Anomaly Returns and FOMC *

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Abstract

We find that anomaly returns are generally unchanged during FOMC days, though a small group of anomalies may have substantial changes. But if they do, their changes exacerbate pricing errors. Hence, our evidence challenges existing studies that find that the CAPM performs better over the FOMC period. In reconciliation, we find further that, similar to existing studies, stocks do respond more to their market betas on announcement days than non-announcement days, and it is just that the alphas are not mitigated. For the exacerbated negative pricing errors, we argue that decreased participation of retail investors contributes to the decline of the profitability.

JEL classifications: G11, G12, G14, G23

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1. Introduction

Why anomalies, long-short portfolios based on firm characteristics, earn abnormal returns has been widely studied in the asset pricing literature, with both systematic risk and mispricing explanations.[1] For example, Stambaugh, Yu and Yuan (2012) relates anomaly returns to market sentiment, Engelberg, Mclean and Pontiff (2018) to earnings announcement, and Filippou, He, Li and Zhou (2022) to ETF ownership. An interesting question is whether anomalies are related to FOMC, one of the most influential economic decisions by the Fed. But, to our knowledge, there are no studies on this important question.

In this paper, we explore the FOMC implication on anomaly returns. We study anomaly returns right before the FOMC and the days around. We analyze three groups of anomalies. The first group includes 11 mispricing anomalies as studied by Stambaugh, Yu and Yuan (2012) and Chu, Hirshleifer and Ma (2020). Empirically, we find the overall returns on these mispricing anomalies stay statistically unchanged on FOMC compared with non-FOMC days, indicating an unattenuated level of pricing error. On the other hand, both the long-leg and short-leg exhibit a significantly positive drift on the FOMC day, supporting the FOMC risk premium theory.[2] The long-leg return and short-leg return rise by 0.2258% (22.58 bps) and 0.2782% (27.82 bps), respectively, on the day of FOMC, an economically significant number compared to their sample mean of 0.0535% (5.35 bps) and 0.0308% (3.08 bps).

The second group of anomalies includes 125 anomalies based on Hou, Xue and Zhang (2020), which are naturally categorized into six clusters with different economic meanings. We empirically examine the FOMC returns on anomalies within each of the six clusters: frictions, intangibles,

[1]For systematic risk, see, for instance, Jegadeesh and Titman (1993), Berk, Green and Naik (1999), Chordia and Shivakumar (2002), Johnson (2002), Griffin, Ji and Martin (2003), Zhang (2005), Lettau and Wachter (2007), Patton and Verardo (2012), Asness, Moskowitz and Pedersen (2013), Hou, Xue and Zhang (2015), Daniel and Moskowitz (2016), Savor and Wilson (2016), and Lochstoer and Tetlock (2020). For mispricing explanations, see Basu (1977), Bondt and Thaler (1985), La Porta, Lakonishok, Shleifer and Vishny (1997), Shleifer and Vishny (1997), Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Daniel, Hirshleifer and Subrahmanyam (2001), Barberis and Thaler (2003), Stambaugh, Yu and Yuan (2012), Engelberg, Mclean and Pontiff (2018), and Chu, Hirshleifer and Ma (2020).

[2]Previous studies find the FOMC days associated with a significant upward drift in the market return, reflecting a heightened FOMC risk premium. A serial of studies includes Savor and Wilson (2013), Lucca and Moench (2015), Ai and Bansal (2018), Cieslak, Morse and Vissing-Jorgensen (2019), Brusa, Savor and Wilson (2020), Laarits (2019), Neuhierl and Weber (2020), Ying (2020), Ai, Bansal and Han (2022a), Ai, Han, Pan and Xu (2022b), Liu, Tang and Zhou (2022), and Hu, Pan, Wang and Zhu (2022).

investment, momentum, profitability and value. We find that for all the six clusters, there is no statistically significant change in anomaly returns on FOMC compared with the non-FOMC days, similar to our previous findings for the 11 mispricing anomalies. We also find both returns on the long-leg and short-leg portfolio within the six clusters to increase substantially on the FOMC announcement days, by around five times or seven times the scale of its sample mean, respectively.

The third group of anomalies includes 207 anomalies based on Chen and Zimmermann (2022), which are categorized into eight clusters with different properties: accounting, analyst, event, options, price, trading, 13F, and other. We find the anomaly returns in five clusters (e.g., accounting, event, options, price, and other) exhibit no significant changes on FOMC day, a similar pattern as documented before in the second group of anomalies. However, we also find three clusters to be quite different: for the analyst cluster, trading cluster, and the 13F cluster, the anomaly return significantly decreases on FOMC day, reaching a negative scale in much larger absolute value than usual. For instance, the analyst cluster anomaly decreases by 0.0622% (6.22 bps) on FOMC day, six times the sample mean of 0.0120% (1.20 bps); the trading cluster anomaly decreases by 0.0814% (8.14 bps) on FOMC day, 19 times its sample mean of 0.0043% (0.43 bps); and the 13F cluster anomaly decreases by 0.1329% (13.29 bps) on FOMC day, seven times its sample mean of 0.0188% (1.88 bps). That is, for these three subsets of anomalies, the significant negative change in return translates into a larger absolute pricing error on FOMC day, and their abnormal profits are significantly lower, too. Combined together, we show that while the main result is an unchanged anomaly return on FOMC, implying an un-decreased pricing error generally, there does exist a small subset of anomalies with absolute pricing errors greater than usual.

Besides previous evidence on the individual-level and cluster-level, we also examine the aggregated-level results based on the third group of 207 anomalies. We first aggregate the 207 anomalies by taking the equal-weighted average across anomalies, following the combination method of Stambaugh, Yu and Yuan (2012). We find that although the aggregated anomaly return decreases by 0.0239% (2.39 bps) on FOMC day with a t-stat of -1.95, it still has an absolute value of 0.0098% ($|-0.0098\%|$, 0.98 bps), comparable to its sample mean of 0.0128 % (1.28 bps). And such effect lasts till one day after FOMC, when the average anomaly return decreases to -0.0407% (4.07 bps in absolute value). Therefore, consistent with previous results, the pricing error for these 207 anomalies does not appear diminishing on FOMC. Meanwhile, the long-leg and short-leg return rise from their non-FOMC's daily average scale of 0.0444% (4.44 bps) and 0.0304% (3.04 bps) by 0.2628% (26.28 bps) and 0.2878% (28.78 bps), respectively, on the day of FOMC. Their upward drift is not persistent, reversing back one day after the FOMC, showing a similar pattern as the market return drift.

As an alternative way of aggregation, we also estimate the FOMC returns on a mispricing-aggregated anomaly, formed by longing the decile of stocks with the lowest net-overpricing score (*NOPS*, hereafter) and shorting the decile with the highest *NOPS*. We calculate the stock-day level *NOPS* following the methodology in Han, Lu, Xu and Zhou (2020), which incorporates the information in 207 firm characteristics (which are also used to form our third testing set of anomalies). We find that for the mispricing aggregated anomaly, its return decreases by 0.0888% (8.88 bps) from its non-FOMC average scale of 0.0476% (4.76 bps), to the scale of -0.0412% ($= 0.0476\% - 0.0888\% = -4.12$ bps), even larger in absolute value when compared with the sample mean of 0.0396% (3.96 bps). The fact that the mispricing-aggregated anomaly does not diminish its return on FOMC day indicates an un-attenuated level of pricing error. Meanwhile, our results are robust that the long-leg and short-leg both significantly drift upward on the FOMC day.

To better assess the FOMC performance of returns on the 207 anomalies, we also individually examine their FOMC returns. We find 29 anomalies that are significant with their drop in returns on FOMC day, meaning that their abnormal profits significantly decrease, too.

In all, for the major anomalies, such as the 11 in Stambaugh, Yu and Yuan (2012), the 125 in Hou, Xue and Zhang (2020), and the 207 in Chen and Zimmermann (2022), there are little changes in return on FOMC day, implying an unchanged level of pricing error and abnormal profits. But there does exist a subset of anomalies on which the returns change significantly negatively on FOMC day. However, their negative changes do not lead to a closer-to-zero anomaly return. Instead, their returns are even larger in absolute value on FOMC day compared with the sample mean, implying an exacerbated pricing error, and a lowered abnormal profit.

Our evidence of an un-mitigated pricing error challenges existing studies such as Savor and Wilson (2014) that find the capital asset pricing model (CAPM) to perform better over the FOMC period. In reconciliation, we further find that, similar to existing studies, stocks do respond more to their market betas on FOMC than non-FOMC days, and it is just that the alphas from the CAPM are not mitigated. For instance, on FOMC day, while the slope of CAPM is significantly higher, the intercept of CAPM is also 0.016% (1.6 bps, though not significantly so) higher for ten testing assets of beta-sorted value-weighted portfolios, and is 0.023% (2.3 bps) higher for equal-weighted portfolios. That is, the significant alphas might even be exacerbated (if not unchanged) to the downside, just like what we find to anomalies. Meanwhile, the higher response to beta risk is obvious as the systematic risk picks up with the announcement, and all stocks respond more to beta risks on FOMC day as we find to the long- and short-legs of anomaly returns. Thus, to interpret the better performance of CAPM using a higher beta response, rather than a lower pricing error, helps our study to reconcile with the CAPM literature, and to provide additional insights for studies that call into question the return explanatory power of the CAPM.[3]

We seek an economic mechanism to explain the lowered profitability of certain anomalies. Anomaly returns, to the extent that they reflect abnormal profits exploited from uninformed trades, will decrease if the uninformed trades decrease. Therefore, if the retail investors decrease their trading activity particularly on a subset of anomalies, so might the profits. Empirically, we then test if the anomalies with significantly lower abnormal profits on FOMC day also witness a significant drop in retail participation. We find supportive evidence that no matter for the long-leg portfolio or the short-leg portfolio, retail investors do participate less in these anomalies as compared with the rest. We also find that the retail investors predict worse next-day returns for these anomalies' short-leg portfolios compared to other anomalies' short-leg portfolios, indicating that the retail investors are less informed on these anomalies. Such un-informativeness possibly contributes to their decreased activity facing macroeconomic uncertainty, according to an uncertainty reduction effect theory as modeled by Goldstein and Yang (2015), which predicts that if the retail investors are less specialized in the type of information these anomalies contained, they will face more uncertainty and hence scale down their trading.

In addition to the work cited thus far, our research is related to several strands of literature. The first strand of literature is on the asset pricing implication of FOMC announcements. The pre-FOMC announcement literature finds a positive drift in market excess return ahead of FOMC an-

[3]A series of studies includes Brennan (1971), Black (1972), Black, Jensen and Scholes (1972), Haugen and Heins (1975), Basu (1977), Basu (1983), Roll (1977), Banz (1981), Bhandari (1988), and Fama and French (1992).

nouncements, including Savor and Wilson (2013), Lucca and Moench (2015), Cieslak, Morse and Vissing-Jorgensen (2019), Brusa, Savor and Wilson (2020), Neuhierl and Weber (2020), and Hu, Pan, Wang and Zhu (2022), along with cross-sectional evidence as in Savor and Wilson (2014) and Ai, Han, Pan and Xu (2022b). Theoretically, Ai and Bansal (2018), Laarits (2019), Ying (2020), and Ai, Bansal and Han (2022a) provide frameworks of uncertainty resolution through information acquisition. Recent studies extend with more than discovering the market return drift, as Fisher, Martineau and Sheng (2022) construct a proxy for macro attention using counts of macro-related news articles, Liu, Tang and Zhou (2022) design a novel method with option data to estimate and recover the FOMC risk premium and drift sizes, and Hong, Pan and Tian (2021) examine the out-performance of government bond funds. Our research adds to the literature from an innovative angle by examining anomaly returns during FOMC days, which is one of the most core variables in asset pricing literature.

Our study adds to the literature on the source of anomaly returns, in the perspective of mis-pricing, risk premia, and statistical bias.[4] Mispricing studies that reflect pricing inefficiency feature channels of biased expectation (see, for instance, Basu (1977), Bondt and Thaler (1985), Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Daniel, Hirshleifer and Subrahmanyam (2001)), limits to arbitrage (see, Shleifer and Vishny (1997), Chu, Hirshleifer and Ma (2020)), and market sentiment (see, Stambaugh, Yu and Yuan (2012)).

Our paper is also related to Engelberg, Mclean and Pontiff (2018) who seem the first to study anomalies and macro news. However, they focus on macroeconomic scheduled news on inflation, unemployment, or interest rates, as in Savor and Wilson (2013), and their study mainly the interaction between firm earning news and macro news. In contrast, we study arguably the most important macro news, the FOMC, and we focus on how anomalies and the degree of market efficiency change during the FOMC days, and we also provide new insights on the early CAPM findings of Savor and Wilson (2014).

