TWO ESSAYS ON EMPIRICAL ASSET PRICING

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PhD

The Hong Kong Polytechnic University

2025

The Hong Kong Polytechnic University
School of Accounting and Finance

Two Essays on Empirical Asset Pricing

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

July 2025

CERTIFICATE OF ORIGINALITY

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ABSTRACT

In the first chapter, we investigate the sources of prominent stock anomaly returns in the global markets by decomposing them into the cash flow news, the discount rate news, and the expected return components. Using analyst forecast data and the valuation model, we document that cash flow news is the primary contributor to anomaly returns across a broad spectrum of well-documented stock anomalies. While the variance of monthly returns for most anomalies is primarily explained by variation in discount rate news, the variance of their longer-term, annual returns tends to be increasingly dominated by variation in cash flow news. In addition, we find little support for the two-beta (CF and DR) model in accounting for the anomaly returns. Overall, the evidence demonstrates the role of investors' dynamic expectations on firm fundamentals in driving prominent anomaly returns in the global markets.

In the second chapter, we investigate the role of risk perceptions in risk premiums and asset prices. We argue that shifts in risk perceptions explain the time-varying nature of risk premiums, including those for prominent factors like size, profitability, and momentum. Using the Price of Volatile Stocks (PVS) as a measure of risk perception, we find significant in-sample and out-of-sample predictive power for various factor premiums. With Instrumented Principal Component Analysis (IPCA), we demonstrate how firms' observable characteristics, like asset-to-me value and past returns, expose individual stocks to risk perception. Stocks with higher PVS betas exhibit significantly lower future returns, indicating that risk perception is a priced factor in the cross-section. We construct a mimicking factor for PVS, confirming its significant negative risk price. Finally, through textual analysis with an LLM, we show how investors' expressed risk perceptions align with our quantitative findings, providing direct evidence of their impact on market dynamics and investment decisions.

ACKNOWLEDGEMENT

My deepest gratitude goes to my chief supervisor – Prof John Wei. My academic path, and indeed my life, took an unexpected and wonderful turn in the summer of 2019 when I first emailed him about his research. I was lucky enough to become Prof John Wei's PhD student later after and now, I am about to graduate with my PhD degree. I really appreciate the patient guidance and encouragement Prof Wei has provided to me along the way. He is always so patient with all my paper drafts, revising word by word from start to the end. His insights and financial intuitions constantly amaze me during our daily conversations. Prof Wei not only guides me as an academic professor, but he also teaches me how to face my daily life. I always enjoy talking with him and admire him as a wise man from every aspect. His devotion and passion for work greatly influence me to be diligent and hard-working.

My sincere thanks also go to my co-supervisor, Prof Te-Feng Chen. Prof Chen has given me immense support throughout my PhD research. From the basic execution of running codes to coming up with ideas, he is always so helpful and supportive to me. I was a green hand to everything and it is his patience and guidance that later trained me to become familiar with all the empirical work and concepts. His devotion to research deeply inspires me to keep on pursuing a research career. I am always moved by his responsiveness to answer all my questions and puzzles, even in his busiest periods. He is such a good teacher and educator, always supporting his students along the path. The help and companionship Prof Chen provided during my PhD study are invaluable. I really thank Prof Chen's help during my PhD journey.

I thank my BoE chair Prof Tim Chue, my two external examiners, Prof Zhanhui Chen and Prof Tse-Chun Lin. They were so helpful on my PhD dissertation and raised a lot of good comments during my oral defense. I also thank my co-authors, Prof Chishen Wei, Prof Mike Qinghao Mao and Dr Linti Zhang. I thank you for working with me and bearing with my clumsiness. I made so much progress during the interactions with you, and it always feels so good when we finish our projects together. You are being so supportive to me and I also learnt so much from you. The AF faculty members, especially Prof Nancy Su, Prof Qiang Wu and Prof Colin Zeng, I thank you for the support and care. You give us the best support so that we can fully focus on our studies. The general office colleagues, Ms. Bobo and Ms. Tracy, are so helpful in everything during my PhD study. My time at PolyU as a PhD student was pleasant and unforgettable. I will cherish this memory with me for the rest of my life.

When I entered the PhD program, it was during Covid-19 pandemic, my PhD cohort and I spent a lot of time together, both on campus and off campus. I enjoyed the conversations we shared and the meals we ate together. My peers gave me a lot of help and encouragement both in life and in research. We discussed papers and ideas, shared happiness and bitterness. I learned so much from you as a newbie who had just graduated from college. My officemates in M1048, you make my life in HK happy and vivid. My warden in Xuemin Hall, Prof. Pearl Lin, taught me so much about how to manage and how to communicate with people. I thank you all so much for making my life in HK colourful.

Lastly, I would like to thank my parents and my friends. I thank my friends for their caring and support, encouragement and company. My mom and dad support me through my ups and downs. You are my unwavering safety net and my constant harbor.

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Chapter 1: What Drives Prominent Anomaly Returns in the Global Markets? A Return Decomposition Approach

1.1 Introduction

One central and fundamental issue in asset pricing is what drives stock price movement (Campbell, 1991; Chen, Da, and Zhao, 2013; Vuolteenaho, 2002). Traditionally, the attention was on understanding individual stock returns and market returns. With the discovery of many cross-sectional return patterns associated with firm characteristics that cannot be explained by traditional asset pricing models, one main task in asset pricing now is to digest portfolio or anomaly returns. These characteristic-based anomalies or factor zoos (Hou, Xue, and Zhang, 2020) are well-established in both the U.S. and the global markets (Jacobs and Muller, 2020; Jensen, Kelly, and Pederson, 2023). In recent years, researchers have explored the sources of selected stock anomaly returns in the U.S. market (e.g., Campbell and Vuolteenaho, 2004; Lochstoer and Tetlock, 2020; Mao and Wei, 2014; 2016). In this study, we extend the scope to the global markets and aim to examine what drives prominent anomaly returns.

We use return decomposition to quantify cash flow return news and discount rate return news. Two popular approaches have been used in the literature, the VAR approach (Campbell, 1991; Campbell and Shiller, 1988) and the valuation model approach (Chen, Da, and Zhao, 2013). Using the VAR-based approach to estimate individual stock CF news and DR news, Vuolteenaho (2002) finds that variations in market returns mainly come from DR news, while movements in stock returns mainly come from CF news. On the other hand, Chen and Zhao (2009) argue that the VAR method that backs out CF news as a residual of DR news can be sensitive and noisy. Chen, Da, and Zhao (2013) apply the valuation models (Paster, Sinha, and Swaminathan, 2008) combined with analysts' earnings forecasts to extract CF news and DR news from unexpected stock returns. They find that the importance of the CF news component in explaining variations in market returns increases as the investment horizon increases.[1] Following the approach in Chen, Da, and Zhao (2013) and Mao and Wei (2016), we use valuation models and analyst earnings forecasts to measure the three components of realized stock returns (i.e., CF news, DR news and the expected return) for the sample of stocks covered by analyst earnings forecasts in the global setting.

Our goal is to investigate the relative contributions of the return components in driving prominent stock anomalies across the global markets. There are a few studies applying return decomposition to digest anomalies in the U.S. market. Campbell and Vuolteenaho (2004) find that the value anomaly is mainly attributed to the comovement between the value portfolio returns and the market CF news (i.e., cash flow beta). Mao and Wei (2016) identify the dominance of CF news in driving the returns of investment anomalies. Mao and Wei (2014) demonstrate a large CF news component partially offset by a sizable DR news for momentum returns. Lochstoer and Tetlock (2020) use a panel VAR to estimate DR news and CF news and study the returns of the Fama-French (2015) five-factor and momentum portfolios. They find that while DR news drives market unexpected returns, CF news dominates in unexpected returns of the other portfolios. In addition, they show that DR and CF shocks to anomaly factor returns are not correlated with market DR news and CF news shocks, casting doubt on the ability of existing behavioral or rational models to explain these anomalies.

To construct the sample, we follow Jensen, Kelly, and Pedersen (2023) by classifying all characteristic-based anomalies in the global market into clusters according to the correlations among anomaly returns. We screen for the common anomalies that are significant in the global

[1] Moreover, De la O and Myers (2021) use analyst earnings forecasts for S&P 500 component stocks to estimate return and dividend growth expectations and then compute one-year revisions in the S&P 500 index. They find that cash-flow growth expectations explain a large proportion of the price movements in the S&P 500 index.

markets and narrow down to 33 anomalies across 23 markets. These prominent anomalies are grouped into 10 clusters: (i) accruals, (ii) debt issuance, (iii) investment, (iv) seasonality, (v) profitability, (vi) quality, (vii) momentum, (viii) profit growth, (ix) short-term reversal, and (x) value. In general, we find that anomaly returns in the global markets are on average larger in magnitude than in the U.S. market; and more anomalies are significant in developed markets than in emerging markets.

We start our main analysis by quantifying the relative contributions of the return components to the significant anomalies in each market. The results show that most anomaly returns are dominated by the CF news component in both the global markets and the U.S. market. The long-short portfolio returns are mainly contributed by CF news. Specifically, anomalies in the clusters of debt issuance, investment, seasonality, quality, and profitability feature sizable and significant CF news in the global markets. For anomalies in the momentum cluster, the long-short portfolio exhibits a positive CF news partially offset by a negative DR news in the global market, consistent with the U.S. finding (Mao and Wei, 2014) that stock winners are associated with persistently higher CF news compared with stock losers. The CF and DR news components of anomalies in the short-term reversal and the value clusters behave the opposite way as momentum anomalies: DR news is positive and statistically significant, while the CF news offsets the magnitude. The overreaction of investors to the future value stock's discount rate leads to future positive DR news. We run Fama-MacBeth for each anomaly-related characteristic in predicting the future 1-month stock return within each country. The regression-based analyses are parallel to the portfolio-sorting analyses. Controlling common characteristics (size, market beta, and BM ratio) that are important factors for stock returns, our findings in the regression analyses hold similarly with the results in the portfolio-sorting analyses.

