.

In Panel A, we report the average improvements in the F2 scores in the in-sample period. These results show that adding MPU to the models improve the estimation of asset price bubbles in the in-sample period for most of the model and resampling groups, therefore the results in Table 9 are not driven by a small subset of pairs. The improvements range from 0.13% to 7.10%. However, a small subset of pairs (5 out of the 18 combinations in the table) results in a decrease in average F2 scores by adding MPU as an explanatory variable to the ML models. We find that undersampling methods combined with Dimensionality Reduction and Bayesian Algorithms work best in the data. We find an improvement of 1.87% in average F2 scores in the in-sample period across all methods.

In Panel B, we repeat the same analysis as in Panel A, but for the out-of-sample period. Consistent with the results in Table 9, we obtain improvements in the average F2 scores by adding MPU to the ML models and these improvements are much greater than the results in the in-sample period. This result suggests that the ML models generalize well to the new data and alleviates any overfitting concerns of the ML models in predicting asset price bubbles. The improvement in the average F2 score is positive across the algorithms and sampling methods, ranging from 0.11% to 35.72%. The improvement in the average F2 scores across all models and resampling methods is an impressive 22.4%, almost 12 times larger than the in-sample results.

Overall, these results confirm that MPU is an important explanatory variable in predicting asset price bubbles in real time. We document a better model fit in the training period by adding MPU to our models and much higher predictive power in the out-of-sample period.

7 Conclusion

Government interest rates that are effectively zero in an expansionary monetary policy have long been recognized to create bubbles in the valuation of risky assets. However, empirical analysis of the second moment of the interest rates in generating asset price bubbles has received far less attention in the literature. Motivated by the theoretical insights from the models of Allen and Gale (2000, 2004), we study the impact of monetary policy uncertainty (MPU) in predicting asset price bubbles. Using U.S. data from 1926-2019, we find that greater monetary policy uncertainty leads to a greater likelihood of industry level bubbles. Our results can not be explained by the expectations about the real economy or the industry level volatilities. We also investigate whether the asset price bubbles are predictable in real time and if MPU is an important input to the prediction models. To do so, we employ an array of 135 machine learning models and document that adding MPU as an explanatory variable in machine learning models substantially improves the predictability. Overall, these findings support the view that an increase in MPU leads to a higher likelihood of asset price bubbles.

Table 1: Summary Statistics

This table reports summary statistics of industry level bubbles between 1931-2019. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Every industry-month between January 1931 and June 2019, is classified into one of 3 groups: "No Price Run-up", "Bubble" or "No Bubble". If the market capitalization value weighted monthly industry return (monthly industry return, hereafter) is below the 95th percentile of the historical industry return distribution, we define the industry-month as "No Price Run-up". If the monthly industry return is above the 95th percentile of the historical industry return distribution, we examine the cumulative industry return over the next 12 months. If the cumulative industry return declines by at least 30% any time over the next 12 months (dubbed a 30% drawdown and is the pattern of a price run up followed by a crash), we classify the current industry-month as a "Bubble". If the cumulative industry return does not decline by at least 30% any time over the next 12 months (the pattern of a price run up not followed by a crash), we classify the current industry-month as a "No Bubble". Panel A reports the number of bubble months (bubbles) for each Fama-French 49 industries (FF 49, hereafter) excluding "Other" during the sample period. Panel B presents the frequency distribution of the number of months that are classified as "No Price run-ups", "Bubbles" and "No Bubbles". Panel C shows the summary statistics (mean and standard error) of industry level characteristics for "No Price run-ups", "Bubbles" and "No Bubbles" months. At the beginning of each month, for all stocks in our sample, we calculate their daily volatility (sum of squared daily returns) in the previous month. Using this distribution of stock volatility for all stocks in the current month, we assign a percentile rank to each stock. Next, for each industry, in each month, we calculate a value weighted (market capitalization) average of the percentile ranks of all stocks in that industry. For each industry-month, Δ *Volatility* is the change in this value weighted measure over the last 12 months. At the beginning of each month, for all stocks in our sample, we calculate their stock turnover (ratio of total shares traded in the previous month to the total number of shares outstanding in the previous month). Using this distribution of stock turnover for all stocks in the current month, we assign a percentile rank to each stock. Next, for each industry, in each month, we calculate a value weighted (market capitalization) average of the percentile ranks of all stocks in that industry. For each industry-month, Δ *Turnover* is the change in this value weighted measure over the last 12 months. At the beginning of each month, we calculate each stock's age in years (defined as today's date - start date in the CRSP database). Using this distribution of stock age for all stocks in the current month, we assign a percentile rank to each stock. Next, for each industry, in each month, we calculate a value weighted (market capitalization) average, *Industry Age*, of the percentile ranks of all stocks in that industry. *Age tilt* (computed for each industry-month) is the difference between the equally weighted and age-weighted (using the age of each stock that makes up the industry) monthly industry return. *Issuance* (computed for each industry, each month) is the percentage of the firms in an industry that have increased their adjusted total shares outstanding by at least 5% in the last 12 months.

Panel A: Number of bubbles in each industry between Jan 1931 - Jun 2019

Number of Bubbles	Number of Unique Industries	Industries
0-1	5	Candy & Soda, Rubber and Plastic Prod., Healthcare, Aircraft, Business Supp.
2-3	11	Print. & Publishing, Pharma. Products, Chemicals, Communication, Wholesale, Retail Food Products, Cons. Goods, Construction Mater., Shipping Cont., Rest. and Hotels
4-5	15	Med. Equip., Machinery, Elec. Equip., Defense, Util., Pers. Serv., Comp. Softw., Transp. Insur., Beer & Liq., Tob. Prod., Fabr. Prod., Auto. & Trucks, Pet. & Nat. Gas, Banking
6-7	5	Textiles, Business Services, Agriculture, Recreation, Precious Metals
8-9	9	Entertainment, Construction, Steel Works, Shipbuilding & Railroad Equip. Electronic Equip., Meas. and Control Equipment, Real Estate, Trading, Apparel
$\geq$ 10	3	Industrial Mining, Computer Hard., Coal

Panel B: Frequency Table

	Jan 1931 - Jun 2019	
	N	%
No Price Run-up	46,516	96.6
No Bubble	1,380	2.9
Bubble	241	0.5
Total	48,137	100

Panel C: Industry Level Characteristics

	No price Run-up		No Bubble		Bubble		Bubble minus No Bubble	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Δ Volatility (%)	-0.15	0.06	1.50	0.34	3.57	1.05	2.07	0.92
ΔTurnover (%)	0.02	0.05	2.38	0.29	4.50	0.93	2.12	0.80
Industry Age (%)	63.24	0.09	65.68	0.56	48.50	1.42	-17.18	1.47
Age tilt (%)	-0.11	0.04	-0.36	0.27	-0.18	0.80	0.18	0.73
Issuance	18.33	0.07	17.38	0.42	20.34	1.31	2.96	1.15

Table 2: Bubbles and Monetary Policy Uncertainty (Jan 1985 - Jun 2019)

This table reports the multinomial logistic regression estimates of the relation between likelihood of industry level bubbles and the Monetary Policy Uncertainty (MPU) Index along with various controls. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Our sample period is between Jan 1985 and Jun 2019 when the "MPU Index" of Baker, Bloom, and Davis (2016) (BBD(2016)) is available. Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "Bubble" or "No Bubble" using the procedure outlined in the caption of Table 1. Unlike Table 1, we use 3 different thresholds to define a price run-up (i.e) the 95th, 90th, and 75th percentile of the historical industry return distribution. The dependent variable in the multinomial logit model takes a value of 0 for "No Price Run-up" months, a value of 1 for "No Bubble" months and a value of 2 for "Bubble" months (three groups). In each specification, we report the coefficients of "No Bubble" and "Bubble" groups, and so all the coefficients are relative to "No Price Run-up" group. z-statistics are reported in parentheses. We also report the economic significance of the *MPU Index* coefficient. Economic significance is defined as the increase in probability for each outcome relative to its unconditional mean (expressed in percentage points), for a 1 standard deviation increase in the MPU Index around the mean. Our control variables include economic policy uncertainty, changes in the interest rate and industry level characteristics. *EPU Index* is the BBD (2016)'s News Based Economic Policy Uncertainty Index. Δ*Interest Rate* is the monthly change in the interest rates. Interest rate is measured as the Effective Federal Funds Rate (`https://fred.stlouisfed.org/series/FEDFUNDS`). The definitions of industry level characteristics are provided in Table 1. All estimations include FF 49 industry fixed effects. We test the equality of the coefficients for *MPU Index*, Δ *Interest Rate* and *EPU Index* between "No Bubble" and "Bubble" groups and report the associated χ^2 and p-values at the bottom of the each of the three models. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

Price Run-up Threshold $\longrightarrow$	95th		90th		75th	
	No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
MPU Index	-0.13**	0.73***	-0.00	0.57***	-0.03	0.64***
	(-2.10)	(3.53)	(-0.05)	(3.26)	(-1.16)	(5.60)
% change in prob. from -s/2 to +s/2 of MPU Index [relative to unconditional (%)]	-13.2	70.7	-0.8	54.2	-3.3	60.6