As for the rational thread of studies which model anomaly returns as risk factor premia (see, Berk, Green and Naik (1999), Johnson (2002), Zhang (2005), Lettau and Wachter (2007), and

[4]For example, see Fama (1998), Harvey, Liu and Zhu (2016), Mclean and Pontiff (2016), and Linnainmaa and Roberts (2018).

Hou, Xue and Zhang (2015)), among various attempts to empirically test the factor premia,[5] there has not yet been a clear answer towards whether macro risk variables can actually explain anomaly returns or not.[6] Our study, by exploiting an unexamined channel of FOMC, casts a new light on its implication for a broad set of anomaly returns.

Finally, we speak to the literature that studies retail investor's trading behavior under uncertainty. Previous studies provide evidence for retail investors' noise trading in terms of negative return predictability and profit loss (see, Glosten and Milgrom (1985), Kyle (1985), Black (1986), Barber and Odean (2000), Peress and Schmidt (2020), Barber, Huang, Odean and Schwarz (2022)), but none on how they behave when assessing FOMC risk and when trading anomalies. Savor and Wilson (2013) suggests a possibly raised risk aversion facing FOMC announcement, Baele, Bekaert, Inghelbrecht and Wei (2020) predicts a flight to safety behavior for retail investors under huge unknowns, and Goldstein and Yang (2015) predict that macroeconomic shocks cause traders who do not specialize in this type of information to face more uncertainty and hence scale down their trading. Our study is the first to utilize a great shock of macroeconomic uncertainty and provide empirical evidence that retail investors do exhibit different trading behavior across different anomalies, and are less informed over some.

The remainder of this paper is organized as follows. We describe the data in Section 2. Section 3 documents the main empirical results. Section 4 provides the economic mechanism. Finally, Section 5 concludes the paper.

[5]Jegadeesh and Titman (1993) with market risk, Asness, Moskowitz and Pedersen (2013) with liquidity risk, and Daniel and Moskowitz (2016) with crash risk and volatility risk. Patton and Verardo (2012) and Savor and Wilson (2016) attribute a higher anomaly return on earnings announcement to time-varying market beta.

[6]While Chordia and Shivakumar (2002) find macro risk variables useful in explaining momentum returns, Griffin, Ji and Martin (2003) debate the opposite using the same conditional forecasting model of Chordia and Shivakumar (2002) and the unconditional model of Chen, Roll and Ross (1986), together with more evidence in Lochstoer and Tetlock (2020) that find a weak correlation between selected macro activity and five more anomaly returns.

2. Data

2.1. *Data Source*

We collect a history of pre-scheduled FOMC meetings from 1994 to 2019 from Bloomberg and Federal Reserve's website. We obtain 11 mispricing anomalies adopted by Stambaugh, Yu and Yuan (2012) and Chu, Hirshleifer and Ma (2020), which include composite equity issuance, investment to asset, failure probability, gross profits-to-assets, asset growth, net operating assets, net stock issues, O-score, momentum, return on assets, and total accruals. We obtain 125 replicated anomalies from Hou, Xue and Zhang (2020).[7] We also obtain a comprehensive set of daily returns for 207 replicated anomalies from Chen and Zimmermann (2022).[8]

Following Lucca and Moench (2015), Cieslak, Morse and Vissing-Jorgensen (2019) and Hu, Pan, Wang and Zhu (2022), our sample period starts from 1994 as it was only post 1994 that the market participants did not have to infer the Fed's monetary decisions from their open market operations. Our sample ends before 2020 to alleviate the compounding effect on retail trading behavior potentially brought on by the Covid-19 shock. Daily factor returns are obtained from Kenneth French's website. Retail trading data is obtained from TAQ using the algorithm in Boehmer, Jones, Zhang and Zhang (2021), and stock characteristics are obtained from CRSP and COMPUSTAT.

2.2. *FOMC Meeting*

FOMC is responsible for open market operations, through which the Fed changes federal funds rate that has a series of impacts on other interest rates, exchange rates, money and credit, and ultimately a range of economic variables. Also reviewed and assessed during the meeting are the risks to price stability and sustainable economic growth (long-run goals of the FOMC Committee) and economic and financial conditions. The FOMC convenes regularly at scheduled meetings eight times per year. During the sample period of January 1994 to December 2019, there are 208

[7] Available on Lu Zhang's website (https://global-q.org/index.html). Note that the website originally includes 188 anomalies, but over one-third of anomalies are sorted based on the same variables with different holding period or formation period. To avoid potential dominance of a specific type of anomaly over the others, for anomalies with the same sorting variable but different holding period or formation period, we take an equal-weighted average to form a representative anomaly for that sorting variable. The consolidation step provides us with 125 representative anomalies.

[8] Available on Chen and Zimmermann's open asset pricing website (https://www.openassetpricing.com/data/).

scheduled meetings in total.

2.3. *Summary Statistics*

Table I reports the pool sample summary statistics for daily anomaly returns during the sample period. The sample anomalies are the 11 mispricing anomalies based on Stambaugh, Yu and Yuan (2012) and Chu, Hirshleifer and Ma (2020) in Panel A, the 125 anomalies provided by Hou, Xue and Zhang (2020) in Panel B, and the 207 anomalies provided by Chen and Zimmermann (2022) in Panel C. We start from anomaly-day level return observations and then report the pool sample mean, standard deviation, 25^{th} quantile, median, and 75^{th} quantile for anomaly returns, long-leg returns, and short-leg returns in percentage.

Table I shows that the mean return, long-leg return, and short-leg return for the mispricing anomalies are 0.023%, 0.054%, and 0.031%, respectively. Meanwhile, for anomalies based on Hou, Xue and Zhang (2020), the mean return, long-leg return, and short-leg return are 0.017%, 0.052%, and 0.035%, respectively. For anomalies based on Chen and Zimmermann (2022), the mean return, long-leg return, and short-leg return are 0.013%, 0.047%, and 0.035%, respectively.

3. Empirical Results

In this section, we present the empirical findings of our paper. We study anomaly returns right before the FOMC and the days around by analyzing three groups of anomalies. We first study FOMC returns on the 11 mispricing anomalies in Section 3.1. In Section 3.2, we study the FOMC returns on the six clusters that categorize the 125 anomalies provided by Hou, Xue and Zhang (2020), as well as the FOMC returns on the eight clusters that categorize the 207 anomalies provided by Chen and Zimmermann (2022). We then uncover an interesting subsample of anomalies that behave differently from the main. In Section 3.3, we report aggregated results for the returns of the 207 anomalies during FOMC and non-FOMC days. We also test the performance of an alternatively mispricing-aggregated anomaly during the period of FOMC. In Section 3.4, we examine the subsample robustness by splitting FOMC days into high-risk days and low-risk days.

3.1. *FOMC Returns for 11 Mispricing Anomalies*

There are 11 commonly adopted anomalies as studied by Stambaugh, Yu and Yuan (2012) and Chu, Hirshleifer and Ma (2020) that are suggested to reflect mispricing, which are composite equity issuance, investment to asset, failure probability, gross profits-to-assets, asset growth, net operating assets, net stock issues, O-score, momentum, return on assets, and total accruals. If the returns on these mispricing anomalies diminish to zero, then there is a lower degree of pricing error as well as abnormal profits. However, if the anomaly returns stay about the same, then so does the pricing error. In this section, we examine the FOMC returns on the 11 anomalies.

Following Stambaugh, Yu and Yuan (2012), we also take the equal-weighted average of the 11 anomalies to form a combination anomaly. For each anomaly, we estimate the following time-series regression as specified in equation (1).

$$R_t = \alpha + \sum_{k=-3}^{3} \beta_k D_k + \varepsilon_t \ . \tag{1}$$

R_t is the anomaly return, long-leg return, or short-leg return on a given day t for an individual anomaly. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). In this way, the average change in an anomaly's return on D_k compared with a non-window day's average is the estimate of β_k in regression (1). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Table II reports results for the change in return on FOMC day compared with non-FOMC days, for the 11 mispricing anomalies. For simplicity, we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in return on FOMC compared with non-FOMC days. We also report the sample mean for each anomaly's return, long-leg return, and short-leg return to facilitate comparison.

In the first "FOMC day" column of Table II, when the dependent variable is the anomaly return, the coefficients of D_0 for the majority of the 11 anomalies are insignificantly different from zero. For instance, in the first row, for the composite equity issuance anomaly, D_0 has an insignificant coefficient of -0.0986% (-9.86 bps), with a t-stat of -1.58; and more generally, as represented by the combination anomaly (in the last row), D_0 has an insignificant coefficient of -0.0524% (-5.24 bps), with a t-stat of -1.46. That is, for these 11 mispricing anomalies, the return on FOMC day is not significantly different from non-FOMC days. Although the negative return change on FOMC day is economically large compared with the sample mean (for the combination anomaly the return decrease is over two times its sample mean (0.0227%) in absolute value), the anomaly return actually deviates more from zero on FOMC day relative to non-FOMC days, meaning that the absolute mispricing is not mitigated.

There're two exceptions, investment-to-asset and net stock issues, that have significant return decreases on FOMC day with significantly negative coefficients for D_0. For instance, the investment-to-asset anomaly decreases by 0.1218% (12.18 bps) on FOMC day, nearly ten times the scale of its sample mean of 0.0136% (1.36 bps), reversing against zero; and the net stock issues anomaly decreases by 0.0974% (9.74 bps), nearly four times its sample mean of 0.0276% (2.76 bps), also moving against zero. Therefore, while their abnormal profits are substantially lower, their absolute pricing errors become even larger on FOMC day.

Interestingly, on the other hand, when the dependent variable is the long-leg return or the short-leg return, D_0 for all 11 anomalies has a significant positive coefficient. For instance, for the combination anomaly in the last row, D_0 for the long-leg return has a positive coefficient of 0.2258% (22.58 bps) with a t-stat of 2.95, more than four times its sample mean of 0.0535% (5.35 bps). That is, the 11 anomalies' long-leg return increases by over four folds on FOMC day. And when the dependent variable is the short-leg return, D_0 has a significant coefficient of 0.2782% (27.82 bps) with a t-stat of 2.94, around nine times its sample mean of 0.0308% (3.08 bps). That is, the short-leg return increases by over nine folds on FOMC day. Therefore, it's clear that both the long-leg and short-leg exhibit a significantly positive drift on the FOMC announcement day, consistent with an FOMC risk premium theory documented in the pre-announcement drift literature.

3.2. *FOMC Returns Within Clusters of Anomalies*

To take care of the heterogeneity between anomalies, in this subsection, we turn to a broader set of anomalies and examine the anomaly returns on FOMC days within each natural cluster. Natural clustering is a way to categorize anomalies into different subgroups based on their economic meanings. By studying the cluster property, we will be able to gauge the difference between anomalies with different economic meanings and understand more of their heterogeneity.

3.2.1. *Six Clusters of 125 Anomalies*

To start with, we follow Hou, Xue and Zhang (2020) to classify the 125 anomalies into six clusters based on their economic contents, i.e., frictions, intangibles, investment, momentum, profitability and value. The distribution of anomalies within the six clusters is reported in Appendix Table AI Panel A, where 8% of the 125 anomalies are within the frictions cluster, 18% within the intangibles, 22% within the investment, 14% within the momentum, 19% within the profitability, and 18% within the value cluster.

Table III reports results for the return changes within these six clusters on FOMC compared with non-FOMC days. Within each cluster, we take the equal-weighted average of anomaly returns to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), where R_t is the cluster anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). The coefficient for D_0 is reported in the "FOMC day" column, which represents the change in a cluster's return on FOMC day compared with non-FOMC days. We also report the sample mean for each cluster anomaly's return, long-leg return, and short-leg return to facilitate comparison.

In the first "FOMC day" column, when the dependent variable is the anomaly return, the coefficients for D_0 in all six clusters are insignificant. For instance, D_0 for the frictions cluster (in the first row) has an insignificant coefficient of -0.0380% (-3.80 bps) with a t-stat of -1.47; D_0 for the intangibles cluster has an insignificant coefficient of -0.0025% (-0.25 bps) with a t-stat of -0.13, and similarly for other clusters. The insignificance means that the cluster anomalies have an unchanged level of abnormal profits and mispricing, similar to our previous findings for the 11 mispricing anomalies.