We then use variance decomposition to examine the contribution of return components to the variance of anomaly returns in the time-series. We measure anomaly returns and the corresponding variance at both the one-month and one-year holding horizons with the focus on what drives short-term variations in anomaly returns. The results show that the one-month return variance for nearly all anomalies is dominated by variations in DR news. The finding holds for all markets. When the anomaly return holding period is extended to one-year, we observe that the CF news variation gradually come to dominate the anomaly return variance. The evidence suggests that DR news drives short-term variations in anomaly returns, but the driving force gradually fades away when the holding period lengthens, in line with the individual stock level finding that DR news dominates short-term price movements but not for the long-term (Chen et al., 2013).

Next, we test whether the significant anomalies in the global markets can be explained by the two-beta model in Campbell and Vuolteenaho (2004). Campbell and Vuolteenaho (2004) propose the two-beta model to explain the value anomaly return and find that the high average returns of value stocks can be explained by their high exposure to the market CF news. Moreover, Campbell, Polk, and Vuolteenaho (2010) find that the cash-flow fundamentals of both value and growth firms shape both the relatively higher correlations of value stock returns with the market CF news and the relatively higher correlations of growth stock returns with the market DR shocks. Specifically, we compute the CF beta (and DR beta) for the long- and the short-leg of each anomaly and test whether the difference in CF beta (and DR beta) is statistically significant. For most anomalies in the U.S. market, the difference in CF or DR beta between the long- and the short-leg does not show a significant pattern. In the non-U.S. international market, results on the beta spreads are mixed. According to Campbell and Vuolteenaho (2004), if the long-short portfolio exhibits a positive return spread, the two-beta model would predict a positive CF beta (i.e., bad beta) spread and a negative DR beta (i.e., good beta) spread between the long- and the short-legs. However, we only find limited evidence supporting this prediction. For example, a handful of momentum and quality anomalies generally show a positive CF beta spread and a negative DR beta spread. The quality-minus-junk-profitability anomaly (*qmj_prof*) in the quality cluster exhibits a negative and significant DR beta spread in four international markets and a significantly positive CF beta spread in three international markets. Therefore, in contrast to the good versus bad beta explanation by Campbell and Vuolteenaho (2004), the two-beta model is unlikely to explain returns of most anomalies in the global markets.

Our paper contributes to the international asset pricing literature. Prior to 2010, most studies have a single anomaly focus and assess different potential explanations. Stambaugh, Yu, and Yuan (2012) are among the earliest to examine a few anomalies collectively which include 11 prominent anomalies. Recent studies expand the scope to even tens and hundreds of anomalies and test the independence and replicability of anomalies. In the U.S. market, McLean and Pontiff (2016) summarize 97 anomaly variables. Green, Hand, and Zhang (2017) examine 94 firm characteristics. Hou, Xue, and Zhang (2020) replicate 452 anomalies. Chen and Zimmermann (2022) examine the predictability of 319 firm characteristics. Using Chinese A-share data, Li, Liu, Liu, and Wei (2024) replicate 469 anomaly variables. All these studies find that most anomalies are not replicable or at least much weaker after their publication. Jacobs and Muller (2020) study the predictability of pre- and post-publication returns of 241 cross-sectional anomalies in 39 stock markets. They find that the United States is the only country with a reliable post-publication decline in the long-short portfolio returns. We focus on the most prominent anomalies in the global markets using the sample of relatively large firms covered by financial analysts and digest the sources of the anomaly returns. We document that the average magnitude of anomalies is larger in the non-U.S.

international markets than in the U.S. market. In addition, we find that the most significant anomalies exist in developed markets instead of emerging markets.

Our paper also adds to the literature exploring the sources of price movements. Traditional studies focus on explaining individual stock return and market return variance. Campbell (1991) and Cochrane (2011) document that the DR news explains most of the market return variations. Other studies emphasize the importance of changes in cash flow expectation (Ang and Bekaert, 2007; Larrain and Yogo, 2008; Chen, Da, and Priestley, 2012). Chen, Da, and Zhao (2013) find that the relative importance of CF versus DR news increases as the horizon increases. Another strand of studies aims to digest anomaly returns. An early study by Fama and French (1995) show that the returns of size- and value-sorted portfolios comove with earnings shocks. Cohen, Polk, and Vuolteenaho (2003; 2009) argue that CFs explain most of the return variance of the value anomaly. Our paper is closest to Lochstoer and Tetlock (2020) who document that cash flow news drives the returns of anomaly portfolio returns in the U.S. market. We extend the scope to the global markets and investigate a broader collection of prominent anomalies. Our finding that cash flow news is the main contributor to most anomaly returns highlight the role of dynamic investors' expectations on firm fundamentals in shaping portfolio price movement.

Finally, our findings shed new light on the two-beta model proposed by Campbell and Vuolteenaho (2004) and Capmbell, Polk, and Vuolteenaho (2010). Different from their findings based on the value premium, the two-beta model is generally unable to explain returns of the anomaly clusters in our sample. The global markets evidence is consistent with that offered by Lochstoer and Tetlock (2020) that the U.S. market anomaly returns are not driven by their relation with market CF and DR shocks.

The remainder of our paper proceeds as follows. We describe the data and sample in Section

2. Section 3 reports the empirical findings. Finally, Section 4 concludes the paper.

1.2 Data and Methodology

1.2.1 Data sources

We retrieve the U.S. stock return data from the Center for Research in Security Prices (CRSP) database and the non-U.S. international stock return data from the Compustat Global Daily Security database. Following Bessembinder, Chen, Choi, and Wei (2023) and Jensen, Kelly, and Pedersen (2023), the stock return data are cleaned and converted into monthly frequency. We keep the primary-issuance stocks and only the ones listed in the main stock exchanges. The accounting information is from Compustat Annual and Quarterly databases and merged with stock price information with a four-month lag. The monthly analyst earnings forecasts are from the Institutional Brokers' Estimate System (I/B/E/S) database. We use analyst earnings forecasts for the future one- to three-year earnings per share (EPS) and the long-term growth (LTG) rates to measure earnings expectation.

All firm characteristics and stock returns are expressed in each market's local currency to ensure the consistency between analyst forecasts and the corresponding stock-level information. We do not convert returns into U.S. dollar returns to avoid the impact of currency price change on the analyst forecasts and anomaly returns under examination. Our original sample period spans from January 1990 to December 2023. The risk-free rate is from the Fama-French website for the U.S. market and from Datastream for the non-U.S. international markets. For the non-U.S. international markets, we use the short-term interest rate as the risk-free rate. In the U.S. markets, if a delisting return is missing and the delisting reason is performance-based, we follow Shumway (1997) to set the delisting returns to -30%. In the non-U.S. global markets, because all delisting returns are not available, we follow Bessembinder et al. (2023) to set the delisting return to -30%.

1.2.2 The sample of stock anomalies

We start with the 153 anomalies selected by Jensen, Kelly, and Pedersen (2023) based on the exhaustive list of 202 different characteristic signals (which could be with a monthly, quarterly, or annually frequency) compiled by Hou, Xue, and Zhang (2020). For a given characteristic, Hou et al. (2020) treat anomaly returns with one-, six-, and 12-month holding horizons as different anomalies. Jensen et al. (2023) instead focus only on a one-month holding horizon and only study the version that updates with the most recent accounting information. We follow the approach in Jensen et al. (2023) and exclude other anomalies for which data are not available or sufficient for the global markets. A total of 153 anomalies in our final sample, which are grouped into 13 clusters according to their correlations.

As we require all information of stock characteristics, analyst earnings forecasts, and stock returns, our sample mainly includes relatively large firms, especially in the non-U.S. markets. For each market, we start our analysis from the first month when there are over 100 stocks with feasible stock returns in the merged sample. For each market and each month, we sort all stocks into quintiles based on the characteristic and define the anomaly return as the long-short portfolio return. We ensure that the anomaly return is always positive as we use the long-leg to minus the short-leg. Moreover, for each characteristic-based anomaly, we require at least 20 stocks in each quintile. Portfolio returns are value-weighted. Since our merged sample tilts towards relatively large firms, we do not impose special breakpoints for each portfolio sort. We follow Jensen et al. (2023) to winsorize stock returns at the bottom 1% and top 99% percentiles in the non-U.S. international market to avoid extreme values potentially caused by data errors. We identify the significant characteristic-related anomalies for each country using the criteria that the absolute value of *t*-statistics for the long-short portfolio return should be greater than 1.65, given our sample mostly is of the larger stocks.

To form the final sample of anomalies, we screen for the commonly significant anomalies in the global markets. We require the anomaly to be significant in at least five markets to be included as a prominent anomaly. Out of the 153 anomalies, the final sample consists of 33 prominent and significant anomalies with valid observations across 23 global markets (including the U.S.). These anomalies are further grouped into ten clusters. The detailed definitions of each anomaly and the associated stock characteristic are explained in Appendix A.

1.2.3 Return decomposition

We follow Chen, Da, and Zhao (2013) and Mao and Wei (2016) to estimate the implied cost of capital (ICC) with the earnings forecast data and then decompose stock return into (i) cash-flow (CF) news, (ii) discount rate (DR) news, and (iii) expected return (ER). We estimate the ICC of each stock using four residual income models: (i) Gebhardt, Lee, and Swaminathan (2001) or GLS; (ii) Claus and Thomas (2001) or CT; (iii) Ohlson and Juettner-Nauroth (2005) or OJ; and (iv) the modified price/earnings-to-growth (PEG) ratio model of Easton (2004) or MPEG. The details of the valuation models can be found in Appendix B. The realized stock return from *t*-1 to *t* (Ret_t) can be expressed as follows:

$$\begin{aligned} Ret_t &= \frac{P(e_t, ICC_t, t) - P(e_{t-1}, ICC_{t-1}, t-1)}{P_{t-1}} \\ &= \frac{\frac{\partial P_t}{\partial e_t} \times \Delta e}{P_{t-1}} + \frac{\frac{\partial P_t}{\partial ICC_t} \times \Delta ICC}{P_{t-1}} + \frac{\frac{\partial P_t}{\partial t} \times \Delta t}{P_{t-1}} \\ &= CF\_News_t + DR\_News_t + ER_t, \end{aligned} \tag{1}$$

where $P(e_t, ICC_t, t)$ is the stock price at time t and is a function of earnings per share (e_t), cost of capital (ICC_t), and time (t). CF_News_t, DR_News_t, and ER_t denote CF news, DR news, and expected return, respectively. Each component represents its effect on the price of the stock from changes in each one of the three parameters in a valuation model.