(To be continued)

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Price Run-up Threshold ⟶	95th		90th		75th	
	No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
Δ Volatility	0.47	1.88**	0.18	1.84***	0.13	0.42
	(0.90)	(1.98)	(0.61)	(2.70)	(0.79)	(0.82)
Industry Age	-0.11	-2.44	-0.07	-2.34*	0.23	-1.77**
	(-0.17)	(-1.47)	(-0.14)	(-1.75)	(0.98)	(-2.23)
Age tilt	-0.17	1.29*	0.10	1.34*	-0.08	0.53
	(-0.47)	(1.78)	(0.37)	(1.88)	(-0.47)	(0.70)
Issuance	-0.32	2.65***	0.09	2.64***	0.18	2.48***
	(-0.65)	(2.80)	(0.36)	(2.91)	(1.28)	(4.78)
Δ Interest Rate	-1.25***	-2.22***	-0.93***	-2.32***	-0.54***	-2.40***
	(-6.51)	(-5.88)	(-6.78)	(-7.50)	(-7.93)	(-10.58)
EPU Index	0.48***	-0.72***	0.35***	-0.57***	0.29***	-0.73***
	(5.71)	(-3.23)	(6.53)	(-3.82)	(9.59)	(-5.48)
Δ Turnover	1.08	2.41	1.06**	1.98	0.55**	2.42**
	(1.64)	(1.59)	(2.44)	(1.48)	(2.27)	(2.11)
Industry Fixed Effects	✓	✓	✓	✓	✓	✓

(To be continued)

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Price Run-up Threshold $\longrightarrow$	95th		90th		75th	
	No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
Observations	19,411		19,824		19,824	
Pseudo R^2	0.102		0.075		0.042	
Coefficient: MPU Index						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	19.83		10.42		33.54	
p-value	0.00		0.00		0.00	
Coefficient: ΔInterest Rate						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	4.69		15.93		67.32	
p-value	0.03		0.00		0.00	
Coefficient: EPU Index						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	34.25		40.10		54.55	
p-value	0.00		0.00		0.00	

Table 3: Bubbles and Monetary Policy Uncertainty (Jan 1931 - Oct 2014)

This table reports the multinomial logistic regression estimates of the relation between likelihood of industry level bubbles and the Monetary Policy Uncertainty (MPU) Index along with various controls. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Our sample period is between Jan 1931 and Oct 2014. Since the "MPU Index" of Baker, Bloom, and Davis (2016) (BBD(2016)) is available only after 1985, we construct an alternative MPU index. We first regress BBD (2016)'s MPU Index (for the time period Jan 1985 - Oct 2014) on their "US Historical News-Based Economic Policy Uncertainty Index" (which is available, but only till Oct 2014), and Lukas Püttmann's (2018) "Financial Stress Indicator" series. We use the estimated coefficients from this regression to obtain the fitted value of the MPU index series between Jan 1931 and Oct 2014. Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "Bubble" or "No Bubble" using the procedure outlined in the caption of Table 1. Unlike Table 1, we use 3 different thresholds to define a price run-up (i.e) the 95th, 90th, and 75th percentile of the historical industry return distribution. The dependent variable in the multinomial logit model takes a value of 0 for "No Price Run-up" months, a value of 1 for "No Bubble" months and a value of 2 for "Bubble" months (three groups). In each specification, we report the coefficients of "No Bubble" and "Bubble" groups, and so all the coefficients are relative to "No Price Run-up" group. z-statistics are reported in parentheses. We also report the economic significance of the *MPU Index* coefficient. Economic significance is defined as the increase in probability for each outcome relative to its unconditional mean (expressed in percentage points), for a 1 standard deviation increase in the MPU Index around the mean. Our control variables include economic policy uncertainty, changes in the interest rate and industry level characteristics. We use BBD (2016)'s *Historical EPU Index* to control for economic policy uncertainty in our model. Δ *Interest Rate* is the monthly change in the interest rates. Interest rate is measured as the Effective Federal Funds Rate (`https://fred.stlouisfed.org/series/FEDFUNDS`) from July 1954- Oct 2014. For the Jan 1934 - June 1954 time period, interest rate is measured as the 3-Month Treasury Bill rate (`https://fred.stlouisfed.org/series/TB3MS`) in the secondary market. Finally, for the Jan 1931-Dec 1933 time period, Interest rate is measured as the yield on short term securities (`https://fred.stlouisfed.org/series/M1329AUSM193NNBR`). These choices were spliced to provide one time series of interest rates for the entire data sample period. In Panel B, we add two interaction terms *MPU Index**Δ *Interest Rate* and *MPU Index*EPU Index* to the model in Panel A to investigate the relation between MPU and bubbles in different interest rate and economic policy uncertainty environments. The definitions of industry level characteristics are provided in Table 1. All estimations include FF 49 industry fixed effects. We test the equality of the coefficients for *MPU Index* in Panel A, and interaction terms *MPU Index**Δ *Interest Rate* and *MPU Index*EPU Index* in Panel B between "No Bubble" and "Bubble" groups and report the associated χ^2 and p-values at the bottom of the each of the three models. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

Panel A: Jan 1931 - Oct 2014

Price Run-up Threshold ⟶	95th		90th		75th	
	No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
MPU Index	1.89***	3.47***	1.17***	2.88***	0.04	2.31***
	(12.73)	(8.13)	(11.23)	(7.56)	(0.41)	(7.06)
% change in prob. from -s/2 to +s/2 of MPU Index [relative to unconditonal (%)]	174.3	327.2	102.2	267.8	-1.6	218.9
Industry Fixed Effects	✓	✓	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓	✓	✓
Observations	45,445		45,445		45,445	
Pseudo R^2	0.087		0.058		0.031	
Coefficient: MPU Index						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	15.41		19.33		56.96	
p-value	0.00		0.00		0.00	

Panel B: Jan 1931 - Oct 2014 Including Interaction Terms

Price Run-up Threshold $\longrightarrow$	95th		90th		75th	
	No Bubble	Bubble	No Bubble	Bubble	No Bubble	Bubble
MPU Index	2.02***	3.32***	1.21***	2.67***	0.10	2.08***
	(12.62)	(7.19)	(11.41)	(6.40)	(1.07)	(5.89)
Δ Int. Rate	-0.53***	0.47**	-0.47***	0.47***	-0.42***	0.32***
	(-15.36)	(2.35)	(-13.36)	(3.77)	(-15.39)	(4.13)
EPU	-1.31***	-2.68***	-0.76***	-2.07***	0.09	-1.54***
	(-9.19)	(-5.72)	(-7.64)	(-4.98)	(1.06)	(-4.42)
MPU Index*EPU Index	-0.07***	-0.15***	-0.02	-0.18***	0.02***	-0.17***
	(-4.52)	(-3.35)	(-1.63)	(-4.63)	(2.69)	(-5.54)
MPU Index*ΔInterest Rate	0.21***	-0.69***	0.16***	-0.79***	0.16***	-0.76***
	(3.11)	(-4.20)	(3.63)	(-6.06)	(4.96)	(-7.48)
Industry Fixed Effects	✓	✓	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓	✓	✓
Observations	45,445		45,445		45,445	
Pseudo R^2	0.091		0.060		0.032	
Coefficient: MPU Index*EPU Index						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	3.34		18.72		36.64	
p-value	0.07		0.00		0.00	
Coefficient: MPU Index*ΔInterest Rate						
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	31.29		48.69		66.86	
p-value	0.00		0.00		0.00	

Table 4: Bubbles and Monetary Policy Uncertainty: Alternative MPU Measures

This table reports the multinomial logistic regression estimates of the relation between likelihood of industry level bubbles and two alternative measures of Monetary Policy Uncertainty (MPU) along with various controls as robustness tests. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Our sample period is between Jan 1985 and Jun 2019. In the first specification, we use the "MPU Index" of Husted, Rogers, and Sun (2020), "*MPU Index*$_{HRS}$". In the secon specification, we use the first principal component of Baker, Bloom, and Davis' (2016) MPU Index and "*MPU Index*$_{HRS}$", denoted as "*MPU Index (1st Princ. Comp.)*". Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "Bubble" or "No Bubble" using the procedure outlined in the caption of Table 1. The dependent variable in the multinomial logit model takes a value of 0 for "No Price Run-up" months, a value of 1 for "No Bubble" months and a value of 2 for "Bubble" months (three groups). In each specification, we report the coefficients of "No Bubble" and "Bubble" groups, and so all the coefficients are relative to "No Price Run-up" group. z-statistics are reported in parentheses. We also report the economic significance of the *MPU Index* coefficient. Economic significance is defined as the increase in probability for each outcome relative to its unconditional mean (expressed in percentage points), for a 1 standard deviation increase in the MPU Index around the mean. Our control variables include economic policy uncertainty, changes in the interest rate and industry level characteristics. *EPU Index* is the BBD (2016)'s News Based Economic Policy Uncertainty Index. Δ*Interest Rate* is the monthly change in the interest rates, measured as the Effective Federal Funds Rate (`https://fred.stlouisfed.org/series/FEDFUNDS`). The definitions of industry level characteristics are provided in Table 1. All estimations include FF 49 industry fixed effects. We test the equality of the coefficients for *MPU Index*, Δ*Interest Rate* and *EPU Index* between "No Bubble" and "Bubble" groups and report the associated χ^2 and p-values at the bottom of the each of the three models. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