On the other hand, when the dependent variable is the long-leg return and short-leg return, D_0 for all six clusters of anomalies has a significant positive coefficient. For instance, when the dependent variable is the long-leg return, the frictions cluster of anomaly (in the first row) has a positive coefficient for D_0 of 0.2249% (22.49 bps) with a t-stat of 2.94, five times its sample mean of 0.0456% (4.56 bps); and the intangibles cluster of anomaly has a positive coefficient for D_0 of 0.2461% (24.61 bps) with a t-stat of 3.05, around four times its sample mean of 0.0581% (5.81 bps); similarly for other clusters. That is, the long-leg returns in all clusters increase substantially on FOMC days. Meanwhile, when the dependent variable is the short-leg return, the frictions cluster's short leg increases by 0.2629% (26.29 bps) on FOMC with a t-stat of 2.91, around seven times its sample mean of 0.0349% (3.49 bps); and the intangibles cluster's short leg increases by 0.2486% (24.86 bps) with a t-stat of 3.01, around eight times its sample mean of 0.0337% (3.37 bps); similarly for other clusters. Therefore, within all of the six clusters, results are robust and consistent that while the long minus short returns do not change significantly on FOMC day, the long-leg and short-leg both drift upward substantially.

3.2.2. *Eight Clusters of 207 Anomalies*

As a crucial complement extending the six natural clusters based on Hou, Xue and Zhang (2020), we move on to examine a more comprehensive set of 207 anomalies that can be categorized into eight clusters based on Chen and Zimmermann (2022): accounting, analyst, event, options, price, trading, 13F and other. The distribution of the 207 anomalies within the eight clusters is summarized in Appendix Table AI Panel B, where the majority of the 207 anomalies are within the cluster of accounting (43%) and price (24%) which constitute over two-thirds of the whole set of anomalies. The other six clusters each takes up less than 10% of the number of anomalies. Although they're relatively small in percentage, they are still economically meaningful in terms of average returns, so it's important to examine their performance on FOMC days cluster by cluster.

Table IV reports results for the equal-weighted return changes on FOMC day compared with non-FOMC days for eight clusters of the 207 anomalies. Within each cluster, we take the equal-weighted average of anomaly returns to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), where R_t now is the cluster anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). For simplicity, we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in a cluster's return on FOMC day compared with the non-FOMC days. We also report the sample mean for each cluster anomaly's return, long-leg return, and short-leg return to facilitate comparison.

In the first "FOMC day" column of Table IV, for five out of the eight clusters, i.e., the accounting, the event, the options, the price, and the other cluster, the coefficient of D_0 is not statistically significant, meaning that the degree of mispricing is not statistically changed on FOMC day. For instance, D_0 for the accounting cluster in the first row has an insignificant coefficient of -0.0247% (-2.47 bps) with a t-stat of -1.78, meaning that the cluster decreases by 2.47 bps on FOMC day. Compared with the sample mean of around 0.0106% (1.06 bps), its absolute return on FOMC day is still statistically comparable to its sample mean. Similarly, for the price cluster which increases by 0.0021% (0.21 bps) with an insignificant t-stat of 0.11, its degree of abnormal profits and mispricing is actually increasing (though not significantly so) on FOMC day. And for the trading cluster which decreases by 0.0254% (2.54 bps) with an insignificant t-stat of -0.70, its negative change on FOMC day is about five times its sample mean of 0.0051% (0.51 bps), meaning that the absolute pricing error is also un-mitigated, if not exacerbated, on FOMC day. Therefore, similar to previous conclusions, for the five clusters that constitute the majority of the 207 anomalies, the absolute returns on the FOMC day are not getting closer to zero when compared with non-FOMC days, meaning that the degree of mispricing is not attenuated then.

On the other hand, for three subsets of clusters, however, the results are interestingly different. For anomalies in the analyst cluster, trading cluster, and 13 F cluster, their return changes on FOMC day are significantly negative. For instance, for the analyst cluster of anomaly, D_0 has a significant coefficient of -0.0622% (-6.22 bps), with a t-stat of -2.13. Compared with its sample mean of 0.0120% (1.20 bps), its return decreases by around five folds, reaching a greater absolute scale (though in negative number). Similarly, for the trading cluster, D_0 has a significant coefficient of

-0.0814% (-8.14 bps) with a t-stat of -2.32, nearly nineteen times its sample mean of 0.0043% (0.43 bps); and for the 13F cluster, D_0 has a significant coefficient of -0.1329% (-13.29 bps) with a t-stat of -2.87, around seven times its sample mean of 0.0188% (1.8 bps). That is, for a small fraction of anomalies within these three clusters (to be specific, 9% of the 207 anomalies are in the analyst cluster, 7% in trading and 4% in 13F, 20% in total), their anomaly returns and thus abnormal profits on FOMC day are significantly lower than other normal days. However, their significant negative changes do not translate into diminishing-to-zero returns, but into negative returns in greater absolute value than usual. Therefore, for these three subsets of anomalies, although they do have negative changes, their pricing errors are not mitigated, but exacerbated on FOMC-day.

Meanwhile, when to look at the performances of the long- and short-leg returns across clusters, D_0 for all eight clusters of anomalies has a significant positive coefficient. For instance, when the dependent variable is the long-leg return, the accounting cluster in the first row has a positive coefficient for D_0 of 0.2559% (25.59 bps) with a t-stat of 3.05, around five times its sample mean of 0.0485% (4.85 bps); and the price cluster of anomaly has a positive coefficient of 0.2930% (29.30 bps) with a t-stat of 3.42, around six times its sample mean of 0.0477% (4.77 bps). And when the dependent variable is the short-leg return, for instance, the accounting cluster of anomaly's short leg in the first row increases by 0.2826% (28.26 bps) on FOMC with a t-stat of 3.19, around seven times its sample mean of 0.0378% (3.78 bps); and the price cluster of anomaly's short leg increases by 0.2920% (29.20 bps) with a t-stat of 3.11, around 10 times its sample mean of 0.0282% (2.82 bps). Therefore, for all of the eight clusters, the long-leg and short-leg returns have a significantly positive drift on the FOMC day, consistent with the previous results in Table III's six clusters.

Extending Table IV, Table V provides robustness results for the value-weighted cluster returns. Within each cluster, instead of taking the equal-weighted average of anomaly returns, we take the value-weighted average to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), similar to Table IV.

We find robust results in Table V that when the returns are value-weighted within each cluster, the FOMC returns are generally unchanged, too. For six clusters, the event, the options, the price, the trading, the 13F, and the other, their coefficients of D_0 are not statistically significant, meaning an unchanged level of pricing error. But there do exist two different subsets of clusters, however, where the results are different from the main, i.e., the accounting and the analyst cluster. For the accounting cluster of anomaly, D_0 has a significant coefficient of -0.0400% (-4.00 bps), with a t-stat of -3.00. Compared with its sample mean of 0.0060% (0.60 bps), its return decreases by around seven-folds, reaching a negative number in a greater absolute value than usual. Similarly, for the analyst cluster, D_0 has a significant coefficient of -0.0743% (-7.43 bps) with a t-stat of -2.31, nearly decreasing by ten times its sample mean (0.0080%, 0.80 bps). That is, for these subsets of anomalies, although their negative changes on FOMC days are significant, their pricing errors do not go down, either.

Meanwhile, when to look at the performances of the long- and short-leg anomaly returns that are value-weighted within clusters, we find that, for all eight clusters, they rise substantially on FOMC days, consistent with the findings in Table IV. When the dependent variable is the long-leg return, D_0 for all eight clusters of anomalies has a significant positive coefficient. For instance, the accounting cluster in the first row has a positive coefficient for D_0 of 0.2517% (25.17 bps) with a t-stat of 3.11, around five times its sample mean of 0.0459% (4.59 bps); and the price cluster of anomaly has a positive coefficient of 0.2686% (26.86 bps) with a t-stat of 3.36, around six times its sample mean of 0.0451% (4.51 bps). Meanwhile, when the dependent variable is the short-leg return, coefficients for D_0 for all eight clusters are also significantly positive. For instance, the accounting cluster of anomaly's short leg in the first row increases by 0.2917% (29.17 bps) on FOMC with a t-stat of 3.32, around nine times its sample mean of 0.0399% (3.99 bps); and the price cluster of anomaly's short leg increases by 0.2633% (26.33 bps) with a t-stat of 3.20, around eight times its sample mean of 0.0375% (3.75 bps). Therefore, results are consistent with previous findings that the long-leg and short-leg have a significantly positive drift on the FOMC day.

3.3. Anomaly Returns on FOMC Days

Besides the previous evidence on individual-level and cluster-level, we also examine the aggregated results based on the third group of 207 anomalies. Firstly, we aggregate the 207 anomalies by taking the equal-weighted average across anomalies, following the combination method of Stambaugh, Yu and Yuan (2012). We also report value-weighted results as robustness. Secondly, as an alternative way of aggregation, we then estimate the FOMC returns on a mispricing-aggregated anomaly, which is formed by longing the decile of stocks with the lowest net-overpricing score (*NOPS*, hereafter) and shorting the decile with the highest *NOPS*.

3.3.1. *Aggregated Anomaly of the 207 Anomalies*

To start with, we first aggregate the 207 anomalies by taking the equal-weighted average across anomalies, following the combination method of Stambaugh, Yu and Yuan (2012), to form a representative anomaly for the 207 anomalies. Table VI reports results for the representative anomaly's return during the FOMC period. We estimate a time-series regression as specified in equation (1), where R_t is the representative anomaly's return, long-leg return and short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). The coefficient of D_k represents the average change in anomaly's return on day k compared with the non-FOMC days' average. To facilitate comparison, we also report the sample mean of the representative anomaly's return, long-leg return, and short-leg return, below the coefficient estimates.

We find that when the dependent variable is the anomaly return, D_0 has a marginally significantly negative coefficient of -0.0239% (-2.39 bps), with a t-stat of -1.95, meaning that the return decreases by 2.39 bps on FOMC day. Combined with its non-FOMC's average return of 0.0141% (1.41 bps) as represented by the coefficient of the $Intercept$ term, the negative change means that on FOMC day, the anomaly return is $0.0141\%-0.0239\% = -0.0098\%$ (0.98 bps in absolute value), comparable with the absolute value of its sample mean of 0.0128% (1.28 bps). Considering that the return continues to decrease by 0.0309% (3.09 bps) on D_1, the deviation from zero actually becomes even larger one day after FOMC, possibly due to the unabsorbed effect of the FOMC day. Therefore, the absolute pricing error is not mitigated since the FOMC announcement.

As a robustness check, we also aggregate the 207 anomalies by taking the value-weighted average across anomalies in Table VII. Similar to Table VI, we find that when the dependent variable is the value-weighted anomaly return, D_0 has a significant coefficient of -0.0205% (-2.05 bps), with a t-stat of -2.28. Compared with its non-FOMC average scale of 0.0077% (0.77 bps) as represented by the coefficient of the intercept term, the negative change means that on FOMC days it's $0.0077\% - 0.0205\% = -0.0128\%$, 1.28 bps in absolute value, two times the scale of its sample mean of 0.0063% (0.63 bps). That is, consistent with what we find in Table VI, the absolute pricing error is not mitigated on FOMC day.

To better assess the return performance of the 207 anomalies during the FOMC period, we also individually examine their FOMC returns compared with the non-FOMC days. For simplicity, those results are not reported in detail, but a list of anomalies that decrease returns significantly on FOMC day is reported in Appendix Table AII. Individual significances are also plotted in Figure I, where the shaded square covers the insignificant anomalies. In short, we find 29 anomalies that are significant with their drops in returns on FOMC day, meaning that their abnormal profits significantly decrease, too. But their decreases do not lead them to a closer-to-zero return, either. Their average return change on FOMC day is -0.1776% (17.76 bps), over ten times their average non-FOMC-scale of 0.0169% (1.69 bps). That is, for these 29 anomalies, their mispricing is not attenuated on FOMC day, either, and their profitability is largely declined. We will elaborate more on this significant subsample in the economic mechanism part.

Coming back to Table VI, when the dependent variable is the equal-weighted long-leg return for the representative anomaly, D_0 has a significant coefficient of 0.2628% (26.28 bps) with a t-stat of 3.21, meaning that the long-leg return increases substantially by 26.28 bps from its non-FOMC scale of 0.0444% (4.44 bps). And when the dependent variable is the short-leg return, D_0 has a significant coefficient of 0.2878% (28.78 bps) with a t-stat of 3.20, meaning that the short-leg return increases substantially by 28.78 bps from its non-FOMC scale of 0.0304% (3.04 bps).

Similarly, in Table VII, when the dependent variable is the value-weighted long-leg return for the representative anomaly, D_0 has a significant coefficient of 0.2563% (25.63 bps) with a t-stat of 3.21, meaning that the long-leg return increases substantially by 25.63 bps from its non-FOMC scale of 0.0414% (4.14 bps). And when the dependent variable is the value-weighted short-leg return, D_0 has a significant coefficient of 0.2767% (27.67 bps) with a t-stat of 3.27, meaning that the short-leg return increases substantially by 27.67 bps from its non-FOMC scale of 0.0337% (3.37 bps). Therefore, for both the long-leg and short-leg, the finding is robust that they show a significantly positive drift on the FOMC announcement day. Such pattern is not persistent, as can be seen from the insignificant coefficients for D_1, meaning that their returns return to a normal scale one day after the announcement.