We apply each model to calculate the expected return (i.e., implied cost of equity capital, ICC) each month, which is the discount rate that equates the stock price and discounted expected future earnings. Because we lack a consensus on the best model, we follow the literature and set ICC as the median estimate of all models (Hail and Leuz, 2006; Chen, Chen, and Wei, 2011; Mao and Wei, 2016). We then use the valuation model corresponding to the ICC to compute the three return components (CF_News_t, DR_News_t, and ER_t) of the realized return, Ret_t, as follows:

$$CF\_News_t = \frac{\{P(e_t, ICC_t, t) - P(e_{t-1}, ICC_t, t) + P(e_t, ICC_{t-1}, t) - P(e_{t-1}, ICC_{t-1}, t)\}/2}{P_{t-1}} \quad (2)$$

$$DR\_News_t = \frac{\{P(e_t, ICC_t, t) - P(e_t, ICC_{t\text{-}1}, t) + P(e_{t\text{-}1}, ICC_t, t) - P(e_{t\text{-}1}, ICC_{t\text{-}1}, t)\}/2}{P_{t-1}} \quad (3)$$

$$ER_t = E_{t-1}(Ret_t) = \frac{\{P(e_{t-1}, ICC_{t-1}, t) - P(e_{t-1}, ICC_{t-1}, t-1)\}}{P_{t-1}} = ICC_{t-1}. \quad (4)$$

Eq. (4) combined with the valuation model indicates that the expected return for time *t* is the ICC determined at time *t*-1. Eq. (2) and Eq. (3) are used to calculate average CF news and average DR news in two hypothetical scenarios, with one assuming that CF news is incorporated first and the other assuming that DR news is added first (Mao and Wei, 2016).

Operational-wise, we use information on earnings forecasts, book equity, and stock price available at time *t*-1 (*t*) to estimate ICC_{t-1} (ICC_t). We then use Eq. (2) to estimate CF news return (CF_News_t) first and then compute DR news return as $DR\_News_t = Ret_t - ICC_{t-1} - CF\_News_t$. For each anomaly, the anomaly-level CF news, DR news, and expected return are the bottom-up value-weighted average of each stock. For the extreme case with CF news return greater than 100%, we attribute the unexpected stock return entirely to CF news return.

1.3 Empirical Results

1.3.1 Summary statistics

Panel A of Table 1 shows the averages of the monthly total return, cash flow news component, discount rate news component, and expected return component for individual stocks in each market. Among all stock markets, the Indonesia and United States markets feature the highest average total returns (1.093% and 0.940%), while the Germany and Thailand markets exhibit the lowest average total returns (0.142% and 0.227%). Most of the markets are associated with negative cash flow news on average[2]; and over half of the markets exhibit negative average discount rate news. Besides, the average expected returns and average total returns have the same (positive) directions and the average expected returns are in larger magnitudes for most markets.

[Insert Table 1 here]

Panel B presents the correlation matrix among the total return and the three components for each market. One commonality is that among the three components, DR news shows the highest correlation with the total return. It suggests that stock price movement at the monthly frequency is mainly explained by DR news. Another common feature across all markets is that DR news and CF news are negatively correlated, consistent with the finding in the U.S. market (Lochstoer and Tetlock, 2020; Mao and Wei, 2016).

1.3.2 Return components of prominent anomalies

Table 2 explores the number of markets demonstrating significant long-short portfolio returns for each of the 33 prominent anomalies in the ten anomaly clusters and the sources of

[2] Negative cash flow news could mean that investors and financial analysts are, on average, overly optimistic about future earnings of stocks in the specific market. They are sluggish in correcting the expectation/forecast errors. As time goes by, analysts tend to make downwards adjustments to earnings forecasts instead of upwards revisions.

anomaly returns in terms of the three return components.[3] This table serves as the main results of our paper. Panel A overviews the prominent anomaly returns across the global 23 markets by cluster. Within a cluster, we sum the number of markets that show significant long-short portfolio returns for each prominent anomaly. The quality anomalies are most common in the global financial markets, followed by the momentum anomalies. For the anomaly return components, more CF news components are shown to be significant than the DR news components in most of the clusters, except for the short-term reversal and value anomalies.

Panel B of Table 2 summarizes the magnitude of each anomaly return and its 3 components across global markets.[4] To investigate the sources of anomaly returns, we count the number of non-U.S. markets with significant CF news, DR news, and expected returns for each anomaly and estimate the mean values of the return components across the markets demonstrating significant anomaly returns. The number of markets with significant anomaly returns is denoted as #Sig. For #Sig CF, #Sig DR and #Sig ER, we define them as the number of markets whose return components are in the same position as the anomaly return and also statistically significant. In comparison, we express the numbers in boldface if the anomaly is significant in the U.S. Additionally, we estimate the mean values of the three return components across the non-U.S. markets exhibiting significant anomaly returns.

The left panel shows the results for the U.S. markets and the right panel corresponds to the findings in the ex-U.S. international markets. The left panel U.S. results can be good comparisons or benchmarks with the ex-U.S. international markets results. In general, returns of anomalies in

[3] As we state earlier in the paper, for a characteristic to be selected as a prominent anomaly characteristic, we require at least five markets to show significant long-short portfolio returns in the sample period.

[4] The details of return decomposition for each anomaly and each market can be seen in Appendix C, Figure C1. For each cluster, we have the candle plot of the magnitude and the confidence interval of the prominent anomalies in the non-U.S. global markets and the U.S. market. It is straightforward to compare the total return of each anomaly and its associated three components in each stock market.

the non-U.S. global markets are in the same direction as those in the U.S. Meanwhile, the return magnitudes are relatively larger compared with those in the U.S. The evidence is in line with the finding by Batram and Grinblatt (2021) that global equity markets are relatively inefficient. The most pervasive anomalies outside the U.S. are, *noa_gr*1*a* (the change in current operating assets) anomaly in the investment cluster, *resff*3_12_1 (the residual momentum *t*-12 to *t*-1) in the momentum cluster, *mispricing_perf* (the mispricing factor performance) anomaly in the quality cluster, and *ocf_me* (the operating cash flow-to-price) in the value cluster, with ten markets demonstrating significant returns.

[Insert Table 2 here]

Table 2, Panel B shows that CF news is the most important contributor to the returns of prominent anomalies. In the U.S. market, 12 (in the accruals, momentum, profit growth, quality, seasonality, short-term reversal and value anomaly clusters, respectively) among the 19 significant anomalies in the U.S. have CF news components that are economically and statistically significant. In the non-U.S. markets, the patterns can be summarized under three categories. In the first category of anomalies, such as in debt issuance, investment, profitability, seasonality, and quality clusters, their anomaly returns are mainly driven by CF news in terms of both the statistical significance and economic magnitude.[5] For instance, one prominent investment anomaly, *noa_gr*1*a* (change in net operating assets), has a significant CF component in three non-U.S. markets with an average monthly CF news of 0.529%. Among the 10 markets that have significant long-short portfolio total returns based on this anomaly, none of them shows a significant DR component and the average magnitude of DR news is only 0.271%. For one anomaly in the quality

[5] As in Table 2, Panel A, we find that the expected return (ER) are pervasively statistically significant across most of the anomalies. However, the magnitude for ER of each anomaly is relatively small, and is economic insignificant compared to the other 2 components.

cluster, *mispricing_perf* (mispricing factor: performance), eight of the 10 markets with significant total returns show significant CF news, while only three markets exhibit significant DR news. The average total return, CF news, and DR news are 1.048%, 1.662%, and -0.436%, respectively.

The second category of anomalies is related to momentum where they have offsetting CF and DR news components. Consistent with Mao and Wei (2014), the momentum anomaly returns have positive CF news and negative DR news across the global markets (including the U.S.). As detailed in Appendix Figure C1, both CF news component and DR news component are statistically significant across different markets. Moreover, the CF news components are all larger in magnitude and in the same direction as the anomaly returns, while the DR news components are in the opposite direction, offsetting the CF news components and leading to a moderate level of momentum anomaly returns. It suggests that the market is too slow to incorporate CF news for the momentum portfolios in both the U.S. market and the international markets.

The last category is the reversal and value cluster anomalies. The short-term reversal and value anomalies behave oppositely to momentum anomalies, and the performance of return components also seems to reverse for them. For instance, the operating cash flow-to-price (*ocf_me*) in the value cluster has average large and more significant DR components in six of the 10 international markets with a significant *ocf_me* anomaly. The CF components in *ocf_me* are negative and less statistically significant. We argue that it is reasonable as the market may overreact to the discount rate news for the value-related stocks, and therefore value-related anomalies show a positive DR news. A similar scenario applies to the short-term reversal anomalies, investors overreact to the discount rate news of the rebounding of past losers. Taken together, the value and short-term reversal anomalies act oppositely to the momentum anomalies.

In general, the portfolio sorting-based analysis shows that most of the prominent anomalies in the global markets are driven by CF news. Exceptions include short-term reversals and value anomalies, where the DR news dominates the anomaly returns. Momentum anomalies are also due to a large and positive CF news component which is partially offset by the negative DR news component in the global financial markets.