	No Bubble	Bubble	No Bubble	Bubble
MPU Index$_{HRS}$	-0.09*	0.23**		
	(-1.84)	(1.98)		
% change in prob. from	-8.9	22.5		
-s/2 to +s/2 of MPU Index				
[relative to unconditional (%)]				
MPU Index (1st Princ. Comp.)			-0.10**	0.36***

(To be continued)

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	No Bubble	Bubble	No Bubble	Bubble
			(-2.18)	(3.51)
% change in prob. from			-9.8	35.0
-s/2 to +s/2 of MPU Index				
[relative to unconditional (%)]				
ΔInterest Rate	-1.08***	-2.97***	-1.16***	-2.74***
	(-6.21)	(-10.11)	(-6.35)	(-8.46)
EPU Index	0.41***	-0.13	0.46***	-0.37***
	(6.83)	(-1.22)	(6.13)	(-3.57)
Additional Controls	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓
Observations	19,411		19,411	
Pseudo R^2	0.100		0.101	
Coefficient: MPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	6.37		20.24	
p-value	0.01		0.00	

(To be continued)

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	No Bubble	Bubble	No Bubble	Bubble
Coefficient: ΔInterest Rate				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	27.95		15.50	
p-value	0.00		0.00	
Coefficient: EPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	19.63		64.83	
p-value	0.00		0.00	

Table 5: Bubbles and Monetary Policy Uncertainty: Controlling for Expected Conditions of the Economy

This table reports the multinomial logistic regression estimates of the relation between likelihood of industry level bubbles and the Monetary Policy Uncertainty (MPU) Index including additional control variables for the Expected Conditions of the Economy as robustness tests. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). We control for real expected GDP growth in the next 6 months (*GDP Growth Forecast*), expected business conditions in the next year (*Exp. Business Conditions Index*) or *Consumer Sentiment Index* in addition to other controls. In specification 1, we use *Exp. Business Conditions Index* and in specification 2, we use *Consumer Sentiment Index* because these two series are highly correlated (0.96). *GDP Growth Forecast*, *Exp. Business Conditions Index* and *Consumer Sentiment Index* are from University of Michigan's Survey of Consumers (`https://data.sca.isr.umich.edu/`). Our sample period is between Jan 1985 and Jun 2019 when the "MPU Index" of Baker, Bloom, and Davis (2016) (BBD (2016)) is available. Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "Bubble" or "No Bubble" using the procedure outlined in the caption of Table 1. Unlike Table 1, we use 3 different thresholds to define a price run-up (i.e) the 95th, 90th, and 75th percentile of the historical industry return distribution. The dependent variable in the multinomial logit model takes a value of 0 for "No Price Run-up" months, a value of 1 for "No Bubble" months and a value of 2 for "Bubble" months (three groups). In each specification, we report the coefficients of "No Bubble" and "Bubble" groups, and so all the coefficients are relative to "No Price Run-up" group. z-statistics are reported in parentheses. We also report the economic significance of the *MPU Index* coefficient. Economic significance is defined as the increase in probability for each outcome relative to its unconditional mean (expressed in percentage points), for a 1 standard deviation increase in the MPU Index around the mean. Our control variables include economic policy uncertainty, changes in the interest rate and industry level characteristics. *EPU Index* is the BBD (2016)'s News Based Economic Policy Uncertainty Index. Δ*Interest Rate* is the monthly change in the interest rates. Interest rate is measured as the Effective Federal Funds Rate (`https://fred.stlouisfed.org/series/FEDFUNDS`). The definitions of industry level characteristics are provided in Table 1. All estimations include FF 49 industry fixed effects. We test the equality of the coefficients for *MPU Index*, Δ *Interest Rate* and *EPU Index* between "No Bubble" and "Bubble" groups and report the associated χ^2 and p-values at the bottom of the each of the three models. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

	No Bubble	Bubble	No Bubble	Bubble
MPU Index	-0.09	0.73***	-0.09	0.63**
	(-1.57)	(2.62)	(-1.47)	(1.99)
% change in prob. from	-9.5	71.4	-8.7	61.2
-s/2 to +s/2 of MPU Index				

(To be continued)

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	No Bubble	Bubble	No Bubble	Bubble
[relative to unconditional (%)]				
ΔInterest Rate	-1.20***	-2.69***	-1.13***	-2.84***
	(-5.23)	(-4.16)	(-5.01)	(-4.02)
EPU Index	0.47***	-0.61*	0.43***	-0.49
	(6.27)	(-1.69)	(6.11)	(-1.17)
GDP Growth Forecast (%)	-0.60***	-0.69**	-0.58***	-0.78**
	(-5.51)	(-2.27)	(-5.17)	(-2.50)
Exp. Bus. Cond. Index	0.01**	0.02*		
	(2.40)	(1.76)		
Cons. Sentiment Index			0.01*	0.05*
			(1.70)	(1.78)
Additional Controls	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓
Observations	19,411		19,411	
Pseudo R^2	0.110		0.109	

(To be continued)

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	No Bubble	Bubble	No Bubble	Bubble
Coefficient: MPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	9.33		5.36	
p-value	0.00		0.02	
Coefficient: ΔInterest Rate				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	4.72		5.40	
p-value	0.03		0.02	
Coefficient: EPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	9.67		5.23	
p-value	0.00		0.02	

Table 6: Bubbles and Monetary Policy Uncertainty: Using Alternative Definitions of a Bubble

This table reports the multinomial logistic regression estimates of the relation between likelihood of industry level bubbles and Monetary Policy Uncertainty (MPU) Index using alternative definitions of a bubble. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "Bubble" or "No Bubble" using the same procedure outlined in the caption of Table 1. If the monthly industry return is above the 95th percentile of the historical industry return distribution, we examine the cumulative industry return over the next 12 months as in Table 1. However, unlike Table 1, if the cumulative industry return declines by at least 40% or 50% any time over the next 12 months (dubbed a 40% or 50% drawdown and is the pattern of a price run up followed by a crash), we classify the current industry-month as a "Bubble". The dependent variable in the multinomial logit model takes a value of 0 for "No Price Run-up" months, a value of 1 for "No Bubble" months and a value of 2 for "Bubble" months (three groups). Our sample period in Panel A is between Jan 1985 and Jun 2019 and the "MPU Index", "EPU Index", Δ*Interest Rate*, and other controls are identical to the measures used in Table 2. Our sample period in Panel B is between Jan 1931 and Oct 2014 and the "MPU Index", "EPU Index", Δ*Interest Rate*, and other controls are identical to the measures used in Table 3. In each specification, we report the coefficients of "No Bubble" and "Bubble" groups, and so all the coefficients are relative to "No Price Run-up" group. z-statistics are reported in parentheses. We also report the economic significance of the *MPU Index* coefficient. Economic significance is defined as the increase in probability for each outcome relative to its unconditional mean (expressed in percentage points), for a 1 standard deviation increase in the MPU Index around the mean. All estimations include FF 49 industry fixed effects. We test the equality of the coefficients for *MPU Index* between "No Bubble" and "Bubble" groups and report the associated χ^2 and p-values at the bottom of the each of the two models. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

Panel A: Jan 1985 - Jun 2019

Threshold to define crash $\longrightarrow$	40%		50%	
	No Bubble	Bubble	No Bubble	Bubble
MPU Index	-0.11	1.03***	-0.08	0.72***
	(-1.54)	(3.71)	(-1.09)	(2.16)
% change in prob. from -s/2 to +s/2 of MPU Index [relative to unconditonal (%)]	-11.3	98.7	-7.7	69.5
Industry Fixed Effects	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓
Observations	19,411		19,411	
Pseudo R^2	0.101		0.094	
Coefficient: MPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	13.20		4.65	
p-value	0.00		0.03	

Panel B: Jan 1931 - Oct 2014

Threshold to define crash ⟶	40%		50%	
	No Bubble	Bubble	No Bubble	Bubble
MPU Index	2.04***	3.98***	2.13***	4.00***
	(12.90)	(7.77)	(13.17)	(6.84)
% change in prob. from -s/2 to +s/2 of MPU Index [relative to unconditonal (%)]	189.8	374.6	198.8	374.1
Industry Fixed Effects	✓	✓	✓	✓
Additional Controls	✓	✓	✓	✓
Observations	45,445		45,445	
Pseudo R^2	0.092		0.091	
Coefficient: MPU Index				
$\chi^2(\beta_{Bubble} = \beta_{NoBubble})$	16.23		11.92	
p-value	0.00		0.00	