3.3.2. *Mispricing-aggregated Anomaly*

In our next step, as an alternative way of aggregation, we also estimate the FOMC returns on a mispricing-aggregated anomaly, formed by longing the decile of stocks with the lowest net-overpricing score (*NOPS*, hereafter) and shorting the decile with the highest *NOPS*. We follow Han, Lu, Xu and Zhou (2020) to calculate the stock-day level *NOPS*. To be specific, we sort stocks into decile portfolios based on each of the 207 firm characteristics provided by Chen and Zimmermann (2022), at the previous month-end. We use the extreme deciles to define the long- and short- side for each predictor. Next, for each stock and day, we sum the number of short-side and long-side anomalies that the stock belongs to. Doing so produces *NShort* and *NLong*. Then the cross-sectional mispricing measure, *NOPS* is defined as $NShort - NLong$. We then construct a new representative mispricing anomaly that longs the lowest *NOPS* decile and shorts the highest *NOPS* decile.

We present the summary statistics of *NOPS* as well as the mispricing-aggregated anomaly in Table VIII Panel A. The mean of *NShort* and *NLong* is 17.49 and 17.36, respectively, meaning that on average, a stock entered 17.49 times out of 207 chances into the short portfolio and 17.36 times to the long portfolio. For the *NOPS* sorted anomaly, that is, the mispricing-aggregated anomaly, the mean return, long-leg return, and short-leg return are 0.04%, 0.07%, and 0.03%, respectively. This newly aggregated anomaly delivers a higher long minus short return compared with the sample mean of the 207 anomalies (in Table I, 0.013%, 0.047%, and 0.035% for the mean return, long-side return and short-side return, respectively) possibly due to the less noise in assigning stocks into portfolios.

In Table VIII Panel B, we study the returns on the mispricing-aggregated anomaly on FOMC days. We estimate a time-series regression as specified in equation (1), where R_t is the mispricing-aggregated anomaly's return, long-leg return and short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). The coefficient of D_k represents the average change in anomaly return on day k compared with the non-FOMC days' average. We also report the sample mean of the representative anomaly's return, long-leg return, and short-leg return to facilitate comparison.

We find that for the mispricing aggregated anomaly, its return decreases by 0.0888% (8.88 bps) from its non-FOMC average scale of 0.0476% (4.76 bps) to the scale of -0.0412% ($= 0.0476\% - 0.0888\% = -4.12$ bps), even larger in absolute value when compared with the sample mean of 0.0396% (3.96 bps). The fact that the mispricing-aggregated anomaly does not diminish its return on FOMC indicates an un-attenuated level of pricing error, as we find in the previous section.

Meanwhile, when the dependent variable is the long-leg return, D_0 has a significant coefficient of 0.2213% (22.13 bps) with a t-stat of 2.93, and when the dependent variable is the short-leg return, D_0 has a significant coefficient of 0.3101% (31.01 bps) with a t-stat of 3.05. Our results are robust that the long-leg and short-leg both significantly drift upward on the FOMC announcement day.

In all, for the major anomalies, such as the 11 in Stambaugh, Yu and Yuan (2012), the 125 in Hou, Xue and Zhang (2020), and the 207 in Chen and Zimmermann (2022), there are little changes in return on FOMC days, implying an unchanged level of pricing error and abnormal profits. But there does exist a subset of anomalies on which the returns change significantly negatively on FOMC days. However, their negative changes do not lead to a closer-to-zero anomaly return. Instead, their returns are even larger in absolute value on FOMC days compared with the sample mean, implying a higher level of mispricing, and a lower level of abnormal profits.

3.4. Anomaly Returns on High-risk and Low-risk FOMC Days

In this section, we examine the performance of anomaly returns on high-risk FOMC days and low-risk FOMC days. We split FOMC days into high- and low-risk days according to their estimated risk premium using the algorithm in Liu, Tang and Zhou (2022). A high-risk (or low-risk) FOMC day is the one with an above-median (or below-median) risk premium.

Table IX reports estimates for the change in anomaly returns on high- or low-risk FOMC days. We estimate a time-series regression as specified by the following equation (2).

$$R_t = \alpha + \sum_{k=-3}^{3} \beta_{H,k} D_{H,k} + \sum_{k=-3}^{3} \beta_{L,k} D_{L,k} + \varepsilon_t \ . \tag{2}$$

R_t is the anomaly return, long-leg return and short-leg return on a given day t. The sample anomalies are the 11 mispricing anomalies in Panel A, the six clusters of 125 anomalies in Panel B, the eight clusters of 207 anomalies in Panel C, and the equal-weighted average of the 207 anomalies in Panel D. The independent variables include high-risk and low-risk FOMC dummy variables. $D_{H,k}$ ($k \in \{-3,-2,-1,0,1,2,3\}$) indicates day k relative to an FOMC day which estimated risk premium is above the median of all FOMC days' estimated risk premium within the sample period. And $D_{L,k}$ indicates day k relative to an FOMC day which estimated risk premium is below the median of all FOMC days' estimated risk premium within the sample period. The sample period is from January 1996 to December 2019 due to the data limit of the estimated risk premium. The coefficient of $D_{H,k}$ (or $D_{L,k}$) represents the average change in anomaly's return on day k relative to the high-risk (or low-risk) FOMC day, compared with the non-FOMC days' average. For simplicity, from Panel A to Panel C, we only report the coefficient and t-statistics for $D_{H,0}$ and $D_{L,0}$ in the "High-risk FOMC" column and "Low-risk FOMC" column, respectively, which represents the change in anomaly's return on a high-risk and low-risk FOMC day compared with non-FOMC days.

In Panel A, we report the FOMC returns on the 11 mispricing anomalies as well as the 12^{th} combination anomaly. When the dependent variable is anomaly return, the coefficients for $D_{H,0}$ and $D_{L,0}$ are all insignificant. For instance, for the combination anomaly, $D_{H,0}$ has an insignificant coefficient of -0.0783% (-7.83 bps) with a t-stat of -1.29, while $D_{L,0}$ has an insignificant coefficient of -0.0452% (-4.52 bps). There is only one exception of anomaly, however, the gross profits-to-assets, which has a significantly negative coefficient for $D_{H,0}$. Nevertheless, its negative change is -0.1561% (-15.61 bps), nearly eight times its sample mean of 0.0209% (2.09 bps), meaning that its negative change reverses against zero to a larger pricing error. In all, for the 11 mispricing anomalies, their returns generally do not change statistically on FOMC day, no matter it is a riskier or less risky one, and the pricing error is not mitigated no matter for a high-risk or low-risk FOMC day.

Meanwhile, when the dependent variable is the 11 anomalies' long-leg return, as is represented by the combination anomaly, the coefficient for $D_{H,0}$ is insignificantly positive while that for the $D_{L,0}$ is significantly positive of 0.2896% (28.96 bps) with a t-stat of 2.60, meaning that the positive return drift of the long-leg is driven more by the low-risk FOMC days, rather than the high-risk days. Nevertheless, the drift on high-risk FOMC days is still positive of 0.1733% (17.33 bps) and economically large, consistent with our baseline result. Similarly, when the dependent variable is the short-leg return, the coefficient of $D_{H,0}$ for the combination anomaly is insignificantly positive of 0.2516% (25.16 bps) while that for the $D_{L,0}$ is significantly positive, being 0.3348% (33.48 bps) with a t-stat of 2.45. Therefore, we provide additional and robust evidence that the positive drifts of FOMC returns for the 11 anomalies' long- and short-legs are higher on less risky FOMC days.

Similarly, in Panel B and Panel C, we estimate average FOMC returns on the six clusters of 125 anomalies and the eight clusters of 207 anomalies. First, similar to the pattern documented above, for all clusters, when the dependent variable is the anomaly return, there is no significant change on high-risk or low-risk FOMC compared with non-FOMC days. Second, for Panel B, when to look at long- and short-leg returns, similar to the 11 mispricing anomalies, their FOMC return drifts come more from the low risk FOMC days, as the coefficients for $D_{H,0}$ are insignificantly positive while those for the $D_{L,0}$ are significantly positive for all six clusters. For Panel C, however, when we extend to 207 anomalies' eight clusters, there is less discrepancy between a high-risk and low-risk FOMC day. The coefficients of $D_{H,0}$ for certain subsets of clusters, i.e., four clusters (event, price, trading and other) for the long-leg returns and three clusters (options, trading and 13F) for the short-leg returns, are significantly positive. Meanwhile, coefficients of $D_{L,0}$ for all eight clusters are significantly positive. meaning that the low risk FOMC days contribute significantly to the rise in returns. In all, we provide consistent evidence that the general return is not statistically changed on FOMC days and the positive drifts of long- and short-leg returns are not going in the opposite direction no matter for a high-risk or low-risk FOMC-day.

Finally, in Panel D when the sample anomaly is the equal-weighted average of the 207 anomalies, we report all coefficient estimates. Supporting our previous findings, in the first column when the dependent variable is the anomaly return, $D_{H,0}$ has an insignificant coefficient of -0.0104% (-1.04 bps) with a t-stat of -0.50. That is, on a high-risk FOMC day, for the 207 anomalies generally, there is no statistical return change. Meanwhile, $D_{L,0}$ has a significant coefficient of -0.0378% (-3.78 bps) with a t-stat of -2.42, meaning that the anomaly return decreases to -2.41 bps ($= 0.0137\% - 0.0378\% = -0.0241\%$) on low-risk FOMC day, which is nearly two-folds in absolute value of the non-FOMC days' average of 0.0137% (1.37 bps) represented by the coefficient of $Intercept$. Therefore, the pricing error is not mitigated during FOMC days.

On the other hand, when the dependent variable is the long-leg return, $D_{H,0}$ has a significantly positive coefficient of 0.2592% (25.92 bps) with a t-stat of 2.05, while $D_{L,0}$ also has a significantly positive coefficient of 0.2894% (28.94 bps) with a t-stat of 2.46, both over six times its non-FOMC scale of 0.0425% (4.25 bps) represented by the $Intercept$'s coefficient. Meanwhile, and similarly, for the short-leg return, $D_{H,0}$ has a significantly positive coefficient of 0.2712% (27.12 bps) with a t-stat of 1.94, while $D_{L,0}$ has a more significantly positive coefficient of 0.3280% (32.80 bps) with a t-stat of 2.56, both around ten times its non-FOMC scale of 0.0289% (2.89 bps). In all, our results are robust that while the mispricing degree is not attenuated on no matter the high- or low-risk FOMC day, the systematic risk picks up with both high and low risk announcements, as is reflected by the positive drifts of the long- and short-leg returns.

4. Economic Mechanism

4.1. Reconciling with the CAPM

Our evidence of an un-mitigated pricing error seems to challenge existing studies such as Savor and Wilson (2014) that find the capital asset pricing model (CAPM) to perform better over the FOMC period. Using a sample period of 1964-2011, Savor and Wilson (2014) find that the stock returns respond more to market beta on announcement days than non-announcements days, where the announcement type includes FOMC, inflation (CPI/PPI) and unemployment announcement. They also find that the result holds for each single announcement type, including FOMC per se. Interestingly, however, their pooled regression results show that the intercept term (that is, the alpha from the CAPM) actually increases on announcement days compared with non-announcement days. For instance, the intercept is 1.6 bps higher on announcement days (t-stat being 0.81) for ten testing assets of value-weighted beta-sorted portfolios, and is 6.1 bps higher (t-stat being a significant 3.01) on announcement days for ten equal-weighted beta-sorted testing assets.[9] Therefore, their results suggest that true that stocks respond more to beta on announcement days, but the alphas might be not decreasing in absolute value, or mitigated. Instead, the pricing error of CAPM might be possibly exacerbating on announcement days.

To figure out whether such relation still holds in our sample period, in reconciliation, we first replicate their main findings by focusing on the announcement type of FOMC, and extend by including our study's sample period. In Table X, we report estimates from pooled panel regressions of daily excess returns on betas for ten beta-sorted portfolios, following Savor and Wilson (2014). We first estimate stock market betas for all stocks using rolling windows of 12 months of daily returns. We then sort stocks into one of ten beta-decile value-weighted portfolios for Panel A and Panel C, or into equal-weighted portfolios for Panel B and Panel D, rebalanced monthly. We then estimate a pooled regression as specified by the following equation (3).

$$R_{j,t} - R_{f,t} = \alpha + \beta_1 FOMC_t + \beta_2 \hat{\beta}_{j,t-1} + \beta_3 FOMC_t\, \hat{\beta}_{j,t-1} + \varepsilon_{j,t}\ . \tag{3}$$

$R_{j,t} - R_{f,t}$ is the test asset j's excess daily return on day t. Independent variables include an intercept, an FOMC dummy ($FOMC_t$), test asset j's stock market beta on day $t-1$ ($\hat{\beta}_{j,t-1}$), and an interaction term between the FOMC dummy and market beta ($FOMC_t\, \hat{\beta}_{j,t-1}$). $FOMC_t$ takes the value of 1 if an FOMC announcement happens on day t. t-statistics are reported below the coefficient estimates, and the standard errors are clustered by date. The sample period is from 1978 to 2011 in Panel A and Panel B to replicate existing studies, and is from 1994 to 2019 in Panel C and Panel D to extend to our study's sample period.[10]

For value-weighted portfolios (Panel A) in the original sample period, the non-FOMC day intercept equals 0.036% (3.6 bps, t-stat$=5.04$) and is 0.002% (0.2 bps) higher (but not significantly so) on FOMC days. The non-FOMC day slope coefficient equals -0.013 (t-stat$=-0.99$) and is

[9] Detailed coefficient estimates can be found in their Table 1.