1.3.3 Regression-based analysis

Our analyses in the previous section are based on the non-parametric portfolio sorts. We now conduct regression-based analyses to further examine the driving force of anomaly returns in the global markets. Specifically, we run Fama-MacBeth regressions with stock-month data within each market:

$$Ret_{i,t+1} = a + b \times Char_{i,t} + c \times ME_{i,t} + d \times BM_{i,t} + e \times Beta_{i,t} + \epsilon_{i,t+1}, \qquad (5)$$

where $Ret_{i,t+1}$ is the stock return of stock *i* in month *t*+1, $Char_{i,t}$ is the anomaly characteristic of stock *i* in month *t*. We control firm size ($ME_{\mathrm{i,t}}$), book-to-market ($BM_{i,t}$) ratio, and market beta ($Beta_{i,t}$) as these 3 characteristics are considered to be most important in influencing stock returns across the global financial markets. This regression-based approach allows us to explore the predictive power of each characteristic-based anomaly while controlling for other firm characteristics.

Analogous to the portfolio sorting approach for stock return decomposition, we replace the independent variable in Eq. (5) with CF news and DR news as follows:

$$CF_{News_{i,t+1}} \left(or\ DR_{News_{i,t+1}} \right) = a + b \times Char_{i,t} + c \times ME_{i,t} + d \times BM_{i,t} + e \times Beta_{i,t} + \epsilon_{i,t+1}, \qquad (6)$$

where $CF\_News_{i,t+1}$ and $DR\_News_{i,t+1}$ are the CF news and DR news returns of stock *i* in month *t*+1, respectively. Eq. (6) helps to examine which component of the return that $Char_{i,t}$ predicts: does the predictive power of a characteristic on future stock return predict the future CF news or

DR news? We run the above three Fama-MacBeth regressions in each market (country) with the prominent anomalies listed in Table 2.

The regression-based results for each significant anomaly in the U.S. market can be found in Table 3. The table only tabulates the coefficient on each anomaly characteristic. Overall, the regression results are similar to the results of portfolio sorting. The only exception is that *niq_at* (quarterly return on assets) loses its statistical significance in the regression, and the remaining of anomalies stay consistent and significant. In predicting future CF news and DR news, 12 of the characteristics have significant predictive power on future CF news and 10 of them can predict future DR news, similar to the numbers in portfolio sorting analyses. Some anomaly characteristics have positive predictability on future CF news but offset by negative DR news: *resff*3_12_1 (residual momentum *t*-12 to *t*-1) in the momentum cluster, *ret*_12_7 (price momentum *t*-12 to *t*-7) in the profit growth cluster. Some have positive DR news but moderated by negative CF news: *cop_atl*1 (cash-based operating profits-to-lagged book assets) in the quality cluster, and *rmax*5_*rvol*_21*d* (highest 5 days of return scaled by volatility) in the short-term reversal cluster. We still observe that in the U.S. market, anomaly characteristics are likely to predict future CF news rather than DR news.

[Insert Table 3 here]

For each of the remaining markets, the regression results are shown in Appendix C, Table C1. We draw a summary table on the international regression in Table 4. We count the number of markets where a characteristic (anomaly) can significantly predict the future return/CF/DR news for each anomaly in the international market. The "correct" direction for each anomaly is designed to be positive. The takeaway is still quite consistent: anomaly characteristics mainly predicts the future CF news instead of the DR news, except in the short-term reversal and value clusters. The momentum related anomaly characteristics mostly predict positive CF news and negative DR news. We see some offsetting predictive power in quality clusters, but not for each one of them. In short-term reversal and value anomalies, the dominance of DR news is still there in regression-based analyses. Our regression-based analyses continue to support our main takeaways in the previous section.

[Insert Table 4 here]

1.3.4 Variance decomposition of anomaly returns

We now shift our focus from the first moment of anomaly returns to the second moment (i.e., variation) of anomaly unexpected returns. The variance of anomaly unexpected returns is decomposed into the covariance between CF news and DR news following Chen, Da, and Zhao (2013):

$$\begin{aligned} &\mathrm{Var}\left(R_{i,t+1} - E_t\left(R_{i,t+1}\right)\right) \\ &= Cov\left(CF_{News_{i,t+1}}, R_{i,t+1} - E_t\left(R_{i,t+1}\right)\right) + Cov(\,DR\_News_{i,t+1}, R_{i,t+1} - E_t(R_{i,t+1})) \end{aligned} \quad (7)$$

$$1 = \frac{Cov\left(CF\_News_{i,t+1}, R_{i,t+1} - E_t(R_{i,t+1})\right)}{\mathrm{Var}\left(R_{i,t+1} - E_t(R_{i,t+1})\right)} + \frac{Cov(\,DR\_News_{i,t+1}, R_{i,t+1} - E_t(R_{i,t+1}))}{\mathrm{Var}\left(R_{i,t+1} - E_t(R_{i,t+1})\right)} \quad (8)$$

where Var and Cov are the variance and covariance operators. $R_{i,t+1}$ is the return for anomaly *i* in month (year) *t*+1, and $E_t(R_{i,t+1})$ is the expected return of anomaly *i* in month (year) *t*+1 as of month (year) *i*. The annual stock return $R_{i,t+1}$for each anomaly is from July in year *t* to June in year *t*+1, constructed on the characteristic each June in year *t*. From Eq. (8), the variance of the unexpected return of each anomaly can be decomposed into (i) the covariance of unexpected returns with the CF news plus (ii) the covariance of unexpected returns with the DR news. Dividing Eq. (8) by the variance of anomaly unexpected returns on both sides yields Eq.(9), where the two components are proportional to the unexpected return variance. On the right-hand side of Eq. (9), the two parts are the slopes of regressing CF news or DR news on unexpected returns.

[Insert Table 5 here]

For all significant anomalies, we calculate the average fractions of the variance of the returns attributed to CF news and DR news across different markets. Table 5 summarizes the results for each anomaly. Consistent with the findings of Chen, Da, and Zhao (2013), the variances of one-month unexpected returns of anomalies are driven by the covariance of the DR news for almost all the anomalies in nearly all markets, as shown in Column (1) and (2). DR news might provide an immediate impact on anomaly returns, especially when updates on analyst forecasts are relatively noisy. The CF news in the near horizon might be mildly diversified away within a portfolio in the short-term, but this might not be the case for the DR news. Column (1) and (2) show the variance when the holding period for the anomalies lasts for one month. Meanwhile, if the holding period for the anomalies extend to 1-year, we observe the rising dominance of CF news in driving the anomaly unexpected return variance for the majority of the anomalies. The short-term dominance of unexpected return variance in DR news, along with the shift to CF news in the longer term is consistent with the findings of Chen et al. (2013).

The detailed variance decomposition for each anomaly and each cluster can be found in Appendix C Figure C2 for the 1-month holding period and Appendix C Figure C3 for the 1-year holding period. We also observe some cases where the CF news or DR news covariance negatively correlates with the anomaly return. Nonetheless, the influence of DR news on the second moment of one-month anomaly returns, along with the increasing significance of CF news over a longer horizon, can be observed in global market anomaly returns.

1.3.5 The Campbell and Vuolteenaho (2004) two-beta model

Campbell (1993, 1996) and Campbell and Vuolteenaho (2004) propose a risk-based explanation for the value anomaly. Investors require compensation by exposing themselves to both cash-flow beta (bad beta) and discount-rate beta (good beta). In the U.S. market, a much larger positive and significant risk premium for the value anomaly is associated with the cash-flow beta. Value stocks are more exposed to market CF news than growth stocks, and the value premium can be explained by the two-beta model in Campbell and Vuolteenaho (2004) and or the four-beta model in Campbell Polk and Vuolteenaho (2010). We explore if the anomaly returns can be explained by such risk-based explanations in this section.

For all markets in our sample, we calculate the value-weighted average unexpected returns in each stock market as the market return. Furthermore, we calculate the market-level CF news and DR news as the weighted-average value of individual stocks within each market. The CF beta and DR beta for each stock are estimated as follows:

$$\beta_{i,CF} = \frac{Cov(ret_{i,t}, N_{CF,t}^{m})}{Var(ret_{m,t})};\ \beta_{i,DR} = \frac{Cov(ret_{i,t}, N_{DR,t}^{m})}{Var(ret_{m,t})} \tag{9}$$

where $ret_{i,t}$ is the unexpected return of anomaly i in month t, $N_{CF,t}^{m}$ is the market cash-flow news in month t, $N_{DR,t}^{m}$ is the market discount-rate news, and $ret_{m,t}$ is the market unexpected return. The CF beta and DR beta are in-sample estimations for the anomaly across all sample periods as in Campbell and Vuolteenaho (2004).[6] We calculate the beat of each anomaly beta by regressing the long-short unexpected return on the scaled market-wide CF news or the scaled market-wide DR news.[7]

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[6] We also use the rolling window to estimate the CF beta and DF beta for each stock in each month and find similar results.

[7] We scale the market-wide news to be $N_{CF,t}^{m} \times Var(ret_{m,t})/Var(N_{CF,t}^{m})$ and $N_{DR,t}^{m} \times Var(ret_{m,t})/Var(N_{DR,t}^{m})$ so that they can add up to the market beta.

Analogously to Campbell and Vuolteenaho (2004) and Campbell et al. (2010), we explore whether the long-leg and short-leg of each anomaly present different exposures to the market-wide CF news and DR news. The intuition is that the higher average return in the long-leg than in the short-leg should be due to the higher risk exposure of the long-leg's stocks to market-level CF (DR) shocks. If consistent patterns emerge in the CF beta and DR beta for each anomaly, we may gain insights into the fundamentals of anomaly returns through the risk-based explanations.