Table 7: Quantile Regressions of Monthly Industry Returns

This table reports quantile regression estimates of the relationship between monthly industry returns and monetary policy uncertainty (MPU) between January 1931 and October 2014. Industry is defined according to the Fama-French 49 industry classification excluding "Others" (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Our sample period ends in 2014 because the regressions use the constructed MPU Index from Table 3. Every industry-month in our sample period is classified into 3 groups as "No Price Run-up", "No Bubble" or "Bubble" using the procedure outlined in the caption of Table 1. To estimate the relationship between MPU and industry returns for each group, we interact MPU Index with indicator variables for "No Price Run-up" ($\mathbb{1}_{NPR}$), "No Bubble" ($\mathbb{1}_{NB}$) and "Bubble" ($\mathbb{1}_{B}$) events. The definitions of additional controls, Δ *Interest Rate* and *EPU Index* are identical to the definitions in Table 1 and Table 3. We include FF 49 industry fixed effects in each regression. Each column shows coefficient estimates and t-values for the explanatory variables in the regression. We test the equality of the coefficients MPU Index * $\mathbb{1}_{NB}$ and MPU Index * $\mathbb{1}_{B}$ and report the associated t and p-values at the bottom of the each model. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

	Industry Return								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
MPU Index * $\mathbb{1}_{NPR}$	-0.08***	-0.06***	-0.05***	-0.04***	-0.03***	-0.02***	-0.01	0.00	0.02*
	(-5.56)	(-6.30)	(-7.12)	(-7.65)	(-6.57)	(-3.59)	(-1.16)	(0.48)	(1.67)
MPU Index * $\mathbb{1}_{NB}$	0.01	0.03***	0.05***	0.06***	0.07***	0.08***	0.09***	0.10***	0.12***
	(0.83)	(3.23)	(5.98)	(9.17)	(11.93)	(12.78)	(12.06)	(10.53)	(8.96)
MPU Index * $\mathbb{1}_{B}$	-0.02	0.03	0.06***	0.09***	0.11***	0.13***	0.16***	0.19***	0.23***
	(-1.05)	(1.53)	(3.59)	(5.19)	(6.40)	(7.22)	(7.72)	(8.00)	(8.07)
Δ Interest Rate	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-8.64)	(-14.16)	(-17.82)	(-18.85)	(-17.84)	(-16.07)	(-14.13)	(-12.21)	(-10.16)

(To be continued)

EPU Index	0.06***	0.05***	0.04***	0.03***	0.02***	0.02***	0.01	0.00	-0.01
	(4.70)	(5.47)	(6.34)	(7.05)	(6.30)	(3.72)	(1.57)	(0.10)	(-0.97)
Additional Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	45,826	45,826	45,826	45,826	45,826	45,826	45,826	45,826	45,826
$\chi^2(\beta_{\text{MPU*Bubble}} = \beta_{\text{MPU*No Bubble}})$	4.09	0.13	0.88	3.52	6.41	8.91	10.88	12.54	13.89
p-value	0.04	0.72	0.35	0.06	0.01	0.00	0.00	0.00	0.00

Table 8: Machine Learning Models and Resampling Techniques

This table reports 9 machine learning models and 15 resampling techniques that we use in predicting asset price bubbles in real time. Brief descriptions of these models and resampling techniques are presented in Appendix A.

Models	Resampling Techniques
Logistic Regression (LR)	SMOTE (SMOTE)
Random Forest (RF)	BorderlineSMOTE (Bord SMOTE)
Support Vector Machine (SVM)	Borderline-SMOTE SVM (SVMSMOTE)
Decision Tree (DTC)	RandomOverSampler (RANDOVER)
Linear Discriminant Analysis	RandomUnderSampler (RANDUND)
Gaussian Naive Bayes (GNB)	CondensedNearestNeighbor (CNN)
Gaussian Process Classifier (GPC)	Tomek Links (TomekLinks)
Quadratic Discriminant Analysis	EditedNearestNeighbors (ENN)
XGBoost (XGB)	OneSidedSelection (OSS)
	NeighborhoodCleaningRule (NeighCl)
	SMOTE Tomek (SMOTETomek)
	SMOTEENN (SMOTEENN)
	ClusterCentroids (CCENT)
	NearMiss (NMISS)
	Adaptive Synthetic Sampling (ADASYN)

Table 9: Machine Learning Predictions of Asset Price Bubbles in Real Time

This table reports the performance, measured as the F2 score, of machine learning models used to predict asset price bubbles in real time. F2 score is a form of F_β score where β assumes a value of 2, and is defined as $F_\beta = \frac{(1+\beta^2)*Precision*Recall}{\beta^2*Precision+Recall}$. Precision is the ratio of number of true positives to the total number of true positives and false positives. Recall is the ratio of number of true positives to the total number of true positives and false negatives. A true positive is defined as an outcome where the machine learning model correctly predicts the asset price bubble in that month. A false positive is defined as an outcome where the machine learning model incorrectly predicts the asset price bubble. A false negative is defined as an outcome where the machine learning model incorrectly predicts the absence of an asset price bubble. We specify the period between January 1931 and December 1989 as the training (in-sample) period for the machine learning models. We predict asset price bubbles between January 1990 and June 2019 (out-of-sample period). Our sample includes industry months with price run-ups. Our dependent variable assumes a value of 1 if the price run-up is a "Bubble" and 0 otherwise ("No Bubble"). Our independent variables include Δ *Interest Rate* as described in Table 2, additional controls as described in Table 1 and the EPU Index. We estimate two models: one model with the MPU index included with all other control variables and a second model with the MPU index excluded but all other control variables included in the estimation. We report the improvement in the F2 score of all models after the inclusion of the MPU index in the model. We use total of 135 models (9 machine learning models $\times$ 15 resampling techniques). In Panel A, we document the summary statistics of the F2 scores of all models that include MPU as a control variable ("With MPU") and all models that exclude MPU as a control variable ("Without MPU"), for both in-sample and out-of-sample periods. In Panel B, we consider 4 out of the 9 models that explicitly consider the costs of prediction errors into account when training a machine learning model. In particular we penalize a model more heavily if it classified an industry bubble as a no bubble rather than vice versa. The penalties for the errors are the inverse of the frequency of the two groups: bubbles and no bubbles. Standard errors are reported in parentheses. Significance levels are denoted by *, **, *** for 10%, 5%, and 1% respectively.

Panel A: F2 Scores - All Models

	With MPU	Without MPU	Difference	Improvement
Mean (In-sample)	0.569	0.562	0.007***	1.2%
	[0.011]	[0.011]	[0.002]	
Median (In-sample)	0.599	0.596	p$(Median_1 = Median_2) = 0.00$	
Mean (Out-of-sample)	0.261	0.238	0.023***	9.7%
	[0.010]	[0.011]	[0.004]	
Median (Out-of-sample)	0.268	0.222	p$(Median_1 = Median_2) = 0.00$	
Observations	135	135	135	

Panel B: F2 Scores - Only Cost Sensitive Models

	With MPU	Without MPU	Difference	Improvement
Mean (In-sample)	0.609	0.603	0.006	1.0%
	[0.021]	[0.026]	[0.006]	
Mean (Out-of-sample)	0.209	0.192	0.017*	8.9%
	[0.057]	[0.062]	[0.009]	
Observations	4	4	4	

Table 10: Comparison of Predictions (of Asset Price Bubbles) across types of Machine Learning Algorithms

In this table, we group 135 machine learning (ML) models (combination of 9 machine learning models × 15 resampling techniques, as described in the Appendix A) by two dimensions. The first dimension is the class of algorithm employed by the ML model (one of 6 groups) and the second dimension is the type of re sampling of the data used by the model (one of three groups). We report the average improvement in performance, measured as the % change in the F2 score (predicting asset price bubbles) between two models. The first model includes MPU as a control variable and the second model excludes MPU as a control variable. All other independent variables and the dependent variable are identical to the ML models in Table 9. We report the results of this exercise for both in-sample (Panel A) and out-of-sample (Panel B) periods in our data. The period between January 1931 and December 1989 is specified as the training (in-sample) period, and the period between January 1990 and June 2019 is specified as the test period (out-of-sample).