[10] Following Savor and Wilson (2014), the dates for the FOMC scheduled announcement are chosen to start from 1978, although the sample period for other types of announcements in their analysis is from 1964.

significantly higher on FOMC day, with a difference of 0.233 (t-stat$= 2.94$). We obtain similar results for equal-weighted portfolios (Panel B). The non-FOMC day intercept equals 0.094% (9.4 bps, t-stat$= 14.85$) and is 0.048% (4.8 bps) lower (yet still not significantly so) on FOMC days. The non-FOMC day slope coefficient equals -0.036 (t-stat$= -2.97$) and is significantly higher on FOMC day, with a difference of 0.212 (t-stat$= 3.03$). Therefore, it is noteworthy that although the market beta is more related to expected returns on FOMC days, which contributes to the better performance of CAPM, the intercept of CAPM (and therefore, the pricing error) is not statistically mitigated.

Extending to our sample period, we get similar results. For value-weighted portfolios (Panel C), the non-FOMC day intercept equals 0.039% (3.9 bps, t-stat$= 4.05$) and is 0.016% (1.6 bps) higher (but not significantly so) on FOMC days. The non-FOMC day slope coefficient equals -0.007 (t-stat$= -0.47$) and is significantly higher on FOMC day, with a difference of 0.214 (t-stat$= 2.60$). Similarly, for equal-weighted portfolios (Panel D), the non-FOMC day intercept equals 0.099% (9.9 bps, t-stat$= 12.06$) and is 0.023% (2.3 bps) higher (though not significantly so) on FOMC days. The non-FOMC day slope coefficient equals -0.040 (t-stat$= -3.24$) and is significantly higher on FOMC day, with a difference of 0.174 (t-stat$= 2.31$).

Therefore, similar to existing studies, we find that stocks do respond more to their market betas on FOMC days than non-FOMC days, and it is just that the alphas from the CAPM are not mitigated. In fact, the significant alphas might be exacerbated to the downside like what we find to anomalies. Meanwhile, the higher response to beta risk is obvious as the systematic risk picks up with the announcement, and all stocks respond more to beta risks on FOMC days as we find for the long- and short-legs of anomaly returns. Thus, to interpret the better performance of CAPM using a higher beta response, rather than a lower pricing error, helps our study to reconcile with the CAPM literature, and to provide additional insights for studies that call into question the return explanatory power of the CAPM.

4.2. Retail Trading Across Anomalies

In this section, we look for the economic mechanism to explain the decline of profitability for certain anomalies. Anomaly returns, to the extent that they reflect abnormal profits exploited from uninformed trades, will decrease if the uninformed trades decrease. Therefore, if the retail investors decrease their trading activity particularly on a subset of anomalies, so might the profits.

Empirically, we test if the anomalies with significantly lower abnormal profits on FOMC day also witness a significant drop in retail participation. Table XI presents estimates for the change in retail participation across anomalies on FOMC day. We estimate an anomaly-day level panel regression as in equation (4).

$$Y_{i,t} = \beta_0 + \beta_1 DEffectAnom_i + \beta_2 D_0 + \beta_3 DEffectAnom_i D_0 + \varepsilon_{i,t} \ . \quad (4)$$

$Y_{i,t}$ refers to the retail participation for anomaly i on day t for either the long leg or the short leg portfolio. Retail participation for the long-leg portfolio in Panel A (or Panel B) is calculated by first forming the top decile portfolio and then taking the value-weighted average (or equal-weighted average) of each stock's retail participation within. Retail participation for the short-leg portfolio in Panel C (or Panel D) is calculated by first forming the bottom decile portfolio and then taking the value-weighted average (or equal-weighted average) of each stock's retail participation within. A stock's retail participation is in percentage (%), using the following three proxies: (a) $retail\, buy\, participation = 100 * \frac{retail\, buy\, volume}{total\, trading\, volume}$; (b) $retail\, sell\, participation = 100 * \frac{retail\, sell\, volume}{total\, trading\, volume}$; and (c) $retail\, buy\, plus\, sell\, participation = 100 * \frac{retail\, buy\, volume + retail\, sell\, volume}{total\, trading\, volume}$. For independent variables, $DEffectAnom_i$ takes the value of one if anomaly i belongs to the list of anomalies with significant return decreases on FOMC day. A detailed list of this subset of anomalies is in Appendix Table AII. D_0 refers to the FOMC day dummy. The sample period for this table starts from 2010 due to the data limit of retail trading. The sample anomalies are the 207 anomalies provided by Chen and Zimmermann (2022). Standard errors are clustered at both anomaly and day level.

β_3 reflects the difference in retail trading between the subset of lower FOMC-profits anomalies as compared with the rest. If our hypothesis is true, then we expect the β_3 coefficient for $DEffectAnom_i D_0$ to be significantly negative.

In Table XI Panel A, when the dependent variable is the value-weighted retail buy participation, $DEffectAnom_i D_0$ has a significantly positive coefficient of 0.006 with a t-stat of 2.89. Although the change in retail buying participation is positive, when the dependent variable is the retail sell participation, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.011 with a t-stat of -3.56, meaning that there is a significantly lower selling of retail investors for the long-legs of the subset of anomalies. Combined together, when to look at retail total (buy plus sell) participation in the third column, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.005 with a t-stat of -3.04. Therefore, for the long-leg portfolio of the subset of lower-profits anomalies, retail investors do additionally decrease their participation as compared with the rest of the anomalies, especially in terms of selling.

Equal-weighted results in Table XI Panel B shed similar light on a decreased retail participation especially in the long-legs of the subset of lower-profit stocks, not only in terms of retail sell participation, but also in terms of retail buy participation and retail total participation. For instance, when the dependent variable is the retail buy participation in the first column, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.015 with a t-stat of -10.80. Unlike the positive results in the first panel, here the negativity possibly attributes to a larger decline in retail participation among the small-cap stocks, on which the retail investors usually trade more actively. Also, when the dependent variable is the retail sell participation in the second column, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.010 with a t-stat of -3.62. Finally, to look at retail total (buy plus sell) participation in the third column, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.026 with a t-stat of -11.85 as well.

Table XI Panel C zooms into the short-leg's value-weighted retail trading. When the dependent variable is the value-weighted retail buy participation in the first column, $DEffectAnom_i D_0$ has an insignificant coefficient of 0.005 with a t-stat of 0.76. However, if to look at retail sell participation in the second column, $DEffectAnom_i D_0$ has a marginally significant negative coefficient of -0.012 with a t-stat of -1.90. And this negativity is again found in Table XI Panel D when the retail participation is equal-weighted. Although $DEffectAnom_i D_0$ for retail buy participation in Panel D is still an insignificant -0.009 with a t-stat of -1.14, the retail sell participation in the second column changes additionally by -0.031 with a t-stat of -3.77 for the lower-profits anomalies. And what's more, when combined together to retail total (buy plus sell) participation, $DEffectAnom_i D_0$ has a significantly negative coefficient of -0.040 with a t-stat of -2.45. Therefore, for the short-leg portfolio of the subset of lower-profits anomalies, retail investors do additionally decrease their participation as compared with the rest of the anomalies, which possibly contribute to the declined profitability.

4.3. Anomaly Return Predictability By Retail Investors

Table XI suggests that no matter for the long-leg portfolio or the short-leg portfolio, retail investors do participate less in the anomalies with significantly lower profitability on FOMC days, as compared with the rest. But why do retail investors favor decreasing their participation especially for these anomalies? We then explore the underlying mechanism by figuring out if these anomalies contain certain information that retail investors are less informed of. Relating to an uncertainty reduction effect theory as modeled by Goldstein and Yang (2015), if the retail investors are less specialized in the type of information these anomalies contained, they might scale down their trading when facing more uncertainty.

To examine this hypothesis, we then test if retail investors are less informed within the subset of anomalies that they particularly decrease participating on FOMC days. In Table XII, we examine the return predictability of retail order imbalances on the long-leg and short-leg portfolios across anomalies that the retail investors participate differently on FOMC days. We estimate an anomaly-day level panel regression as specified by equation (5).

$$Ret_{i,t} = \beta_0 + \beta_1\, oib_{i,t-1} + \beta_2\, oib_{i,t-1}\, DEffectAnom_i + \varepsilon_{i,t}\ . \tag{5}$$

$Ret_{i,t}$ refers to the return (in percentage, %) on the long or short-leg for anomaly i on day t. For independent variables, $oib_{i,t}$ refers to the value-weighted (or equal-weighted) retail order imbalances among stocks within the long-leg or short-leg portfolio for anomaly i on day t. Retail trading order imbalances for an individual stock is proxied by $oib = \frac{retail\,buy\,volume - retail\,sell\,volume}{retail\,buy\,volume + retail\,sell\,volume}$. The long-leg and short-leg portfolios are constructed by forming the top decile and bottom decile portfolio, respectively, at the previous month-end. $DEffectAnom_i$ takes the value of one if the anomaly i significantly decreases return on FOMC day. D_0 refers to the FOMC day dummy.

Standard errors are clustered at both anomaly and day level.

The β_2 coefficient for $oib_{i,t-1} DEffectAnom_i$ reflects the difference in overall return predictability of retail order imbalances for the subset of lower-profit anomalies as compared with the rest. If our hypothesis is true, then we expect to see a significantly negative β_2 coefficient.

Table XII presents estimates for the return predictability of retail trading within the long-leg and short-leg portfolio across anomalies. When the dependent variable is the next-day long-leg return, $oib_{i,t-1} DEffectAnom_i$ has an insignificant coefficient of 0.069 with a t-stat of 0.77. However, when the dependent variable is the next-day value-weighted short-leg return, there is a significantly negative coefficient for $oib_{i,t-1} DEffectAnom_i$ of -0.437 with a t-stat of -2.85. Therefore, we find supportive evidence that the retail investors indeed predict worse next-day returns for the subset of anomalies that the retail investors particularly avoid trading on FOMC days compared to other anomalies, in terms of the short-leg return predictability. Therefore, evidence supports our hypothesis that retail investors are indeed less informed on these anomalies, especially on the short-leg portfolios. The relatively less informativeness on these anomalies possibly contributes to their decreased activity when facing macroeconomic uncertainty, according to an uncertainty reduction effect theory as modeled by Goldstein and Yang (2015).

5. Conclusion

In this study, we find that anomaly returns are generally unchanged during FOMC days. We study three groups of anomalies: the 11 mispricing anomalies as studied by Stambaugh, Yu and Yuan (2012), the 125 anomalies based on Hou, Xue and Zhang (2020), and the 207 anomalies based on Chen and Zimmermann (2022). We find similar results that there are little changes in anomaly returns on FOMC days, implying an unchanged level of pricing error and abnormal profits. But there does exist a subset of anomalies on which the returns change substantially negatively on FOMC days. However, their negative changes do not lead to closer-to-zero anomaly returns. Instead, their returns are even larger in absolute value on the FOMC days compared with the sample mean, implying a higher level of mispricing, and a lower level of abnormal profits.

On the other hand, consistent with the FOMC premium theory, we find that the average return on the long-leg and short-leg of a comprehensive set of 207 anomalies increases by 26.3 bps and 28.8 bps, respectively, prior to the FOMC and reverses back afterwards. Their FOMC upward drifts are substantial, compared with their non-FOMC daily average scale of 4.44 bps and 3.04 bps, respectively.

Our evidence of an un-mitigated pricing error seems to challenge existing studies such as Savor and Wilson (2014) that find the capital asset pricing model (CAPM) to perform better over the FOMC period. In reconciliation, we find that, similar to existing studies, stocks do respond more to their market betas on FOMC days than non-FOMC days, and it is just that the alphas from the CAPM are not mitigated. In fact, the significant alphas might be exacerbated to the downside like what we find to anomalies. Meanwhile, the higher response to beta risk is obvious as the systematic risk picks up with the announcement, and all stocks respond more to beta risks on FOMC days as we find for the long- and short-legs of anomaly returns.