We first show the CF beta and DR beta and the spreads for significant anomalies in the U.S. market in Table 6. The beta significance between the long-leg and the short-leg of the anomaly is calculated with Newey-West (1987) adjusted standard errors. We ensure that the difference is aligned with the direction of the high-return quintile (long-leg) minus the low-return quintile (short-leg) for each anomaly, so that the anomaly return is always positive. In Table 6, only two anomalies, *cop_atl*1 (cash-based operating profits-to-lagged book assets) and *fcf_me* (free cash flow-to-price), show a significantly different CF beta between the long-leg and short-leg during our sample period. The CF beta spread between the long-leg and short-leg for *fcf_me* is negative in magnitude, which is inconsistent with Campbell and Vuolteenaho (2004) and Campbell et al. (2010). For the DR beta spreads, we identify four negative and significant anomaly DR betas in the profitability (*ocf_at* (operating cash flow to assets)) and quality clusters (*cop_at* (cash-based operating profits-to-book assets), *cop_atl*1(cash-based operating profits-to-lagged book assets) and *niq_at* (quarterly return on assets)). Campbell and Vuolteenaho (2004) argue that CF beta is "bad beta" so that stocks exposed more to CF beta demand higher returns. In our long-minus-short anomaly portfolios, we fail to find a prevailing positive association between the anomaly return and the CF beta spread during our sample period. Although we identify four significantly negative DR beta spreads, the rest of the anomalies do not show divergence in market risk exposures. We conclude that at least in our sample period, the risk-based explanation does not work for the prominent U.S. anomalies.

[Insert Table 6 here]

We further explore the beta spread for each anomaly in the non-U.S. international market. Table 7 summarizes the number of significant CF or DR beta spreads for each anomaly across non-U.S. international markets. In Column (1), (4), (7) and (10), we report the summary in the international beta spreads for each anomaly. Some markets show significant CF beta spreads, but the directions of the CF beta spreads are not consistent for one anomaly across different markets. Anomalies such as the *fnl_gr*1*a* (change in financial liabilities) in the debt issuance cluster, the *resff*3_12_1 (residual momentum *t*-12 to *t*-1) in the momentum cluster, the *sale_bev* (asset turnover) anomaly and *qmj_prof* (quality minus junk: profitability) in the quality cluster, as well as the *ocf_me* (operating cash-flow-to-price) in the value cluster show significantly negative CF beta spreads in some markets, but positive in other markets. Apart from that, the significant CF beta spreads are more likely to be positive in the international market. However, it is more often that the anomalies do not have clear patterns in terms of CF beta spreads. Again, the CF beta itself and the risk-based explanation are not sufficient for prominent anomalies in the non-US. global markets.

[Insert Table 7 here]

For the DR beta spread, the majority of markets that have significant anomaly DR beta spreads show significant negative DR spreads. Exceptions including *cowc_gr*1*a* (change in current operating working capital) anomaly in the accrual cluster, the *noa_gr*l*a* (change in net operating assets) in the investment cluster, and *seas*_6_10*an* (years 6-10 lagged returns) in the seasonality cluster show positive and significant DR beta spread for some markets. Other anomalies that have statistically significant patterns for anomaly DR beta spreads are more likely to be negative rather than positive, which is consistent with the "good beta" arguments. Still, it is not sufficient to support a risk-based explanation for anomaly returns in the international markets, as the number of significant DR/CF beta spreads is small compared to the number of significant anomalies.

The subsample statistics on non-U.S. developed markets and emerging markets further display whether the directions of beta spreads differ with different market development levels. The Developed (Columns (2), (5), (8,) and (11)) and Emerging (Columns (3), (6), (9), and (12)) compare the number of beta spreads of each anomaly in markets with different development levels. We find that the majority of significant anomaly beta spreads are from the non-U.S. developed markets. It is not surprising, as our previous results find more significant anomalies in the developed markets. Still, the directions of those beta spreads do not converge to a clear pattern. Interestingly, all significant DR beta spreads are negative in the emerging markets. Those significant negative DR beta spreads come from the anomalies of *cowc_gr*1*a* (change in current operating working capital) in the accruals cluster, *ret*_6_1 (price momentum *t*-6 to *t*-1) in the momentum cluster, and *niq_be* (quarterly return on equity) in the profitability cluster. Meanwhile, the CF beta spreads in the emerging markets show limited numbers of significance across anomalies, and the directions also vary.

In summary, we cannot digest most of the anomaly returns in the global markets based on the two-beta model of Campbell and Vuolteenaho (2004). The momentum anomalies likely have a positive CF beta spread between the long-leg and short-leg anomaly portfolios and anomalies DR news more often have a negative exposure to the market return. Not surprisingly, the risk-based explanations cannot explain the anomaly returns in the global markets.

1.3.6 Robustness test

We conduct a robustness test to examine whether the patterns differ based on different levels of market development by conducting subsample analysis. Table 8 summarizes the anomaly return and decomposition components for the subsamples of non-U.S. developed markets in Panel A and emerging markets in Panel B. The detailed return decomposition components of each anomaly in each stock market are presented in Appendix C, Figure C1.

[Insert Table 8 here]

From Table 8, we find that most of the significant anomalies in the non-U.S. global markets are from the developed markets. Consistent with the findings in Table 2, most anomalies are driven by CF news except the short-term reversal and value cluster whose dominance is by DR news. Momentum anomalies continue to show offsetting CF news and DR news in the non-U.S. developed market. The value anomaly *ocf_me* (operating cash flow-to-price) is significant in eight of the non-U.S. developed markets, and four of them have negative significant DR news. The other value anomaly *ni_me* (net income-to-price) has a significant DR news component in two of the four non-U.S. developed markets. For both, the significant CF news component is not usual, inconsistent with the finding by Cohen, Polk, and Vuolteenaho (2003) that CF news drives the value premium in the U.S. Panel B reveals that the number of significant anomalies has largely dropped in emerging markets. Among the small number of significant anomalies, we continue to find that the CF news component plays a dominant role in explaining anomaly returns. The offsetting effects of CF news and DR news also hold for the momentum anomaly in emerging markets. The more dominance of DR news for value anomalies is also seen in the emerging markets.

To conclude, both Table 2 and Table 8 show that the prominent anomaly returns are mainly contributed by the CF news component, especially in developed markets. Anomalies in the momentum clusters have significant offsetting CF and DR news components, while short-term reversal and value anomaly returns are more likely to be dominated by the DR news.

1.4 Conclusion

In this paper, we examine the sources of the prominent anomalies in the global financial markets. Unlike the traditional VAR approach, where the DR news is predicted with macroeconomic variables and the CF news is the residual, we follow the approach in Chen et al. (2013) and Mao and Wei (2016) with valuation models and expected earnings to calculate the CF news of a stock in a particular month. With analyst forecasts of future earnings and valuation models, we are able to decompose the return of a stock into the CF news, DR news, and expected return. From all the characteristic-based anomalies, our article focuses on the ones that are prevalent across global markets.

We have three main takeaways from our empirical analyses. First, our anomaly return decomposition on the first moment shows that the CF news mainly drives the anomaly returns for our specified prominent anomalies. Consistent with previous findings (Mao and Wei, 2014), momentum returns have the offsetting effects of the CF news and DR news in the global markets. The CF news is highly positive for momentum anomaly returns, and the negative DR news cancels out part of the overly high CF news. The effects are statistically and economically significant. Short-term reversal and value anomaly returns behave oppositely to momentum anomalies.

Second, the one-month anomaly return variation (i.e., the second moment of our empirical specifications) is almost all dominated by the DR news component across all the markets, but the dominance shifts to CF news variation as the holding period lengthens. The short-term impact of DR news on anomaly return variance shifting to CF news over a longer horizon aligns with previous findings in the U.S. market (Chen et al., 2013). Finally, we cannot find supporting evidence for the risk-based explanation for the anomaly returns using the two-beta model of Campbell and Vuolteenaho (2004) in our sample. The exposure of anomaly returns to the market-wide CF or DR shocks is not closely associated with the anomaly return performance in both the U.S. market and the non-U.S. global markets.

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Table 1. Summary statistics and the correlation matrix

This table tabulates average monthly stock returns in % for each market. Panel A shows averages of the total return, the cash flow news component (CF), the discount rate news component (DR), and the expected return component (ER). N is the number of observations. Panel B displays the correlation matrix among the total return and the return components. All returns are measured in the local currency and winsorized at 1% and 99%.

Panel A: Average stock return, CF news, DR news and expected return

Country	Country code	Starting month	N	Mean (Ret)	Mean (CF)	Mean (DR)	Mean (ER)
Australia	AUS	1990-01	114,509	0.584	-0.600	0.385	0.798
Brazil	BRA	2007-09	20,117	0.611	-0.751	-0.082	1.444
China	CHN	2004-11	209,374	0.864	0.100	-0.305	1.068
France	FRA	1990-01	111,894	0.423	-0.822	0.052	1.192
Germany	DEU	1990-01	127,343	0.142	-0.864	-0.222	1.227
Hong Kong	HKG	1992-12	118,194	0.613	-0.249	-0.385	1.246
India	IDN	1995-02	25,381	0.802	-0.635	-0.238	1.675
Indonesia	IND	1994-11	106,763	1.093	-0.424	0.124	1.392
Italy	ITA	1991-02	50,320	0.250	-1.116	0.105	1.262
Japan	JPN	1990-01	323,878	0.474	-0.174	-0.137	0.785
Korea	KOR	1994-06	84,200	0.229	-0.458	-0.553	1.240
Malaysia	MYS	1991-12	71,198	0.527	-0.451	-0.295	1.273
Netherlands	NLD	1990-11	34,328	0.343	-0.866	0.051	1.158
Norway	NOR	2005-01	24,441	0.673	-0.125	-0.297	1.095
Poland	POL	2010-11	16,791	0.313	-0.010	-0.797	1.121
Singapore	SGP	1993-10	47,816	0.349	-0.369	-0.612	1.329
South Africa	ZAF	1993-07	46,861	0.930	-0.467	0.031	1.366
Sweden	SWE	1996-06	53,958	0.788	-0.210	-0.190	1.188
Switzerland	CHE	1993-10	46,314	0.654	-0.493	0.068	1.078
Taiwan	TWN	1991-10	90,485	0.423	-0.683	-0.263	1.368
Thailand	THA	1991-12	48,688	0.227	-1.173	0.040	1.360
United Kingdom	GBR	1990-01	253,982	0.646	-1.265	-0.811	2.722
United States	USA	1990-01	1,204,636	0.940	-0.777	0.892	0.825