Panel A: In-Sample Average F-2 Score Improvements by categories (%)

	Oversampling	Undersampling	Mixed	Average
Regression Algorithms	0.18	0.13	0.58	0.21
Ensemble Algorithms	0.58	1.53	1.14	1.16
Instance-based Algorithms	-0.67	0.84	-0.33	0.18
Decision Tree Algorithms	0.13	1.38	3.63	1.27
Dimensionality Reduction Algorithms	-0.93	7.10	-0.70	3.38
Bayesian Algorithms	-0.59	3.99	1.24	2.10
Average	-0.25	3.07	0.80	1.87

Panel B: Out-of-Sample Average F-2 Score Improvements by categories (%)

	Oversampling	Undersampling	Mixed	Average
Regression Algorithms	-1.90	1.38	0.03	0.11
Ensemble Algorithms	41.33	32.51	34.50	35.72
Instance-based Algorithms	40.87	20.54	51.86	31.49
Decision Tree Algorithms	14.22	55.69	8.01	35.51
Dimensionality Reduction Algorithms	0.62	34.30	5.00	19.17
Bayesian Algorithms	-7.53	7.19	-1.14	1.17

Average	13.56	25.07	15.18	22.40

Figure 1: Illustration of Allen and Gale (2000) model

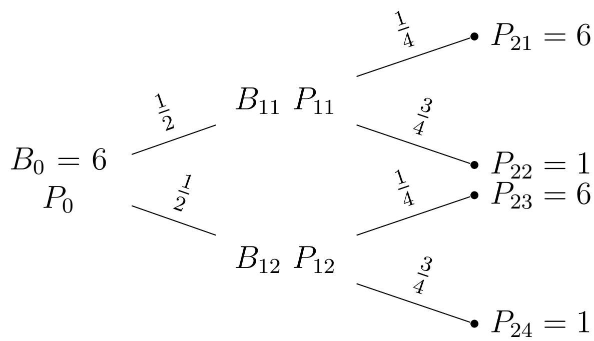


Figure 2: Equally Weighted (EW) Cumulative Industry Returns Around Price Run-ups

This figure shows the equally weighted average of cumulative industry returns in event time. Industry is defined according to the Fama-French 49 industry classification excluding ”Others” (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Every industry-month between January 1931 and June 2019, is classified into one of 3 groups: ”No Price Run-up”, ”Bubble” or ”No Bubble”. If the monthly industry return is below the 95th percentile of the historical industry return distribution, we define the industry-month as ”No Price Run-up”. If the monthly industry return is above the 95th percentile of the historical industry return distribution, we examine the equally weighted cumulative industry return over the [-1,12] months around the event date. If the cumulative industry return declines by at least 30% any time over the next 12 months (dubbed a 30% drawdown and is the pattern of a price run up followed by a crash), we classify the current industry-month as a ”Bubble” (event date 0, left panel). If the cumulative industry return does not decline by at least 30% any time over the next 12 months (the pattern of a price run up not followed by a crash), we classify the current industry-month as a ”No Bubble” (event date 0, right panel). According to the data, 241 industry months (or about 0.5% of the data) are classified as bubble months and 1,380 (or about 2.9% of the data) are classified as no bubble months.

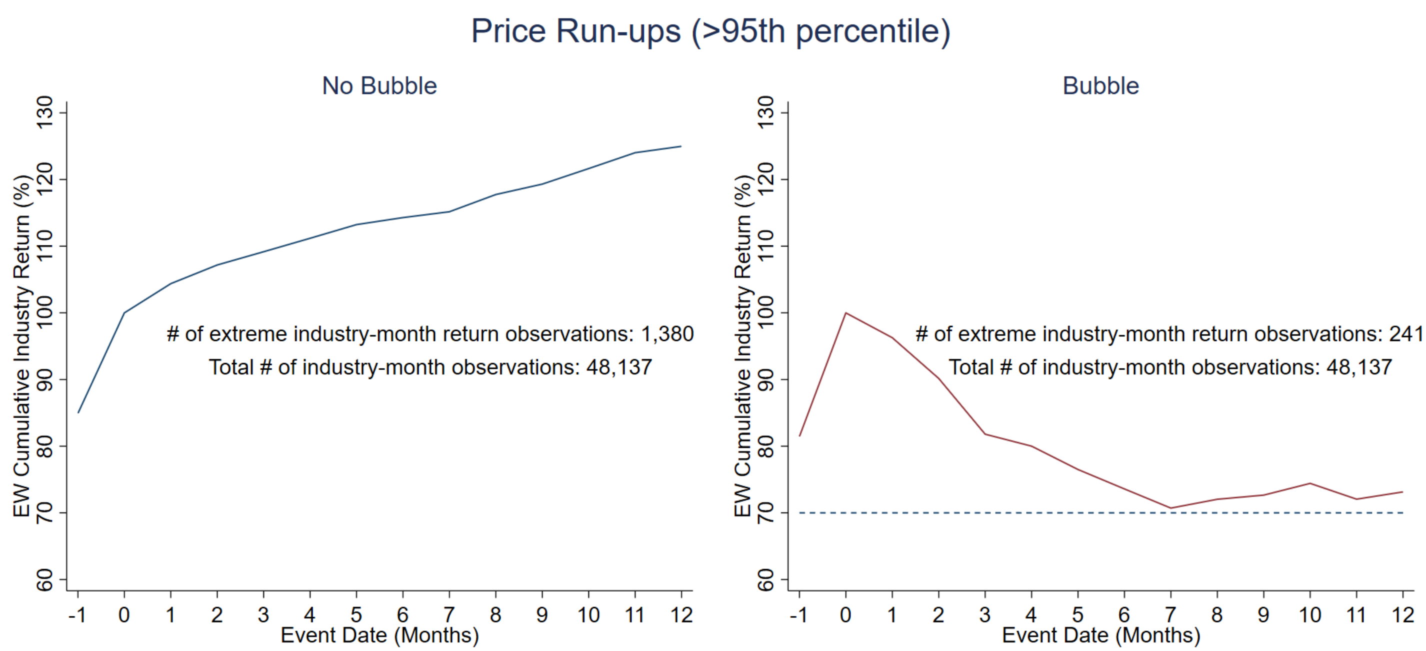


Figure 3: Industry Bubbles

This figure shows the dates (x-axis) of industry level asset price bubbles and price run ups with no asset price bubbles between January 1931 and June 2019. Industry is defined according to the Fama-French 49 industry classification excluding "Others" and is labelled on the y-axis. (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html`). Every industry-month between January 1931 and June 2019, is classified into one of 3 groups: "No Price Run-up", "Bubble" or "No Bubble". If the monthly industry return is below the 95th percentile of the historical industry return distribution, we define the industry-month as "No Price Run-up". If the cumulative industry return declines by at least 30% any time over the next 12 months (dubbed a 30% drawdown and is the pattern of a price run up followed by a crash), we classify the current industry-month as a "Bubble" (right panel). If the cumulative industry return does not decline by at least 30% any time over the next 12 months (the pattern of a price run up not followed by a crash), we classify the current industry-month as a "No Bubble" (left panel). According to the data, 241 industry months (or about 0.5% of the data) are classified as bubble months and 1,380 (or about 2.9% of the data) are classified as no bubble months.

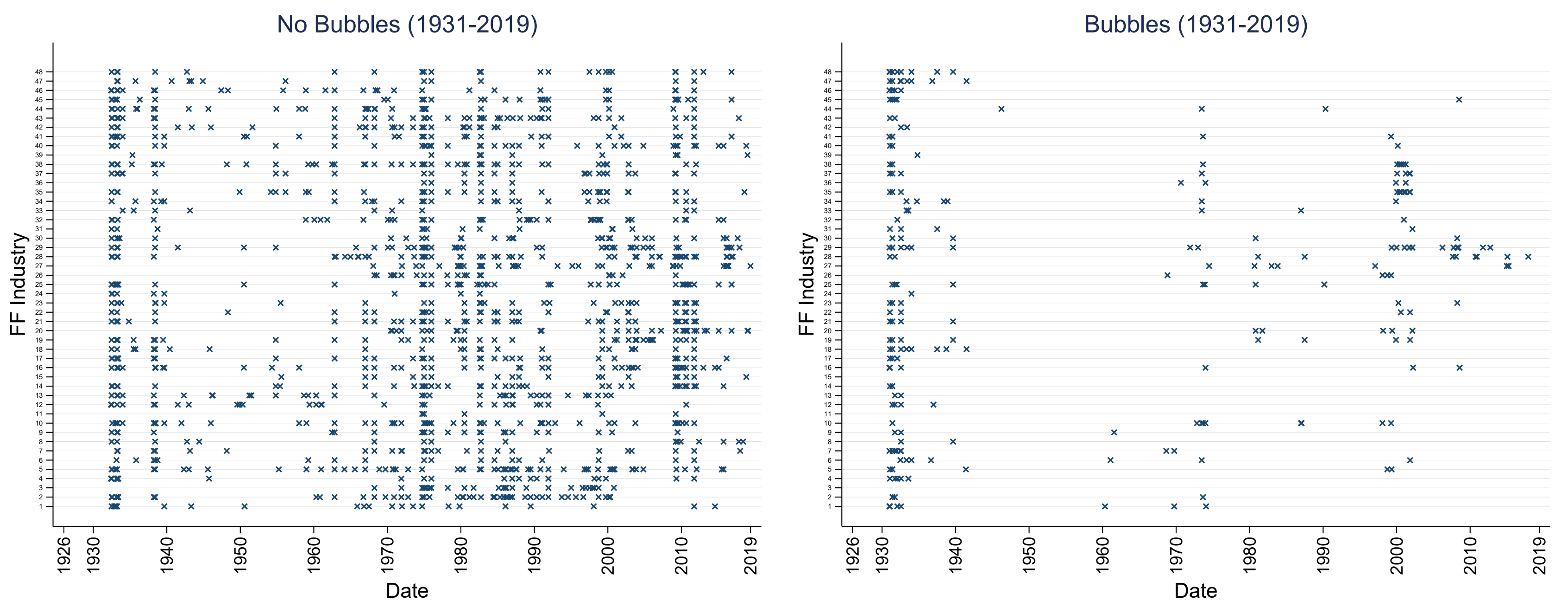
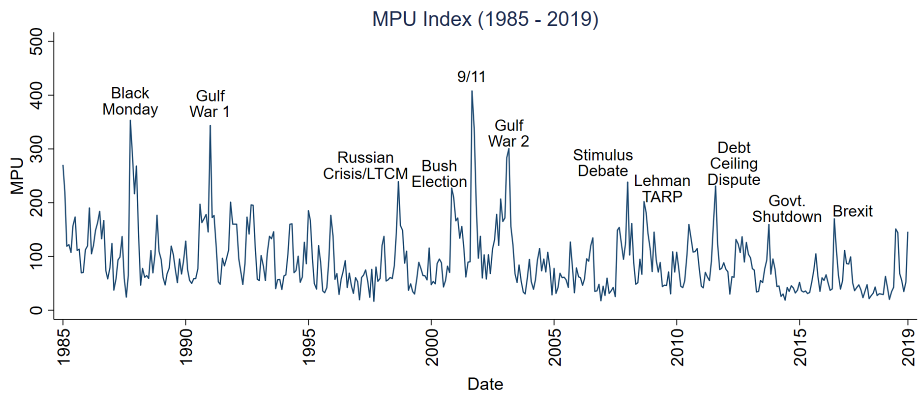