To study the decline in profitability for certain anomalies on FOMC days, we also examine the participation of retail trading across anomalies. We uncover that the less participation of retail investors in certain anomalies might contribute to their profitability decline. And we also argue that the less participation of retail investors possibly attributes to their less informativeness of these anomalies, so they scale down their trading when facing more uncertainty according to the uncertainty reduction effect theory.

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Table I. Summary Statistics

This table reports the summary statistics for daily anomaly returns from January 1994 to December 2019. The sample anomalies are the 11 mispricing anomalies based on Stambaugh, Yu and Yuan (2012) in Panel A, the 125 anomalies provided by Hou, Xue and Zhang (2020) in Panel B, and 207 anomalies provided by Chen and Zimmermann (2022) in Panel C. We start from anomaly-day level return observations and then report the pool sample summary statistics: the mean, standard deviation, 25^{th} quantile, median, and 75^{th} quantile for anomaly returns, long-leg returns, and short-leg returns. Numbers are reported in percentage (%).

	mean	std	p25	p50	p75	count
Panel A. 11 mispricing anomalies based on Stambaugh et al. (2012)						
Anomaly return	0.023	0.924	-0.418	0.012	0.456	72006
Long leg return	0.054	1.245	-0.516	0.092	0.674	72006
Short leg return	0.031	1.497	-0.628	0.092	0.756	72006
Panel B. 125 anomalies based on Hou et al. (2020)						
Anomaly return	0.017	0.941	-0.419	0.013	0.449	818250
Long leg return	0.052	1.301	-0.545	0.092	0.697	818250
Short leg return	0.035	1.415	-0.589	0.084	0.719	818250
Panel C. 207 anomalies based on Chen and Zimmermann (2022)						
Anomaly return	0.013	1.025	-0.389	0.008	0.409	1327620
Long leg return	0.047	1.342	-0.521	0.086	0.667	1329581
Short leg return	0.035	1.460	-0.576	0.080	0.698	1332676

Table II. FOMC Returns for 11 Mispricing Anomalies

This table reports results for the return changes on FOMC day compared with non-FOMC days for 11 mispricing anomalies. The sample period is from January 1994 to December 2019. The sample anomalies are the 11 anomalies adopted by Stambaugh, Yu and Yuan (2012) and Chu, Hirshleifer and Ma (2020), which include composite equity issuance, investment to asset, failure probability, gross profits-to-assets, asset growth, net operating assets, net stock issues, O-score, momentum, return on assets, and total accruals. We also take the equal-weighted average of the 11 anomalies to form a combination anomaly. For each individual anomaly, we estimate a time-series regression as specified in equation (1), where R_t is the individual anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. For simplicity we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in return on FOMC day compared with non-FOMC days. We also report the sample mean for each anomaly's return, long-leg return, and short-leg return.

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	FOMC day	Sample mean	FOMC day	Sample mean	FOMC day	Sample mean
Composite equity issuance	-0.0986	0.0202	0.1391	0.0505	0.2377	0.0302
	-1.58	1.88	2.08	3.91	2.56	1.79
Investment to asset	-0.1218	0.0136	0.1999	0.0509	0.3217	0.0373
	-1.96	1.39	2.44	3.42	3.28	2.11
Failure probability	-0.0148	0.0432	0.2558	0.0561	0.2706	0.0129
	-0.15	2.47	3.41	3.91	2.02	0.54
Gross profits-to-assets	-0.0828	0.0209	0.1798	0.0557	0.2626	0.0349
	-1.72	2.31	2.27	3.96	3.1	2.4
Asset growth	-0.0926	0.0112	0.2157	0.0485	0.3083	0.0373
	-1.44	1.07	2.62	3.2	3.22	2.14
Net operating assets	0.0026	0.0403	0.2431	0.0582	0.2405	0.0179
	0.05	4.12	2.65	3.37	2.81	1.08
Net stock issues	-0.0974	0.0276	0.1814	0.0555	0.2788	0.0279
	-1.96	3.06	2.66	4.27	3.06	1.67
O-score	-0.0091	0.0268	0.2499	0.0525	0.2590	0.0257
	-0.14	2.36	2.99	3.29	2.43	1.33
Momentum	0.0521	0.0230	0.3398	0.0576	0.2876	0.0346
	0.71	1.63	3.33	3.07	2.61	1.72
Return on assets	-0.0197	0.0246	0.2461	0.0541	0.2659	0.0295
	-0.29	2.08	3.09	3.62	2.41	1.44
Total accruals	-0.0941	-0.0018	0.2332	0.0493	0.3274	0.0510
	-1.64	-0.2	2.50	2.90	3.3	2.75
Combination	-0.0524	0.0227	0.2258	0.0535	0.2782	0.0308
	-1.46	3.61	2.95	3.74	2.94	1.79

Table III. FOMC Returns for Six Clusters of 125 Anomalies

This table reports results for the return changes on FOMC day compared with non-FOMC days for six clusters of 125 anomalies based on Hou, Xue and Zhang (2020). The sample anomalies are the 125 anomalies categorized into six natural clusters: frictions, intangibles, investment, momentum, profitability and value. Within each cluster, we take the equal-weighted average of anomaly returns to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), where R_t is the cluster anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. For simplicity we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in cluster's return on FOMC day compared with non-FOMC days. We also report the sample mean for each cluster anomaly's return, long-leg return, and short-leg return.

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	FOMC day	Sample mean	FOMC day	Sample mean	FOMC day	Sample mean
Frictions	-0.0380	0.0108	0.2249	0.0456	0.2629	0.0349
	-1.47	2.29	2.94	3.3	2.91	2.14
Intangibles	-0.0025	0.0244	0.2461	0.0581	0.2486	0.0337
	-0.13	6.93	3.05	3.95	3.01	2.18
Investment	-0.0345	0.0144	0.2396	0.0493	0.2741	0.0349
	-1.34	3.16	3.02	3.32	3.15	2.15
Momentum	0.0309	0.0154	0.2710	0.0517	0.2401	0.0363
	0.95	2.39	3.32	3.46	2.67	2.23
Profitability	-0.0193	0.0271	0.2430	0.0530	0.2624	0.0259
	-0.49	3.81	3.04	3.6	2.79	1.51
Value	-0.0480	0.0066	0.2349	0.0515	0.2829	0.0449
	-1.02	0.73	2.82	3.46	3.21	2.74

Table IV. Equal-weighted FOMC Returns for Eight Clusters of 207 Anomalies

This table reports results for the equal-weighted return changes on FOMC day compared with non-FOMC days for eight clusters of 207 anomalies based on Chen and Zimmermann (2022). The sample anomalies are the 207 anomalies categorized into eight clusters: accounting, analyst, event, options, price, trading, 13F, and other. Within each cluster, we take the equal-weighted average of anomaly returns to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), where R_t is the cluster anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. For simplicity we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in cluster's return on FOMC day compared with non-FOMC days. We also report the sample mean for each cluster anomaly's return, long-leg return, and short-leg return.

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	FOMC day	Sample mean	FOMC day	Sample mean	FOMC day	Sample mean
Accounting	-0.0247	0.0106	0.2559	0.0485	0.2826	0.0378
	-1.78	4.5	3.05	3.29	3.19	2.42
Analyst	-0.0622	0.0120	0.2391	0.0453	0.3057	0.0342
	-2.13	2.27	3.13	3.29	3.22	2.06
Event	-0.0025	0.0117	0.2449	0.0470	0.2474	0.0353
	-0.14	3.87	3.08	3.32	2.89	2.36
Options	-0.0207	0.0329	0.2699	0.0535	0.2906	0.0206
	-0.56	5.15	2.86	3.2	2.92	1.18
Price	0.0021	0.0195	0.2930	0.0477	0.2920	0.0282
	0.11	5.07	3.42	3.18	3.11	1.72
Trading	-0.0814	0.0043	0.2307	0.0428	0.3121	0.0385
	-2.32	0.68	3.46	3.89	3.48	2.49
13F	-0.1329	0.0188	0.2869	0.0433	0.4198	0.0246
	-2.87	2.28	2.77	2.43	3.73	1.3
Other	0.0309	0.0078	0.2594	0.0490	0.2273	0.0419
	1.67	2.20	3.18	3.28	2.82	2.94

Table V. Value-weighted FOMC Returns for Eight Clusters of 207 Anomalies

This table reports results for the value-weighted return changes on FOMC day compared with non-FOMC days for eight clusters of 207 anomalies based on Chen and Zimmermann (2022). The sample anomalies are the 207 anomalies categorized into eight clusters: accounting, analyst, event, options, price, trading, 13F, and other. Within each cluster, we take the value-weighted average of anomaly returns to form a representative anomaly for that cluster. Then for each cluster's anomaly, we estimate equation (1), where R_t is the cluster anomaly's return, long-leg return or short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. For simplicity we only report the coefficient and t-statistics for D_0 in the "FOMC day" column, which represents the average change in cluster's return on FOMC day compared with non-FOMC days. We also report the sample mean for each cluster anomaly's return, long-leg return, and short-leg return.

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	FOMC day	Sample mean	FOMC day	Sample mean	FOMC day	Sample mean
Accounting	-0.0400	0.0060	0.2517	0.0459	0.2917	0.0399
	-3.00	2.54	3.11	3.19	3.32	2.55
Analyst	-0.0743	0.0080	0.2412	0.0453	0.3155	0.0373
	-2.31	1.23	3.14	3.31	3.24	2.16
Event	0.0816	0.0711	0.2677	0.0540	0.1861	-0.0170
	0.64	3.41	2.87	3.14	1.31	-0.72
Options	-0.0358	0.0369	0.2809	0.0503	0.3167	0.0134
	-0.64	3.85	2.8	2.83	3.08	0.73
Price	0.0053	0.0076	0.2686	0.0451	0.2633	0.0375
	0.41	3.03	3.36	3.11	3.2	2.55
Trading	-0.0254	0.0051	0.2523	0.0455	0.2777	0.0404
	-0.70	0.77	3.56	3.87	3.32	2.73
13F	0.0055	0.0087	0.2597	0.0492	0.2542	0.0404
	0.11	0.88	2.89	3.15	2.71	2.48
Other	0.0533	0.0010	0.2603	0.0426	0.2070	0.0416
	1.49	0.13	2.94	2.59	2.81	3.1

Table VI. Equal-weighted Anomaly Returns on FOMC Days

This table reports results for the equal-weighted average return of 207 anomalies on FOMC days. The sample period is from January 1994 to December 2019, and the sample anomaly is a representative anomaly formed by taking the equal-weighted average of the 207 anomalies. We estimate a time-series regression as specified in equation (1), where R_t is the representative anomaly's return, long-leg return and short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. The coefficient of D_k represents the average change in anomaly's return on day k compared with the non-FOMC days' average. We also report the sample mean of the representative anomaly's return, long-leg return, and short-leg return.

	Anomaly return (%)	Long leg return (%)	Short leg return (%)
Intercept	0.0141	0.0444	0.0304
	5.42	2.71	1.70
D_{-3}	-0.0006	-0.0887	-0.0889
	-0.05	-1.09	-1.01
D_{-2}	0.0145	-0.1031	-0.1173
	1.52	-1.62	-1.69
D_{-1}	0.0154	0.0585	0.0437
	1.26	0.64	0.45
D_0	-0.0239	0.2628	0.2878
	-1.95	3.21	3.20
D_1	-0.0309	-0.0570	-0.0271
	-2.11	-0.63	-0.27
D_2	-0.0106	-0.0106	0.0019
	-0.89	-0.14	0.02
D_3	-0.0053	0.0336	0.0381
	-0.39	0.39	0.40
Sample mean	0.0128	0.0475	0.0348
	5.66	3.29	2.21
Adj. R2	0.001	0.001	0.001
Obs.	6546	6546	6546

Table VII. Value-weighted Anomaly Returns on FOMC Days

This table reports results for the value-weighted average return of 207 anomalies on FOMC days. The sample period is from January 1994 to December 2019, and the sample anomaly is a representative anomaly formed by taking the value-weighted average of the 207 anomalies. We estimate a time-series regression as specified in equation (1), where R_t is the representative anomaly's return, long-leg return and short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. The coefficient of D_k represents the average change in anomaly's return on day k compared with the non-FOMC days' average. We also report the sample mean of the representative anomaly's return, long-leg return, and short-leg return.