Panel B: Correlation matrix among total return and the three return components for each market

Country		Ret	CF	DR	Country		Ret	CF	DR	Country		Ret	CF	DR
	CF	0.203				CF	0.228				CF	0.181		
AUS	DR	0.446	-0.705		ITA	DR	0.389	-0.769		TWN	DR	0.472	-0.742	
	ER	0.010	-0.081	0.042		ER	0.006	-0.077	0.030		ER	-0.019	-0.089	0.020
	CF	0.218				CF	0.145				CF	0.208		
BRA	DR	0.442	-0.737		JPN	DR	0.476	-0.756		ZAF	DR	0.430	-0.736	
	ER	-0.048	-0.135	0.047		ER	0.033	-0.075	0.053		ER	0.013	-0.165	0.118
	CF	0.092				CF	0.166				CF	0.050		
CHE	DR	0.481	-0.782		KOR	DR	0.483	-0.723		USA	DR	0.318	-0.931	
	ER	0.015	-0.111	0.063		ER	0.016	-0.091	0.053		ER	0.013	-0.073	0.058
	CF	0.091				CF	0.182							
CHN	DR	0.564	-0.732		MYS	DR	0.489	-0.716						
	ER	0.058	-0.107	0.100		ER	0.037	-0.086	0.061					
	CF	0.206				CF	0.196							
DEU	DR	0.355	-0.710		NLD	DR	0.424	-0.746						
	ER	0.009	-0.094	0.036		ER	0.019	-0.102	0.060					
	CF	0.221				CF	0.202							
FRA	DR	0.424	-0.727		NOR	DR	0.400	-0.765						
	ER	0.011	-0.093	0.049		ER	0.001	-0.103	0.056					
	CF	0.289				CF	0.137							
GBR	DR	0.200	-0.826		POL	DR	0.405	-0.811						
	ER	0.009	-0.032	-0.009		ER	-0.011	-0.080	0.037					
	CF	0.174				CF	0.185							
HKG	DR	0.548	-0.661		SGP	DR	0.470	-0.731						
	ER	0.025	-0.108	0.065		ER	0.010	-0.095	0.039					
	CF	0.350				CF	0.155							
IDN	DR	0.487	-0.571		SWE	DR	0.490	-0.722						
	ER	0.062	-0.077	0.072		ER	0.005	-0.106	0.054					
	CF	0.140				CF	0.182							
IND	DR	0.550	-0.698		THA	DR	0.456	-0.740						
	ER	0.012	-0.108	0.059		ER	0.022	-0.111	0.075					

Table 2. Stock anomalies

This table tabulates the summary statistics of anomalies by cluster in the global markets. Panel A shows the number of significant anomaly returns and each return component by cluster. Panel B is about the average total returns and return components of the stock anomalies by cluster. For each market and in each month, we sort all stocks into quintiles based on the anomaly characteristic and estimate the value-weighted total return and return components of the long-short (long-leg minus short-leg) portfolio in the following month. We then estimate the time-series averages. #Sig denotes the number of markets with significant anomaly returns. #Sig_CF, #Sig_DR, and #Sig_ER represent the number of ex-U.S. markets with statistically significant average cash flow news, discount rate news, and expected return, respectively, and the return components are in the same direction as the anomaly return for each anomaly. For the markets with significant total returns associated with the long-short portfolio, we present the mean values of the total return (Return) and the three return components (CF, DR, ER). For comparison, we also show average total returns and return components of the corresponding anomaly for the U.S. market. The values are shown in boldface if they are statistically significant.

Panel A: Number of significant anomalies and components across the global markets

Cluster =	Accruals	Debt Issuance	Investment	Seasonality	Profitability	Quality	Momentum	Profit Growth	Short-Term Reversal	Value
#Sig	12	13	26	5	21	58	50	8	5	34
#Sig CF	2	4	6	2	10	23	45	6	0	2
#Sig DR	1	2	3	0	3	15	1	0	5	12

Panel B: Anomaly returns, CF return and DR return in global markets

		U.S. Market				ex-U.S. International Markets							
Cluster	Anomaly	Return	CF	DR	ER	#Sig	Return	#Sig CF	CF	#Sig DR	DR	#Sig ER	ER
Accruals	*cowc_gr1a*	0.473	**1.300**	-0.784	**-0.042**	5	0.941	1	0.736	1	0.331		-0.126
	oaccruals_at	0.524	0.177	0.408	**-0.061**	5	0.651		0.417		0.357		-0.122
Debt Issuance	*debt_gr3*					8	0.754	4	0.638	1	0.179	1	-0.063
	fnl_gr1a	0.298	0.451	-0.158	0.005	4	0.786		-0.022	1	0.848	1	-0.041
Investment	*capx_gr1*	0.444	0.003	0.432	0.008	4	0.768	2	0.273		0.483	1	0.012
	inv_gr1a					5	0.555		0.055	2	0.501	1	-0.002
	noa_gr1a	0.369	0.382	-0.058	**0.046**	10	0.789	3	0.529		0.271	1	-0.011
Seasonality	*seas_2_5na*					5	0.810	1	0.361	1	0.411	4	0.039
	seas_6_10an	0.680	**0.845**	-0.132	**-0.034**	4	0.661	1	0.360		0.332		-0.031
Profitability	*ebit_bev*	0.367	**0.825**	-0.364	**-0.095**	5	0.655	2	0.466	1	0.272		-0.083
	niq_be					7	0.856	4	0.736	1	0.218	1	-0.099
	ocf_at	0.531	0.302	0.415	**-0.187**	7	0.692	3	0.741	1	0.124		-0.173

Table 2. Continue

		U.S. Market				ex-U.S. International Markets							
Cluster	Anomaly	Return	CF	DR	ER	#Sig	Return	#Sig CF	CF	#Sig DR	DR	#Sig ER	ER
Quality	*cop_at*	0.519	**0.704**	-0.018	**-0.167**	6	0.675		0.066	3	0.706	1	-0.097
	*cop_atl*1	0.463	**0.697**	-0.069	**-0.165**	4	0.726		-0.091	2	1.014		-0.198
	gp_at					7	0.681	2	0.319	2	0.496		-0.134
	*gp_atl*1					5	0.816	1	0.109	2	0.822		-0.116
	mispricing_perf					10	1.048	8	1.662		-0.436	1	-0.178
	niq_at	0.360	**1.361**	**-0.87**	**-0.131**	4	1.043	1	0.780	1	0.449		-0.186
	opex_at	0.316	**0.957**	-0.534	**-0.107**	4	0.675		0.002	2	0.629	1	0.045
	qmj_prof					7	0.695	3	0.520	1	0.332	1	-0.158
	sale_bev	0.625	**1.260**	-0.548	**-0.087**	6	0.630	3	0.320	2	0.330	1	-0.021
Momentum	*resff*3_12_1	0.428	**2.009**	**-1.551**	**-0.030**	10	0.701	8	1.132		-0.409		-0.022
	*resff*3_6_1					7	1.066	6	1.471	1	-0.405	1	-0.001
	*ret*_12_1					9	1.097	9	2.370		-1.140		-0.134
	*ret*_6_1					8	1.239	6	2.346		-0.974		-0.133
	*ret*_9_1					9	1.180	9	2.596		-1.280		-0.137
	*seas*_1_1*na*					6	1.193	6	2.835		-1.460		-0.183
Profit Growth	*ret*_12_7	0.547	**1.588**	**-0.992**	**-0.049**	7	0.870	5	1.048		-0.094		-0.084
Short-Term Reversal	*rmax*5_*rvol*_21*d*	0.516	**-1.060**	**1.556**	**0.020**	4	0.622		-1.056	4	1.669		0.009
Value	*fcf_me*	0.569	0.092	0.425	**0.053**	9	0.797		0.444	1	0.350	2	0.005
	netis_at	0.413	0.121	0.355	**-0.062**	6	0.851	2	0.683		0.256		-0.088
	ni_me					6	0.860		-0.385	4	1.028	4	0.218
	ocf_me	0.495	**-1.531**	**1.89**	**0.135**	10	0.842		-0.192	6	0.979	5	0.055

Table 3. Regression results for each anomaly return, CF news and DR news in U.S.

We run Fama-MacBeth regression with the following empirical specification in the U.S. market:

$$Y_{i,t+1} = a + b * Char_{i,t} + c * ME_{i,t} + d * BM_{i,t} + e * Beta_{i,t} + \epsilon_{i,t+1}$$

where $Y_{i,t+1}$ can be stock return, CF news, DR news for stock *i* in month *t+1*, $Char_{i,t}$ is the anomaly characteristic of stock *i* in month *t.* We control firm size (ME), book-to-market (BM) ratio and market Beta while examine the predictability of each anomaly characteristic on future stock return, CF news and DR news. We examine as to attribute the predictability of anomaly characteristics for future stock returns to their ability to predict future cash flow (CF) news or discount rate (DR) news. Beta is estimated with 1-month daily stock return of stock *i* within month *t* with the market daily return. We show the t-statistic and coefficient on $Char_{i,t}$.