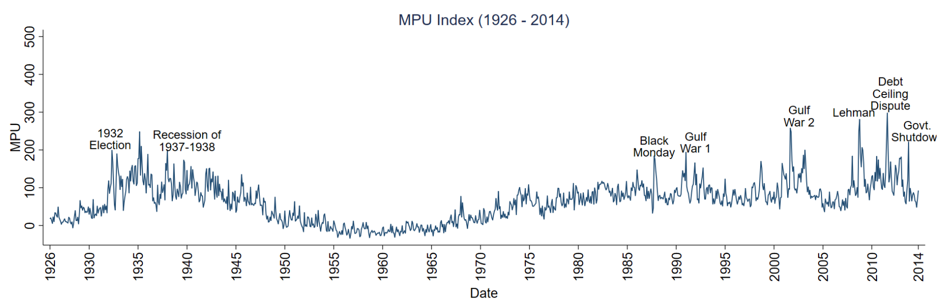
Figure 4: Monetary Policy Uncertainty Indexes

This figure shows the time series of two different MPU indexes that we use in our main analyses. Panel A shows Baker, Bloom, and Davis' (2016) MPU Index which is constructed by using U.S. newspapers covered by Access World News and available from January 1985 (`https://www.policyuncertainty.com/bbd_monetary.html`). Panel B shows the longer time series of MPU Index that is constructed as follows: we first regress the Baker, Bloom, and Davis' (2016) MPU Index on their "Historical EPU" series (`https://www.policyuncertainty.com/us_monthly.html`) and Lukas Püttmann's (2018) "Financial Stress" series (`https://www.policyuncertainty.com/financial_stress.html`) between Jan 1985 and Oct 2014. We then use the fitted values from the regression to obtain a series from Jan 1931 until Oct 2014. In Panel C, we plot the indexes from Panel A and Panel B between Jan 1985 - Oct 2014, when the data for both series are available.

Panel A: Monetary Policy Uncertainty Index Jan 1985 - Jun 2019



Panel B: Monetary Policy Uncertainty Index Jan 1931 - Oct 2014



Panel C: Monetary Policy Uncertainty Indexes Between Jan 1985 - Oct 2014

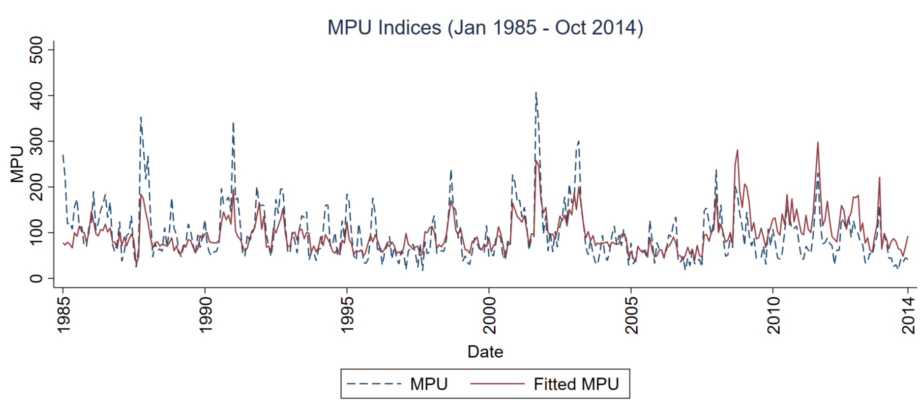


Figure 5: FED's Disclosure Policy and the Relationship between MPU and Asset Price Bubbles

This figure shows the role of FED's disclosure policy on the strength of the relationship between the constructed MPU Index and industry asset price bubbles. Disclosure policy is defined as the elapsed time lag between the FOMC (Federal Open Market Committee) meetings and the publication of the official minutes of the meeting. We estimate expanding window multinomial logistic regressions (specification in Equation 1 of the text) increasing the window by 1 month at a time. The first regression is estimated using data from January 1931 and December 1935 and the last regression is estimated using data from January 1931 to October 2014. For each regression, we plot the coefficient of MPU for the "Bubble" event. The three figures represent the time series of coefficient estimates based on three different thresholds used to define a price run-up and a bubble (see caption to Table 2 for details). The vertical lines show the major changes in FED's disclosure policy over the sample period. In 1964, the FOMC made the minutes for the years 1936-1960 available to the public through the National Archives.

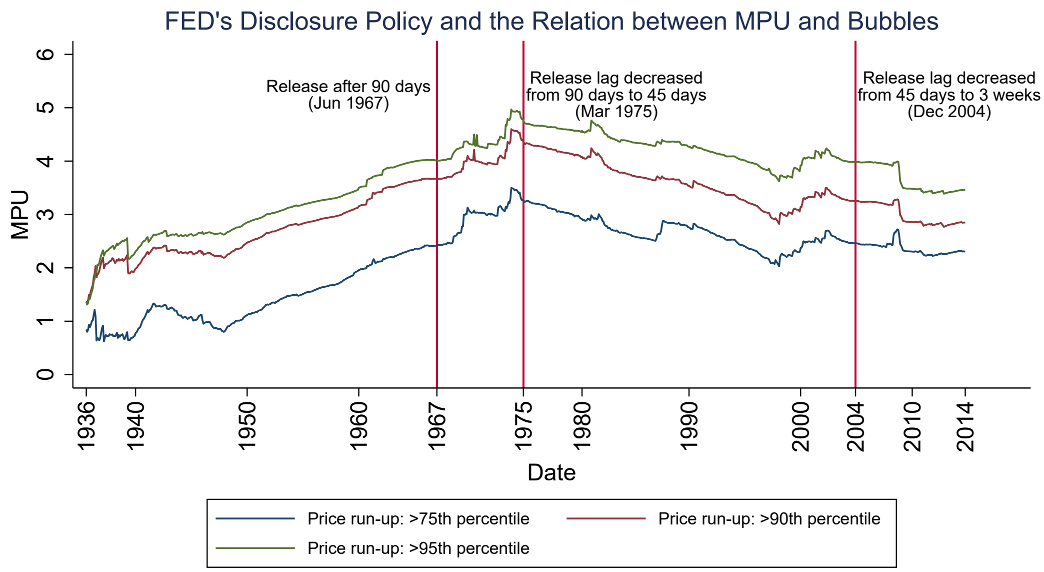


Figure 6: Are Bubbles Simply an Artifact of a Random Walk Model of Returns?

This figure documents the expected lowest cumulative return over a 12 month period [expected maximum drawdown, the definition of a crash used to define a bubble in the paper] against different initial volatilities. The goal is to assess using a simulation exercise if the observed drawdown in the data is simply an artifact of a random walk model of returns and CGARCH volatility model of Engle and Lee (1999). For each initial volatility, we simulate monthly log market returns for a 12 month period for 10,000 times as explained in Appendix B and calculate the maximum drawdown for each simulation. Then, we calculate expected maximum drawdown as an equally weighted average of all the maximum drawdown values for the 10,000 simulations. This produces an expected drawdown, initial volatility tuple. We repeat this procedure and generate the curve in the picture for initial volatilities ranging from 5% to 80% with 2.5% increments. We also plot three horizontal lines that denote the maximum drawdown thresholds that we use to define a crash and thus a bubble in the paper. The picture also marks the unconditional volatility for all the FF-48 industries over our entire sample period (Jan 1926-Jun 2019). The figure shows that our definition of bubbles for all the industries are not simply an artifact of a random walk model of returns. This can be seen from the fact that for all our sample industry volatilities, expected drawdowns at 30%, 40%, or 50% levels lie well above the simulated curve.