	Anomaly return (%)	Long leg return (%)	Short leg return (%)
Intercept	0.0077	0.0414	0.0337
	3.88	2.55	1.97
D_{-3}	-0.0023	-0.0931	-0.0909
	-0.27	-1.14	-1.07
D_{-2}	0.0106	-0.0871	-0.0977
	1.44	-1.38	-1.46
D_{-1}	0.0078	0.0917	0.0839
	0.90	1.01	0.88
D_0	-0.0205	0.2563	0.2767
	-2.28	3.21	3.27
D_1	-0.0276	-0.0516	-0.0240
	-2.43	-0.57	-0.25
D_2	-0.0007	-0.0188	-0.0180
	-0.09	-0.25	-0.23
D_3	-0.0087	0.0313	0.0400
	-0.87	0.37	0.44
Sample mean	0.0063	0.0455	0.0391
	3.72	3.18	2.59
Adj. R2	0.001	0.001	0.001
Obs.	6546	6546	6546

Table VIII. Mispricing-aggregated Anomaly Returns on FOMC Days

This table reports results for the mispricing-aggregated anomaly returns on FOMC days. The sample period is from January 1994 to December 2019, and the sample anomaly is a mispricing-aggregated anomaly constructed as followed. The long-leg and the short-leg portfolio are re-constructed based on the net overpricing score (*NOPS*) among stocks on every day, following Han, Lu, Xu and Zhou (2020). To calculate the stock-day level *NOPS*, we sort stocks into decile portfolios based on each of the 207 characteristics provided by Chen and Zimmermann (2022), at the previous month-end. We use the extreme deciles to define the long and short side for each predictor. Next, for each stock and day, we sum the number of short-side and long-side anomalies that the stock belongs to. Doing so produces *NShort* and *NLong*. Then the cross-sectional mispricing measure, *NOPS* is defined as $NShort - NLong$. We then construct a new representative mispricing anomaly that longs the lowest *NOPS* decile and shorts the highest *NOPS* decile. Finally, we estimate a time-series regression as specified in equation (1), where R_t is the mispricing-aggregated anomaly's return, long-leg return and short-leg return on a given day t. The independent variables include day dummy variables D_k ($k \in \{-3,-2,-1,0,1,2,3\}$) indicating day k relative to day 0 (i.e., the FOMC day). All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates. The coefficient of D_k represents the average change in anomaly's return on day k compared with the non-FOMC days' average. We also report the sample mean of the representative anomaly's return, long-leg return, and short-leg return.

Panel A. Summary statistics of *NOPS* and mispricing-aggregated anomaly

	mean	std	p25	p50	p75	count
NShort	17.49	11.89	8.00	17.00	24.00	2089446
NLong	17.36	10.29	8.00	18.00	24.00	2089446
NOPS	0.13	9.35	-5.00	-1.00	4.00	2089446
Anomaly return (%)	0.04	0.83	-0.33	0.03	0.41	6546
Long leg return (%)	0.07	1.14	-0.46	0.10	0.65	6546
Short leg return (%)	0.03	1.46	-0.57	0.07	0.70	6546

Panel B. Mispricing-aggregated anomaly returns on FOMC days

	Anomaly return (%)	Long leg return (%)	Short leg return (%)
Intercept	0.0476	0.0702	0.0225
	4.06	4.34	1.10
D_{-3}	0.0104	-0.1095	-0.1199
	0.20	-1.40	-1.24

D_{-2}	0.0020	-0.1084	-0.1104
	0.04	-1.73	-1.47
D_{-1}	0.0566	0.0769	0.0203
	0.97	0.87	0.18
D_0	-0.0888	0.2213	0.3101
	-1.59	2.93	3.05
D_1	-0.1983	-0.1491	0.0492
	-3.00	-1.79	0.43
D_2	-0.0162	-0.0286	-0.0124
	-0.26	-0.37	-0.13
D_3	-0.0203	0.0393	0.0596
	-0.32	0.48	0.53
Sample mean	0.0396	0.0683	0.0288
	3.84	4.83	1.60
Adj. R2	0.001	0.001	0.001
Obs.	6546	6546	6546

Table IX. Anomaly Returns on High-risk and Low-risk FOMC Days

This table reports results for the anomaly returns on high-risk or low-risk FOMC days. We split FOMC days into high-risk and low-risk days according to their estimated risk premium using the algorithm in Liu, Tang and Zhou (2022). A high-risk (or low-risk) FOMC day is the one with an above-median (or below-median) risk premium. The sample period is from January 1996 to December 2019 due to the data limit of estimated risk premium. The sample anomalies are the 11 mispricing anomalies in Panel A, the six clusters of 125 anomalies in Panel B, the eight clusters of 207 anomalies in Panel C, and the equal-weighted average of the 207 anomalies in Panel D. We estimate a time-series regression as specified in equation (2), where R_t is the anomaly return, long-leg return and short-leg return on a given day t. The independent variables include high-risk and low-risk FOMC dummy variables: $D_{H,k}$ ($k \in \{-3,-2,-1,0,1,2,3\}$) indicates day k relative to an FOMC day which estimated risk premium is above the median of all FOMC days' estimated risk premium within the sample period; and $D_{L,k}$ indicates day k relative to an FOMC day which estimated risk premium is below the median of all FOMC days' estimated risk premium within the sample period. The coefficient of $D_{H,k}$ (or $D_{L,k}$) represents the average change in anomaly's return on day k relative to a high-risk (or low-risk) FOMC day, compared with the non-FOMC days' average. For simplicity, from Panel A to Panel C, we only report the coefficient and t-statistics for $D_{H,0}$ and $D_{L,0}$ in the "High-risk FOMC" column and "Low-risk FOMC" column, respectively, which represents the change in anomaly's return on a high-risk and low-risk FOMC compared with non-FOMC days. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980), reported below the coefficient estimates.

Panel A. Returns on high/low-risk FOMC days for 11 mispricing anomalies

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC
Composite equity issuance	-0.1530	-0.0882	0.0719	0.2064	0.2249	0.2946
	-1.48	-1.07	0.73	2.04	1.58	2.19
Investment to asset	-0.1573	-0.0645	0.1825	0.2448	0.3398	0.3093
	-1.44	-0.87	1.46	2.08	2.28	2.19
Failure probability	-0.0012	-0.0929	0.2318	0.2790	0.2330	0.3719
	-0.01	-0.63	2.10	2.56	1.15	1.88
Gross profits-to-assets	-0.1561	-0.0360	0.1377	0.2226	0.2937	0.2587
	-2.23	-0.50	1.21	1.85	2.27	2.09
Asset growth	-0.0078	-0.1429	0.1964	0.2749	0.2042	0.4178
	-0.07	-1.76	1.62	2.24	1.42	3.08
Net operating assets	-0.0703	0.0609	0.1365	0.3493	0.2068	0.2885
	-0.87	0.86	0.96	2.74	1.64	2.27
Net stock issues	-0.1002	-0.0834	0.1653	0.2231	0.2655	0.3065
	-1.23	-1.29	1.64	2.23	1.90	2.33
O-score	-0.1282	0.0282	0.1610	0.3238	0.2892	0.2956
	-1.27	0.33	1.27	2.75	1.75	1.91
Momentum	0.1021	-0.0367	0.3086	0.3813	0.2065	0.4180
	0.94	-0.35	1.96	2.71	1.21	2.62
Return on assets	-0.0850	0.0021	0.1451	0.3461	0.2300	0.3439
	-0.8	0.02	1.23	3.00	1.31	2.25
Total accruals	-0.1044	-0.0442	0.1701	0.3341	0.2745	0.3783
	-1.13	-0.61	1.18	2.55	1.84	2.69
Combination	-0.0783	-0.0452	0.1733	0.2896	0.2516	0.3348
	-1.29	-0.99	1.51	2.60	1.74	2.45

Panel B. Returns on high/low-risk FOMC days for six clusters of 125 anomalies

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC
Frictions	-0.0426	-0.0431	0.1978	0.2653	0.2404	0.3084
	-0.98	-1.35	1.74	2.33	1.72	2.40
Intangibles	0.0011	-0.0174	0.2010	0.2991	0.1999	0.3164
	0.04	-0.7	1.64	2.58	1.60	2.62
Investment	-0.0198	-0.0382	0.2017	0.3032	0.2215	0.3413
	-0.44	-1.32	1.69	2.62	1.69	2.73
Momentum	0.0590	-0.0251	0.2453	0.2972	0.1863	0.3224
	1.16	-0.57	2.02	2.50	1.36	2.45
Profitability	-0.0901	0.0092	0.1617	0.3229	0.2518	0.3137
	-1.62	0.15	1.36	2.80	1.75	2.28
Value	0.0504	-0.1535	0.2580	0.2163	0.2076	0.3698
	0.73	-2.21	2.17	1.67	1.55	2.95

Panel C. Returns on high/low-risk FOMC days for eight clusters of 207 anomalies

Dep.var	Anomaly return (%)		Long-leg return (%)		Short-leg return (%)	
	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC	High-risk FOMC	Low-risk FOMC
Accounting	-0.0156	-0.0315	0.2483	0.2868	0.2656	0.3208
	-0.64	-1.93	1.92	2.38	1.93	2.56
Analyst	-0.0616	-0.0754	0.2225	0.2714	0.2944	0.3462
	-1.29	-1.90	1.95	2.41	1.95	2.61
Event	0.0254	-0.0222	0.2432	0.2716	0.2178	0.2937
	0.88	-0.95	1.96	2.41	1.63	2.41
Options	-0.0740	0.0331	0.2372	0.3028	0.3112	0.2697
	-1.39	0.67	1.69	2.46	2.12	2.04
Price	0.0270	-0.0303	0.2947	0.3106	0.2681	0.3431
	0.91	-1.03	2.22	2.55	1.85	2.53
Trading	-0.0551	-0.0873	0.2569	0.2431	0.3121	0.3304
	-1.09	-1.74	2.44	2.56	2.27	2.55
13F	-0.1735	-0.0983	0.2409	0.3614	0.4144	0.4597
	-2.15	-1.80	1.51	2.42	2.28	3.03
Other	0.0637	-0.0013	0.2774	0.2675	0.2161	0.2639
	2.39	-0.05	2.22	2.26	1.79	2.21

Panel D. Returns on high/low-risk FOMC days for the equal-weighted average of 207 anomalies

	Anomaly return (%)	Long leg return (%)	Short leg return (%)
Intercept	0.0137	0.0425	0.0289
	4.89	2.42	1.50
$D_{H,-3}$	-0.0191	-0.1191	-0.1007
	-1.15	-0.88	-0.69
$D_{L,-3}$	0.0200	-0.0455	-0.0666
	1.30	-0.42	-0.56
$D_{H,-2}$	0.0229	-0.1377	-0.1602
	1.40	-1.18	-1.25
$D_{L,-2}$	0.0109	-0.0813	-0.0918
	0.92	-1.22	-1.28
$D_{H,-1}$	0.0402	-0.0067	-0.0476
	2.07	-0.04	-0.27
$D_{L,-1}$	-0.0126	0.1628	0.1774
	-0.75	1.69	1.64
$D_{H,0}$	-0.0104	0.2592	0.2712
	-0.50	2.05	1.94
$D_{L,0}$	-0.0378	0.2894	0.3280
	-2.42	2.46	2.56
$D_{H,1}$	-0.0241	-0.1365	-0.1128
	-0.96	-0.85	-0.64
$D_{L,1}$	-0.0353	-0.0249	0.0091
	-1.89	-0.23	0.08
$D_{H,2}$	-0.0189	0.0960	0.1171
	-0.93	0.75	0.86
$D_{L,2}$	-0.0009	-0.1347	-0.1321
	-0.06	-1.43	-1.31
$D_{H,3}$	-0.0309	0.1636	0.1925
	-1.30	1.16	1.21
$D_{L,3}$	0.0193	-0.0745	-0.0937
	1.17	-0.64	-0.74
Sample mean	0.0125	0.0459	0.0335
	5.13	2.96	1.98
Adj. R2	0.001	0.001	0.001
Obs.	6042	6042	6042

Table X. Daily Excess Returns on FOMC and Non-FOMC Days

The table reports estimates from panel regressions of daily excess returns on betas for ten beta-sorted portfolios, following Savor and Wilson (2014). We first estimate stock market betas for all stocks using rolling windows of 12 months of daily returns from 1964 to 2011 in Panel A and Panel B, or from 1994 to 2019 in Panel C and Panel D. We then sort stocks into one of ten beta-decile value-weighted portfolios in Panel A and Panel C, or equal-weighted portfolios in Panel B and Panel D, rebalanced monthly. We then estimate a pooled regression as specified by equation (3). The dependent variable ($R_{j,t} - R_{f,t}$) is the test asset j's excess daily return on day t. Independent variables include an intercept ($Intercept$), a FOMC dummy ($FOMC_t$), test asset j's stock market beta for day $t-1$ ($\hat{\beta}_{j,t-1}$) and an interaction term between the FOMC dummy and market beta ($FOMC_t\,\hat{\beta}_{j,t-1}$). $FOMC_t$ takes the value of 1 if a FOMC announcement happens on day t. t-statistics are reported below the coefficient estimates, and the standard errors are clustered by date.