Cluster	Anomaly	Ret	*t*-stat	CF	*t*-stat	DR	*t*-stat
Accruals	*-cowc_gr*1*a*	**2.241**	(6.92)	**2.335**	(3.53)	0.050	(0.07)
	-oaccruals_at	**1.900**	(6.74)	0.700	(1.45)	**1.258**	(2.36)
Debt Issuance	*-fnl_gr*1*a*	**0.886**	(5.35)	**1.020**	(2.94)	-0.115	(-0.31)
Investment	*-capx_gr*1	**0.012**	(1.96)	**0.032**	(2.24)	-0.016	(-1.12)
	*-noa_gr*1*a*	**0.342**	(5.62)	**0.309**	(2.43)	0.040	(0.28)
Seasonality	*seas*_6_10*an*	**3.083**	(5.43)	-0.271	(-0.25)	**3.429**	(2.85)
Profitability	*ebit_bev*	**0.033**	(2.24)	0.012	(0.43)	0.033	(1.09)
	ocf_at	**1.291**	(3.38)	**0.921**	(1.75)	0.895	(1.45)
Quality	*cop_at*	**1.757**	(8.90)	-0.007	(-0.02)	**1.903**	(5.26)
	*cop_atl*1	**0.303**	(3.28)	**-0.295**	(-1.65)	**0.633**	(3.30)
	niq_at	0.955	(1.12)	**3.844**	(3.03)	**-2.486**	(-1.77)
	opex_at	**0.231**	(4.50)	-0.009	(-0.13)	**0.232**	(2.93)
	sale_bev	**0.011**	(4.02)	-0.003	(-0.80)	**0.013**	(2.63)
Momentum	*resff*3_12_1	**0.889**	(5.00)	**2.736**	(13.84)	**-1.788**	(-6.99)
Profit Growth	*ret*_12_7	**0.510**	(2.73)	**1.831**	(8.88)	**-1.322**	(-4.83)
Short-Term Reversal	*-rmax*5_*rvol*_21*d*	**0.502**	(5.29)	**-1.115**	(-9.07)	**1.610**	(10.67)
Value	*fcf_me*	**0.500**	(4.22)	**0.667**	(3.19)	-0.138	(-0.59)
	-netis_at	**0.351**	(2.42)	**0.602**	(3.19)	-0.154	(-0.71)
	ocf_me	**0.404**	(3.45)	0.294	(1.55)	0.109	(0.51)

Table 4. Summary of regression results for each anomaly return, CF news and DR news in international markets
This table summarizes the significant regression coefficients for each characteristic and future stock return, CF news and DR news. We run Fama-MacBeth regression for each market outside the U.S. market:

$$Y_{i,t+1} = a + b * Char_{i,t} + c * ME_{i,t} + d * BM_{i,t} + e * Beta_{i,t} + \epsilon_{i,t+1}$$

where $Y_{i,t+1}$ can be stock return, CF news, DR news for stock *i* in month *t+1*, $Char_{i,t}$ is the anomaly characteristic of stock *i* in month *t*. We control firm size (ME), book-to-market (BM) ratio and market Beta while examine the predictability of each anomaly characteristic on future stock return, CF news and DR news. We examine as to attribute the predictability of anomaly characteristics for future stock returns to their ability to predict future cash flow (CF) news or discount rate (DR) news. Beta is estimated with 1-month daily stock return of stock *i* within month *t* with the market daily return. We count the number of significant characteristic coefficients with the positive direction. The column direction is the correct direction of the characteristic's predictive power.

Cluster	Anomaly	#Return	#CF news	#DR news
Accruals	*cowc_gr*1*a*	2	0	2
	oaccruals_at	3	1	2
Debt Issuance	*debt_gr*3	1	1	0
	*fnl_gr*1*a*	3	1	0
Investment	*capx_gr*1	0	1	0
	*inv_gr*1*a*	2	1	1
	*noa_gr*1*a*	6	5	0
	*seas*_2_5*na*	2	2	0
Seasonality	*seas*_6_10*an*	3	1	2
Profitability	*ebit_bev*	2	0	1
	niq_be	2	1	0
	ocf_at	7	2	4
Quality	*cop_at*	6	1	4
	*cop_atl*1	3	0	2
	gp_at	3	0	1
	*gp_atl*1	1	0	3
	mispricing_perf	8	8	0
	niq_at	3	0	1
	opex_at	3	1	2
	qmj_prof	7	0	7
	sale_bev	5	0	2
Momentum	*resff*3_12_1	10	10	0
	*resff*3_6_1	6	7	0
	*ret*_12_1	7	8	0
	*ret*_6_1	8	7	0
	*ret*_9_1	9	8	0
	*seas*_1_1*na*	5	6	0
Profit Growth	*ret*_12_7	4	3	1
Short-Term Reversal	*rmax*5_*rvol*_21*d*	4	0	4
Value	*fcf_me*	4	1	2
	netis_at	5	4	0
	ni_me	2	1	0
	ocf_me	8	1	6

Table 5. Variance decomposition for anomaly returns

We present the average fraction of the return variance explained by CF news and DR news for each anomaly. For each market, we sort all stocks into quintiles based on the anomaly characteristic and estimate the value-weighted total return and return components of the long-short (long-leg minus short-leg) portfolio in the following month. We calculate both the monthly anomaly return and the annual anomaly return. Following Chen et al. (2013), we decompose the variance of the unexpected return into its covariance with CF news and its covariance with DR news. For each long-short portfolio, we then average the fraction of return variance explained by CF news and DR news across all markets.

Cluster	Anomaly	(1)	(2)	(3)	(4)
		Horizon: 1-month		Horizon: 1-year	
		CF news	DR news	CF news	DR news
Accruals	*cowc_gr*1*a*	0.276	0.724	0.340	0.660
	oaccruals_at	0.301	0.699	0.559	0.441
Debt Issuance	*debt_gr*3	0.252	0.747	-0.180	1.180
	*fnl_gr*1*a*	0.092	0.908	0.458	0.542
Investment	*capx_gr*1	0.187	0.813	0.768	0.232
	*inv_gr*1*a*	0.194	0.806	0.170	0.830
	*noa_gr*1*a*	0.215	0.785	0.742	0.258
Seasonality	*seas*_2_5*na*	0.194	0.805	0.724	0.276
	*seas*_6_10*an*	0.292	0.708	0.500	0.500
Profitability	*ebit_bev*	0.215	0.785	0.643	0.357
	niq_be	0.183	0.817	0.444	0.556
	ocf_at	0.194	0.806	0.800	0.200
Quality	*cop_at*	0.259	0.741	0.156	0.844
	*cop_atl*1	0.157	0.843	0.898	0.102
	gp_at	0.236	0.764	0.931	0.069
	*gp_atl*1	0.257	0.743	1.531	-0.531
	mispricing_perf	0.286	0.714	0.664	0.336
	niq_at	0.224	0.776	0.770	0.230
	opex_at	0.167	0.832	0.190	0.810
	qmj_prof	0.254	0.746	0.693	0.307
	sale_bev	0.083	0.917	0.214	0.786
Momentum	*resff*3_12_1	0.186	0.813	0.507	0.493
	*resff*3_6_1	0.144	0.856	0.564	0.436
	*ret*_12_1	0.271	0.729	0.743	0.257
	*ret*_6_1	0.229	0.771	0.616	0.384
	*ret*_9_1	0.263	0.737	0.540	0.460
	*seas*_1_1*na*	0.271	0.729	0.586	0.414
Profit Growth	*ret*_12_7	0.199	0.801	0.413	0.587
Short-Term Reversal	*rmax*5_*rvol*_21*d*	0.192	0.808	0.673	0.327
Value	*fcf_me*	0.224	0.776	0.423	0.577
	netis_at	0.251	0.749	0.065	0.935
	ni_me	0.248	0.752	0.150	0.850
	ocf_me	0.276	0.724	0.560	0.440

Table 6. Anomaly long-short portfolio beta difference in the U.S. market

This table presents the differences in CF beta or DR beta between the long and short quintiles of each anomaly (d(β_{CF}) and d(β_{DR})) in the U.S. market. The t-statistics (*t*-stat) are based on the Newey-west adjusted standard errors with three lags.

Cluster	Anomaly	d(β_{CF})	*t*-stat	d(β_{DR})	*t*-stat
Accruals	*cowc_gr1a*	0.021	(0.80)	-0.049	(-1.29)
	oaccruals_at	0.032	(1.24)	0.000	(-0.01)
Debt Issuance	*fnl_gr1a*	-0.025	(-1.47)	0.043	(1.41)
Investment	*capx_gr1*	-0.046	(-1.41)	0.036	(0.78)
	noa_gr1a	-0.020	(-0.68)	0.025	(0.54)
Seasonality	*seas*_6_10*an*	0.016	(0.50)	-0.007	(-0.12)
Profitability	*ebit_bev*	-0.025	(-0.67)	-0.087	(-1.47)
	ocf_at	0.015	(0.45)	**-0.091**	**(-1.84)**
Quality	*cop_at*	0.039	(1.21)	**-0.142**	**(-3.18)**
	cop_atl1	**0.064**	**(1.92)**	**-0.146**	**(-3.12)**
	niq_at	-0.007	(-0.19)	**-0.128**	**(-2.57)**
	opex_at	-0.008	(-0.27)	-0.058	(-1.02)
	sale_bev	-0.010	(-0.38)	-0.052	(-1.03)
Momentum	*resff*3_12_1	0.001	(0.03)	0.019	(0.36)
Profit Growth	*ret*_12_7	-0.037	(-0.96)	-0.040	(-0.55)
Short-Term Reversal	*rmax*5_*rvol*_21*d*	0.019	(0.54)	-0.037	(-0.57)
Value	*fcf_me*	**-0.056**	**(-1.86)**	0.050	(1.22)
	netis_at	-0.007	(-0.16)	-0.010	(-0.19)
	ocf_me	-0.035	(-1.08)	0.078	(1.54)

Table 7. The number of significant anomaly beta differences in the international markets

This table displays the number of significant CF beta or DR beta differences between the long and short quintiles of each anomaly in the ex-U.S. global markets (ex-U.S.), developed markets (Dev) and emerging markets (Eme). We count the number of significant beta spreads between each significant anomaly's long-leg and short-leg and also record the directions. The *t*-stat is based on the Newey-West adjusted standard errors with three lags.