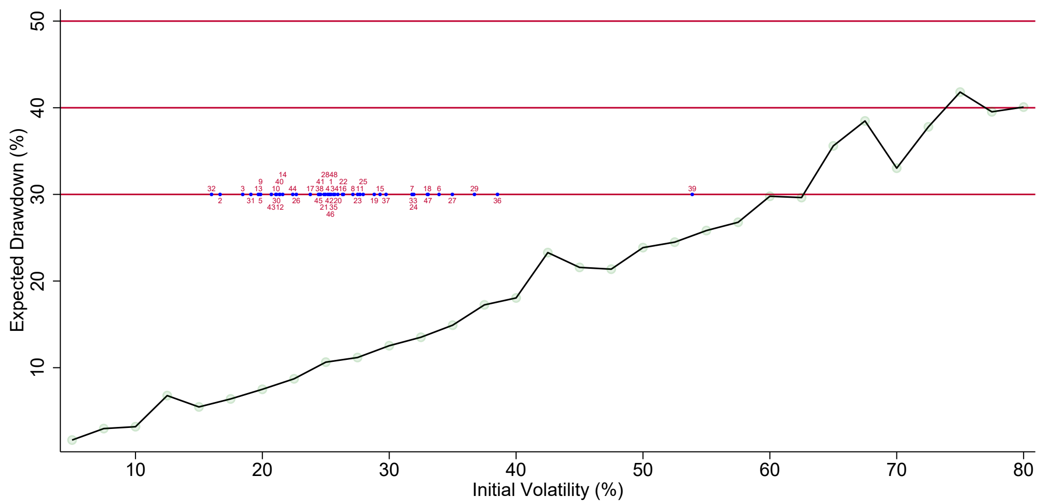
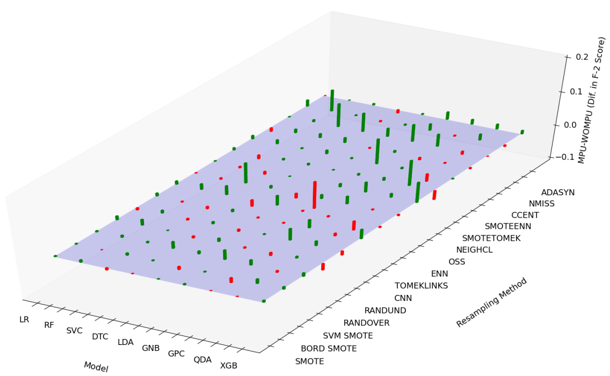
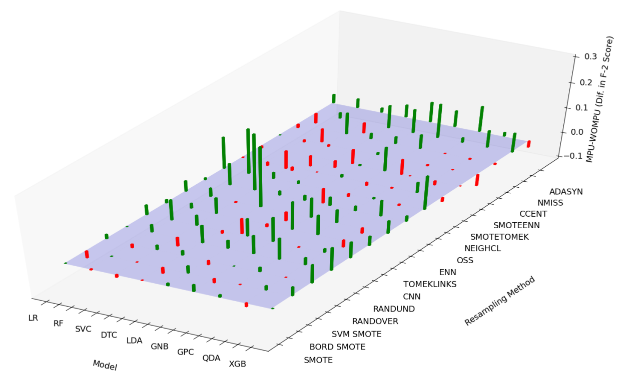


Figure 7: F2 Score Comparison: Machine Learning Models with MPU vs Machine Learning Models without MPU

This figure reports the performance, measured as the F2 score, of machine learning models used to predict asset price bubbles in real time. F2 score is a form of F_β score where β assumes a value of 2, and is defined as $F_\beta = \frac{(1+\beta^2)*Precision*Recall}{\beta^2*Precision+Recall}$. Precision is the ratio of number of true positives to the total number of true positives and false positives. Recall is the ratio of number of true positives to the total number of true positives and false negatives. A true positive is defined as an outcome where the machine learning model correctly predicts the asset price bubble in that month. A false positive is defined as an outcome where the machine learning model incorrectly predicts the asset price bubble. A false negative is defined as an outcome where the machine learning model incorrectly predicts the absence of an asset price bubble. We specify the period between January 1931 and December 1989 as the training (in-sample) period for the machine learning models. We predict asset price bubbles between January 1990 and June 2019 (out-of-sample period). Our sample includes industry months with price run-ups. Our dependent variable assumes a value of 1 if the price run-up is a "Bubble" and 0 otherwise ("No Bubble"). Our independent variables include Δ *Interest Rate* as described in Table 2, additional controls as described in Table 1 and the EPU Index. We estimate two models: one model with the MPU index included with all other control variables and a second model with the MPU index excluded but all other control variables included in the estimation. We report the improvement in the F2 score of all models after the inclusion of the MPU index in the model. We use total of 135 models (9 machine learning models $\times$ 15 resampling techniques). In Panel A (Panel B), we report the F2 score difference between the two models for the in-sample (out-of-sample) periods. The x-axis shows the models, the y-axis the sampling technique used, and the z-axis the F2 score difference. The surface is plotted at z=0 to show the models that result in a performance improvement (green bars in the figure) when we add MPU as an explanatory variable.



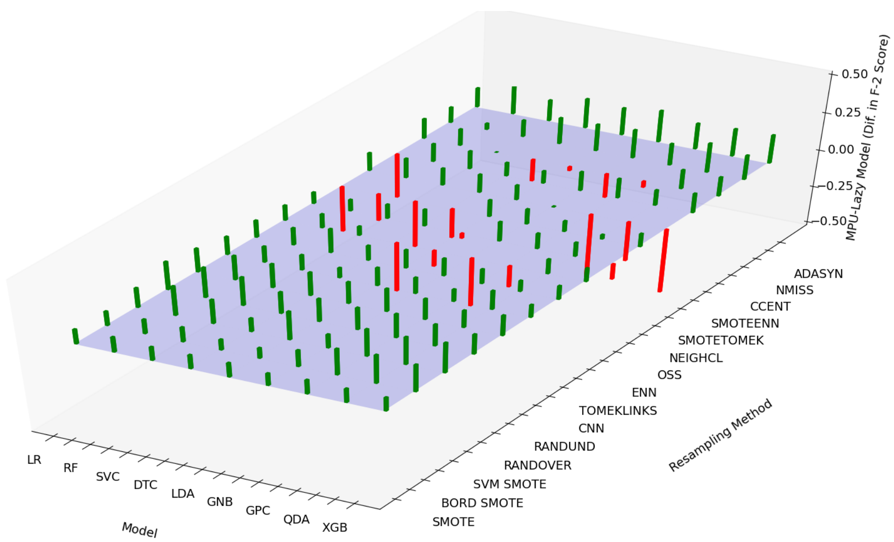
Panel A: F2 Score Difference (In-sample)



Panel B: F2 Score Difference (Out-of-sample)

Figure 8: F2 Score Comparison: Models with MPU vs Lazy Model

This figure reports the performance, measured as the F2 score, of machine learning models used to predict asset price bubbles in real time. F2 score is a form of F_β score where β assumes a value of 2, and is defined as $F_\beta = \frac{(1+\beta^2)*Precision*Recall}{\beta^2*Precision+Recall}$. Precision is the ratio of number of true positives to the total number of true positives and false positives. Recall is the ratio of number of true positives to the total number of true positives and false negatives. A true positive is defined as an outcome where the machine learning model correctly predicts the asset price bubble in that month. A false positive is defined as an outcome where the machine learning model incorrectly predicts the asset price bubble. A false negative is defined as an outcome where the machine learning model incorrectly predicts the absence of an asset price bubble. We specify the period between January 1931 and December 1989 as the training (in-sample) period for the machine learning models. We estimate two models: one model with the MPU index included with all other control variables and a second model dubbed the "lazy model" which always predicts a bubble. Our sample includes industry months with price run-ups. Our dependent variable assumes a value of 1 if the price run-up is a "Bubble" and 0 otherwise ("No Bubble"). Our independent variables include Δ *Interest Rate* as described in Table 2, additional controls as described in Table 1 and the EPU Index. We report the F2 score of all models relative to the lazy model (green (red) bars mean the F2 score is greater (lesser) than the F2 score of the lazy model). We use total of 135 models (9 machine learning models $\times$ 15 resampling techniques). The x-axis shows the models, the y-axis the sampling technique used, and the z-axis the F2 score difference.