	$Intercept$	$FOMC$	$\hat{\beta}$	$FOMC * \hat{\beta}$	Adj. R2
Panel A. Value-weighted, 1978-2011					
$Coef.$	0.036	0.002	-0.013	0.233	0.001
t-Stat	5.04	0.07	-0.99	2.94	
Panel B. Equal-weighted, 1978-2011					
$Coef.$	0.094	-0.048	-0.036	0.212	0.001
t-Stat	14.85	-1.62	-2.97	3.03	
Panel C. Value-weighted, 1994-2019					
$Coef.$	0.039	0.016	-0.007	0.214	0.001
t-Stat	4.05	0.35	-0.47	2.60	
Panel D. Equal-weighted, 1994-2019					
$Coef.$	0.099	0.023	-0.040	0.174	0.001
t-Stat	12.06	0.60	-3.24	2.31	

Table XI. Retail Participation Changes Across Anomalies on FOMC

In this table we present estimates for the change in retail participation across anomalies on FOMC day. We estimate an anomaly-day level panel regression as in equation (4). $Y_{i,t}$ refers to the retail participation for anomaly i on day t for either the long leg or the short leg portfolio. Retail participation for the long-leg portfolio in Panel A (or Panel B) is calculated by first forming the top decile portfolio and then taking the value-weighted average (or equal weighted average) of each stock's retail participation within. Retail participation for the short-leg portfolio in Panel C (or Panel D) is calculated by first forming the bottom decile portfolio and then taking the value-weighted average (or equal weighted average) of each stock's retail participation within. A stock's retail participation is in percentage, including the following three proxies: (a) $retail\,buy\,participation = 100 * \frac{retail\,buy\,volume}{total\,trading\,volume}$; (b) $retail\,sell\,participation = 100 * \frac{retail\,sell\,volume}{total\,trading\,volume}$; and (c) $retail\,buy\,plus\,sell\,participation = 100 * \frac{retail\,buy\,volume + retail\,sell\,volume}{total\,trading\,volume}$. For independent variables, $DEffectAnom_i$ takes the value of one if anomaly i belongs to the list of anomalies with significantly return decreases on FOMC day. A detailed list for this subset of anomalies is in Appendix Table AII. D_0 refers to the FOMC day dummy. The sample period for this table starts from 2010 due to data limit of retail trading. The sample anomalies are the 207 anomalies based on Chen and Zimmermann (2022). Standard errors are clustered at both anomaly and day level. We report the t-statistics below the coefficient estimates.

Panel A. Value-weighted long-leg retail participation

	retail buy (%)	retail sell (%)	retail buy plus sell (%)
$Intercept$	2.858	2.897	5.755
	53.35	54.06	53.76
$DEffectAnom$	-0.304	-0.278	-0.582
	-2.08	-1.81	-1.94
D_0	-0.090	-0.104	-0.194
	-3.33	-3.25	-3.38
$DEffectAnom * D_0$	0.006	-0.011	-0.005
	2.89	-3.56	-3.04
Cluster	Double	Double	Double
Adj.R2	0.009	0.007	0.009
Observations	501236	501236	501236

Panel B. Equal-weighted long-leg retail participation

	retail buy (%)	retail sell (%)	retail buy plus sell (%)
$Intercept$	3.463	3.599	7.062
	42.04	42.04	42.07
$DEffectAnom$	-0.201	-0.182	-0.383
	-0.80	-0.69	-0.75
D_0	-0.071	-0.091	-0.163
	-1.56	-1.88	-1.80
$DEffectAnom * D_0$	-0.015	-0.010	-0.026
	-10.80	-3.62	-11.85
Cluster	Double	Double	Double
Adj.R2	0.002	0.002	0.002
Observations	501201	501201	501201

Panel C. Value-weighted short-leg retail participation

	retail buy (%)	retail sell (%)	retail buy plus sell (%)
$Intercept$	2.982	3.01	5.991
	77.20	80.82	79.12
$DEffectAnom$	0.649	0.628	1.277
	3.88	3.75	3.82
D_0	-0.094	-0.103	-0.197
	-3.00	-2.89	-3.00
$DEffectAnom * D_0$	0.005	-0.012	-0.007
	0.76	-1.90	-0.68
Cluster	Double	Double	Double
Adj.R2	0.043	0.041	0.047
Observations	497710	497710	497710

Panel D. Equal-weighted short-leg retail participation

	retail buy (%)	retail sell (%)	retail buy plus sell (%)
$Intercept$	3.264	3.376	6.640
	64.33	65.10	64.81
$DEffectAnom$	0.522	0.525	1.047
	2.57	2.51	2.54
D_0	-0.086	-0.091	-0.177
	-2.24	-2.26	-2.34
$DEffectAnom * D_0$	-0.009	-0.031	-0.040
	-1.14	-3.77	-2.45
Cluster	Double	Double	Double
Adj.R2	0.025	0.024	0.029
Observations	497568	497568	497568

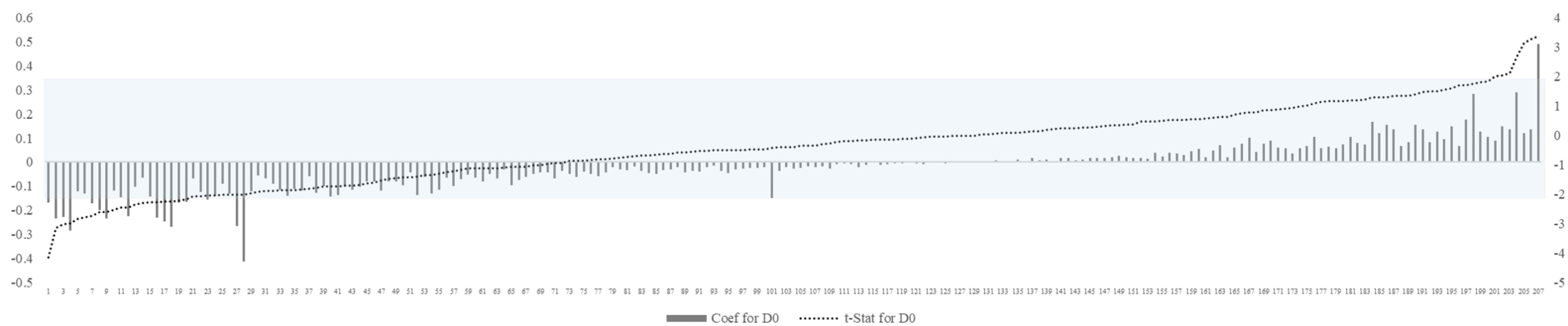
Table XII. Retail Trading Predicts Anomaly Returns

In this table we examine the return predictability of retail order imbalances on the long-leg and short-leg portfolios across anomalies that have different performances on FOMC day. We estimate an anomaly-day level panel regression as specified by equation (5). $Ret_{i,t}$ refers to the return (in percentage, %) on the long or short-leg for anomaly i on day t. For independent variables, $oib_{i,t}$ refers to the value-weighted (or equal-weighted) retail order imbalances among stocks within the long-leg or short-leg portfolio for anomaly i on day t. The long-leg and short-leg portfolios are constructed by forming the top decile and bottom decile portfolio, respectively, at the previous month-end. A stock's oib is calculated as (retail buy volume - retail sell volume) / (retail buy volume + retail sell volume). $DEffectAnom_i$ takes the value of one if the anomaly i significantly decreases return on FOMC day. D_0 refers to the FOMC day dummy. Standard errors are clustered at both anomaly and day level. We report the t-statistics below the coefficient estimates.

Dep.var	Long-leg return (%)		Short-leg return (%)	
Retail oib	value-weighted	equal-weighted	value-weighted	equal-weighted
$Intercept$	0.051	0.051	0.045	0.045
	2.51	2.53	2.13	2.14
$oib(-1)$	0.114	0.033	0.226	0.069
	0.69	0.30	1.22	0.66
$oib(-1) * DEffectAnom$	0.069	0.029	-0.437	-0.164
	0.77	0.49	-2.85	-1.50
Cluster	Double	Double	Double	Double
Adj.R2	0.00	0.00	0.00	0.00
Observations	498733	498733	497216	497216

Figure I. Anomaly Return During FOMC

This figure reports change in anomaly returns on FOMC day for individual anomalies. The sample period is from January 1994 to December 2019, and the sample anomaly is a broad set of 207 anomalies from Chen and Zimmermann (2022). For each anomaly we estimate equation (1) and report the coefficient estimate as well as t-statistics for D_0. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).



Appendix Table AI. Distribution of Anomalies Within Clusters

In this table, we report the distribution of anomalies within clusters. In Panel A, we report the distribution of 125 anomalies within six natural clusters based on Hou, Xue and Zhang (2020), which include frictions, intangibles, investment, momentum, profitability and value. In Panel B, we report the distribution of 207 anomalies within eight natural clusters based on Chen and Zimmermann (2022), which include accounting, analyst, event, options, price, trading, 13F and other.

Panel A. Distribution of anomalies within six clusters based on Hou, Xue and Zhang (2020)

Cluster	Number of anomalies	Percentage of anomalies
Frictions	10	8%
Intangibles	23	18%
Investment	28	22%
Momentum	18	14%
Profitability	24	19%
Value	22	18%
Total	125	1

Panel B. Distribution of anomalies within eight clusters based on Chen and Zimmermann (2022)

Cluster name	Number of anomalies	Percentage of anomalies
Accounting	89	43%
Analyst	18	9%
Event	13	6%
Options	2	1%
Price	50	24%
Trading	14	7%
13F	8	4%
Other	13	6%
Total	207	1

Appendix AII. Anomalies with Significant Return Decreases on FOMC

This table presents the individual anomalies that experience significant return drops on FOMC day. The sample period is from January 1994 to December 2019, and the sample is a broad set of 207 anomalies from Chen and Zimmermann (2022). For each individual anomaly, we estimate equation (1). We then find the following subset of anomalies with significantly negative coefficients of D_0. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Anomaly name	Coef for D0	Coef for Intercept	Anomaly meaning	Anomaly Economics	Anomaly Cluster
ChInvIA	-0.1684	0.0146	Change in capital inv (ind adj)	investment growth	Accounting
zerotrade	-0.2329	0.0051	Days with zero trades	liquidity	Trading
zerotradeAlt1	-0.2268	0.0113	Days with zero trades	liquidity	Trading
CF	-0.2862	0.0229	Cash flow to market	valuation	Accounting
ShareIss5Y	-0.1221	0.0082	Share issuance (5 year)	external financing	Accounting
MeanRankRevGrowth	-0.1300	0.0003	Revenue Growth Rank	sales growth	Accounting
PredictedFE	-0.1705	-0.0036	Predicted Analyst forecast error	earnings forecast	Accounting
ForecastDispersion	-0.1999	0.0110	EPS Forecast Dispersion	volatility	Analyst
RIO_Volatility	-0.2329	-0.0068	Inst Own and Idio Vol	short sale constraints	13F
AOP	-0.1173	0.0074	Analyst Optimism	other	Analyst
AssetGrowth	-0.1457	0.0273	Asset growth	investment	Accounting
Recomm_ShortInterest	-0.2265	0.0145	Analyst Recommendations and Short-Interest	recommendation	Analyst
OrgCap	-0.1022	0.0232	Organizational capital	R&D	Accounting
DelLTI	-0.0634	0.0038	Change in long-term investment	investment	Accounting
NetEquityFinance	-0.1433	0.0307	Net equity financing	external financing	Accounting
std_turn	-0.2301	0.0044	Share turnover volatility	liquidity	Trading
IdioVol3F	-0.2458	0.0373	Idiosyncratic risk (3 factor)	volatility	Price
IdioRisk	-0.2678	0.0360	Idiosyncratic risk	volatility	Price
GrAdExp	-0.1669	0.0233	Growth in advertising expenses	investment alt	Accounting
RIO_Turnover	-0.1642	-0.0102	Inst Own and Turnover	short sale constraints	13F
RDcap	-0.0673	0.0285	R&D capital-to-assets	asset composition	Accounting
VarCF	-0.1240	-0.0066	Cash-flow to price variance	cash flow risk	Accounting
fgr5yrLag	-0.1570	-0.0099	Long-term EPS forecast	earnings forecast	Analyst
MomOffSeason06YrPlus	-0.1394	0.0471	Off season reversal years 6 to 10	other	Price
GP	-0.0911	0.0314	gross profits / total assets	profitability	Accounting
FR	-0.1295	-0.0025	Pension Funding Status	composite accounting	Accounting
MaxRet	-0.2660	0.0198	Maximum return over month	volatility	Price
IO_ShortInterest	-0.4143	0.1002	Inst own among high short interest	ownership	13F
VolumeTrend	-0.1199	0.0205	Volume Trend	volume	Trading