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Appendix

A Machine Learning

A.1 Machine Learning Models

A.1.1 Logistic Regression (LR) In Logistic Regression, the dependent variable is the log of odds and probability of occurrence is predicted using a logit function.

$$\begin{aligned} log\frac{p}{1-p} &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... \\ \frac{p}{1-p} &= e^{\beta_0 + \beta_1 x_1 + \beta 2 x_2 + ...} \\ p &= \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta 2 x_2 + ...)}} \end{aligned}$$

The probabilities are estimated by minimizing the negative log likelihood as follows:

$$\min_{\beta} \sum_{i=1}^{n} -(log(\hat{p}_i) \times y_i + log(1 - \hat{p}_i) \times (1 - y_i))$$

If the predicted probability is greater than 0.5, the predicted y value becomes 1, otherwise 0.

A.1.2 Decision Tree (DTC)

Decision trees are constructed to divide a data set into smaller portions based on different features. Decision trees are tree-like graphs that consist of internal nodes representing the features of the dataset and branches representing the decision rules. The end of the branch that can not be divided anymore is the leaf that shows the outcome.

A.1.3 Random Forest (RF)

Random forest is an ensemble of large number of decision trees on randomly selected subsets of the training data set. When predicting class labels, the final decision is made by majority vote across the trees in the ensemble. Unlike a single decision tree, random forests use multiple decision tree predictions, thereby reducing overfitting.

A.1.4 Support Vector Machine (SVM)

The objective of the support vector machine algorithm is to find a hyperplane that separate the classes with the largest margin. Largest margin can be achieved by choosing a hyperplane with the maximum distance to the nearest data point on each side. This allows us to classify the observations in the prediction sample with more confidence.

The dimension of the space, N, is equal to the number of features. If N is equal to 2, then the hyperplane is just a line. If N is equal to 3, then the hyperplane becomes a two-dimensional plane.

A.1.5 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis can be derived from class conditional distribution of the data. By using Bayes theorem, LDA estimates the probabilities of the new data belonging to each class. The final class prediction is the one that maximizes estimated probability. There are two underlying assumptions: Data is Gaussian and each class has the same variance-covariance matrix.

A.1.6 Quadratic Discriminant Analysis (QDA)

Quadratic Discriminant Analysis is same as Linear Discriminant Analysis except that each class uses its own estimate of variance-covariance matrix.

A.1.7 Gaussian Naive Bayes (GNB)

Gaussian Naive Bayes is equivalent to QDA if we assume that the covariance matrices are diagonal, therefore the inputs are assumed to be conditionally independent in each class.

A.1.8 Gaussian Process Classifier (GPC)

Gaussian Process Classifier is a nonparametric classification method based on Bayesian methodology. This algorithm places a Gaussian Process prior on the kernel that defines the covariance function of the data. The final classification is based on the posterior probabilities that can be calculated through a Logistic link function.

A.1.9 XGBoost (XGB)

XGBoost, or Extreme Gradient Boosting, is an ensemble method that combines several decision trees using Gradient boosting approach. Gradient boosting builds sequential decision tree models to correct the errors of the previous models until no improvement can be made. The final decision is made based on the predictions of all models.

A.2 Resampling Techniques

A.2.1 Synthetic Minority Oversampling Technique (SMOTE)

SMOTE is an oversampling technique that creates synthetic observations by using two observations from the minority class. First observation is randomly selected. Then, among the k-neighbors of the initial observation, another observation is randomly selected. Finally, a synthetic observation is created at a randomly selected point between these two observations.

A.2.2 Borderline-SMOTE (Bord SMOTE)

Borderline-SMOTE is an extension of SMOTE that does not use the minority class observations with all neighbors belong to majority group in creating new observations. Instead, this method selects the observations that have neighbors belong to both minority and majority classes, namely around the borderline. This extension prevents us from selecting extreme observations in creating a new synthetic observation.

A.2.3 Borderline-SMOTE SVM (SVMSMOTE)

Borderline-SMOTE SVM uses SVM algorithm to identify observations around the borderline rather than using k nearest neighbor method. SVM classifier is applied to the original imbalanced training dataset and the borderline area is determined by the support vectors, which are the data points closer to the separating hyperplane and influence the position and orientation of it. New synthetic observations are created by interpolation between support vectors and their neighbors.

A.2.4 Random OverSampler (RANDOVER)

Randomly selected observations in the minority class are duplicated with replacement.

A.2.5 Random UnderSampler (RANDUND)

Randomly selected observations in the majority class are deleted.

A.2.6 Condensed Nearest Neighbor (CNN)

Condensed Nearest Neighbor is an undersampling method that constructs a subset of observations that can correctly classify all the observations in the training data using a k nearest neighbor algorithm. The subset includes all observations from the minority class and only the observations from the majority class that cannot be classified correctly.

A.2.7 Tomek Links

Tomek Links is very similar to CNN except that initial selection of majority class observations is not random. Tomek Links selects pairs of observations (a and b) from different classes based on the following criteria:

i) The observation a's nearest neighbor is b

ii) The observation b's nearest neighbor is a

These cross-class pairs are called Tomek Links and the majority class observations in Tomek Links are removed. The idea is to make decision border less ambiguous and the minority region more distinct.

A.2.8 Edited Nearest Neighbors (ENN)

Edited Nearest Neighbors finds k nearest neighbors of each observation in the training sample. If the observation belongs to the majority class and more than half of the k neighbors belong to the minority class, then this majority class observation is removed from the sample. In addition, if the observation belongs to the minority class and more than half of the k neighbors belong to the majority class, then the majority class neighbors are removed.

A.2.9 SMOTE-Tomek

SMOTE Tomek combines SMOTE and Tomek Links techniques together. First, the training sample is oversampled using SMOTE and then undersampled using Tomek Links.

A.2.10 SMOTE-ENN

SMOTE ENN combines SMOTE and ENN techniques together. First, the training sample is oversampled using SMOTE and then undersampled using ENN.

A.2.11 Adaptive Synthetic Sampling (ADASYN)

Adaptive Synthetic Sampling is an oversampling technique that is a modified version of SMOTE. Instead of randomly selecting minority class observations to create synthetic observations, ADASYN creates synthetic observations in regions of the feature space inversely proportional to the density of minority class observations. There will be more synthetic observations in the regions where the density of minority observations is low and vice versa.

A.2.12 One-Sided Selection (OSS)

One-Sided Selection is an undersampling method that combines Tomek Links and the Condensed Nearest Neighbor techniques. First, the observations in Tomek Links that belong to majority class are removed. Then, the sample is further undersampled by using CNN technique to remove redundant examples from the majority class.

A.2.13 Neighborhood Cleaning Rule (NeighCl)

The Neighborhood Cleaning Rule is an undersampling method that combines Edited Nearest Neighbors and Condensed Nearest Neighbor techniques. First, noisy or ambiguous observations are removed from the majority class by using ENN technique. Then, the sample is further undersampled by using CNN to remove redundant observations from the majority class.

A.2.14 Cluster Centroids (CCENT)

Cluster Centroids is an undersampling technique that replaces a cluster of observations from majority class with the cluster centroids. The number of clusters will be equal to the number of observations in the minority class, therefore final sample will consist of equal number of observations in each group.

A.2.15 NearMiss (NMISS)

Near Miss is an undersampling technique that selects a subset of observations from the majority class. There are 3 versions of Near Miss technique:

1) NearMiss-1: Selects the majority class observations with the smallest average distance to the three closest neighbors from the minority class.

2) NearMiss-2: Selects the majority class observations with the smallest average distance to the three furthest neighbors from the minority class.

3) NearMiss-3: For each minority class observation, selects n closest majority class neighbors. If there are m minority class observations, there will be m*n majority class observations.

We refer to Euclidean distance in each version. We prefer to use NearMiss-3 since this version allows us to keep the majority class observations on the decision boundary.

B Are the Identified Bubbles Really Bubbles?: Simulation Evidence

We closely follow the setup postulated by Kim and Richardson (2022, KR hereafter) and model the market volatility using the CGARCH(1,1) variance model of Engle and Lee (1999). The model and the parameters can be summarized as follows:

$$log(1 + r_t) = \mu + \epsilon$$
$$\sigma_t^2 \text{ - m}_t = \alpha(\epsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1})$$
$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\epsilon_{t-1}^2 - \sigma_{t-1}^2)$$
$$\epsilon_t \sim \mathcal{N}(0, \sigma_t^2)$$

μ	α	β	ω	ρ	ϕ
0.00933	-0.088849	0.892267	0.004536	0.980319	0.178896

We choose initial values for annualized volatility (σ_t) ranging from 5% to 80% with 2.5% increments, and repeat the CGARCH process simulation 10,000 times for each initial volatility level. For each of the initial volatility level, we run a simulated price path of length 12 months 10,000 times. We use 12 months because our definition of drawdown is defined over a 12 month period. For each of these price paths, we compute a maximum drawdown, defined as the most negative cumulative return during the 12 month period, and then compute the expected maximum drawdown as the average of the maximum drawdown across the 10,000 price paths.