Cluster	Anomaly	#Sig positive d(β_{CF})			#Sig negative d(β_{CF})			#Sig positive d(β_{DR})			#Sig negative d(β_{DR})		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme
Accruals	*cowc_gr1a*	0	0	0	0	0	0	1	1	0	1	0	1
	oaccruals_at	0	0	0	0	0	0	0	0	0	0	0	0
Debt Issuance	*debt_gr*3	0	0	0	3	1	2	0	0	0	0	0	0
	*fnl_gr*1*a*	1	1	0	1	1	0	0	0	0	0	0	0
	*capx_gr*1	0	0	0	1	0	1	0	0	0	0	0	0
Investment	*inv_gr*1*a*	0	0	0	0	0	0	0	0	0	1	1	0
	*noa_gr*1*a*	1	1	0	0	0	0	2	2	0	1	1	0
	*seas*_2_5*na*	0	0	0	0	0	0	0	0	0	0	0	0
Seasonality	*seas*_6_10*an*	0	0	0	2	2	0	1	1	0	0	0	0
	ebit_bev	0	0	0	1	1	0	0	0	0	1	1	0
Profitability	*niq_be*	1	1	0	0	0	0	0	0	0	3	2	1
	ocf_at	1	1	0	0	0	0	0	0	0	2	2	0
	cop_at	0	0	0	0	0	0	0	0	0	0	0	0
	*cop_atl*1	0	0	0	0	0	0	0	0	0	1	1	0
	gp_at	0	0	0	0	0	0	0	0	0	1	1	0
	*gp_atl*1	0	0	0	0	0	0	0	0	0	1	1	0
Quality	*mispricing_perf*	1	1	0	0	0	0	0	0	0	2	2	0
	niq_at	1	1	0	0	0	0	0	0	0	1	1	0
	opex_at	0	0	0	0	0	0	0	0	0	0	0	0
	qmj_prof	3	3	0	1	1	0	0	0	0	4	4	0
	sale_bev	1	0	1	2	2	0	0	0	0	0	0	0
	*resff*3_12_1	2	2	0	1	0	1	0	0	0	2	2	0
	*resff*3_6_1	3	3	0	0	0	0	0	0	0	1	1	0
Momentum	*ret*_12_1	0	0	0	0	0	0	0	0	0	1	1	0
	*ret*_6_1	2	2	0	0	0	0	0	0	0	1	0	1
	*ret*_9_1	1	1	0	0	0	0	0	0	0	1	1	0
	*seas*_1_1*na*	1	0	1	0	0	0	0	0	0	0	0	0
Profit Growth	*ret*_12_7	0	0	0	0	0	0	0	0	0	1	1	0

Table 7. Continue

Cluster	Anomaly	#Sig positive d(β_{CF})			#Sig negative d(β_{CF})			#Sig positive d(β_{DR})			#Sig negative d(β_{DR})		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(6)
		ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme	ex-U.S.	Dev	Eme
Short-Term Reversal	$rmax5\_rvol\_21d$	0	0	0	0	0	0	0	0	0	0	0	0
Value	*fcf_me*	0	0	0	0	0	0	0	0	0	1	1	0
	netis_at	1	1	0	0	0	0	0	0	0	2	1	1
	ni_me	0	0	0	1	1	0	0	0	0	0	0	0
	ocf_me	1	1	0	1	1	0	0	0	0	0	0	0

Table 8. Stock anomalies in the ex-U.S. developed markets and emerging markets

This table tabulates stock anomalies' average total returns and return components by cluster in the ex-U.S. developed markets (Panel A), the emerging markets (Panel B). For each market and in each month, we sort all stocks into quintiles based on the anomaly characteristic and estimate the value-weighted total return and return components of the long-short (long-leg minus short-leg) portfolio in the following month. We then estimate the time-series averages. #Sig denotes the number of markets with significant anomaly returns. #Sig_CF, #Sig_DR, and #Sig_ER represent the number of ex-U.S. markets with statistically significant average cash flow news, discount rate news, and expected return, respectively, and the return components are in the same direction as the anomaly return for each anomaly. For the markets with significant total returns associated with the long-short portfolio, we present the number of significant anomaly returns in Panel A1 and Panel B1, mean values of the total return (Return) and the three return components (CF, DR, ER) in Panel A2 and Panel B2. The mean values of the significant components of each significant anomaly in different markets are also reported as Mean CF, Mean DR, and Mean ER.

Panel A1: Number of significant anomalies and components in ex U.S. developed markets

Cluster =	Accruals	Debt Issuance	Investment	Seasonality	Profitability
#Sig	9	9	18	4	16
#Sig CF	1	2	4	1	8
#Sig DR	1	1	2	0	3
Cluster =	Quality	Momentum	Profit Growth	Short-Term Reversal	Value
#Sig	39	25	3	4	25
#Sig CF	14	24	2	0	2
#Sig DR	12	1	0	4	7

Panel A2: ex U.S. developed markets

Cluster	Anomaly	#Sig	Return	#Sig CF	CF	#Sig DR	DR	#Sig ER	ER
Accruals	*cowc_gr1a*	4	1.039	1	0.859	1	0.340		-0.161
	oaccruals_at	5	0.651		0.417		0.357		-0.122
Debt Issuance	*debt_gr3*	6	0.610	2	0.369	1	0.272	1	-0.032
	fnl_gr1a	3	0.642		0.056		0.597	1	-0.011
Investment	*capx_gr1*	3	0.792	2	0.518		0.271	1	0.003
	inv_gr1a	4	0.465		0.101	1	0.348	1	0.015
	noa_gr1a	7	0.819	1	0.656		0.145	1	0.018
Seasonality	*seas_2_5na*	4	0.819	1	0.393	1	0.404	3	0.022
	seas_6_10an	4	0.661	1	0.360		0.332		-0.031
Profitability	*ebit_bev*	4	0.669	2	0.509	1	0.261		-0.102
	niq_be	5	0.792	3	0.751	1	0.188		-0.147
	ocf_at	7	0.692	3	0.741	1	0.124		-0.173
Quality	*cop_at*	6	0.675		0.066	3	0.706	1	-0.097
	cop_atl1	3	0.755		0.056	1	0.823		-0.125
	gp_at	5	0.708	1	0.316	2	0.479		-0.087
	gp_atl1	4	0.863	1	0.124	2	0.832		-0.094
	mispricing_perf	6	0.997	6	1.697		-0.550	1	-0.151
	niq_at	3	1.042	1	0.850	1	0.413		-0.221
	opex_at	2	0.723		-0.212	1	0.835	1	0.100
	qmj_prof	7	0.695	3	0.520	1	0.332	1	-0.158
	sale_bev	3	0.492	2	0.260	1	0.223	1	0.009

Table 8. Continue

	*resff*3_12_1	6	0.686	6	1.282		-0.577		-0.020
	*resff*3_6_1	4	1.148	3	1.443	1	-0.300	1	0.004
Momentum	*ret*_12_1	6	0.993	6	2.332		-1.234		-0.106
	*ret*_6_1	3	0.853	3	2.828		-1.851		-0.124
	*ret*_9_1	4	1.106	4	2.780		-1.559		-0.115
	*seas*_1_1*na*	2	1.106	2	2.893		-1.591		-0.196
Profit Growth	*ret*_12_7	3	0.848	2	0.852		0.082		-0.086
Short-Term Reversal	*rmax*5_*rvol*_21*d*	4	0.622		-1.056	4	1.669		0.009
	fcf_me	8	0.808		0.444	1	0.346	2	0.019
Value	*netis_at*	5	0.920	2	0.797		0.213		-0.090
	ni_me	4	0.700		-0.356	2	0.696	3	0.360
	ocf_me	8	0.675		-0.174	4	0.658	5	0.191

Panel B1: Number of significant anomalies and components in emerging markets

Cluster =	Accruals	Debt Issuance	Investment	Profitability	Quality
#Sig	1	3	6	3	14
#Sig CF	0	2	2	1	4
#Sig DR	0	1	1	0	3
Cluster =	Momentum	Profit Growth	Value		
#Sig	24	4	6		
#Sig CF	20	3	0		
#Sig DR	0	0	4		

Panel B2: Emerging markets

Cluster	Anomaly	#Sig	Return	#Sig CF	CF	#Sig DR	DR	#Sig ER	ER
Accruals	*cowc_gr*1*a*	1	0.553		0.243		0.297		0.014
Debt Issuance	*debt_gr*3	2	1.188	2	1.442		-0.100		-0.156
	*fnl_gr*1*a*	1	1.217		-0.256	1	1.602		-0.129
	*capx_gr*1	1	0.696		-0.462		1.117		0.041
Investment	*inv_gr*1*a*	1	0.915		-0.128	1	1.114		-0.070
	*noa_gr*1*a*	3	0.717	2	0.230		0.566		-0.079
	*seas*_2_5*na*	1	0.778		0.234		0.435	1	0.109
Profitability	*ebit_bev*	1	0.600		0.296		0.314		-0.011
	niq_be	2	1.015	1	0.700		0.294	1	0.022
	cop_atl1	1	0.639		-0.531	1	1.588		-0.418
	gp_at	2	0.613	1	0.325		0.539		-0.251
	*gp_atl*1	1	0.630		0.050		0.784		-0.204
Quality	*mispricing_perf*	4	1.126	2	1.610	1	-0.267		-0.219
	niq_at	1	1.047		0.571		0.554		-0.080
	opex_at	2	0.628		0.215	1	0.424		-0.011
	sale_bev	3	0.768	1	0.380	1	0.437		-0.050

Table 8. Continue									
	*resff*3_12_1	4	0.724	2	0.905		-0.157		-0.024
	*resff*3_6_1	3	0.957	3	1.509		-0.546		-0.006
Momentum	*ret*_12_1	3	1.305	3	2.447		-0.953		-0.189
	*ret*_6_1	5	1.471	3	2.056		-0.448		-0.138
	*ret*_9_1	5	1.239	5	2.449		-1.056		-0.154
	*seas*_1_1*na*	4	1.236	4	2.806		-1.395		-0.176
Profit Growth	*ret*_12_7	4	0.887	3	1.195		-0.225		-0.083
	fcf_me	1	0.712		0.443		0.377		-0.108
Value	*netis_at*	1	0.505		0.109		0.471		-0.075
	ni_me	2	1.182		-0.445	2	1.692	1	-0.066
	ocf_me	2	1.511		-0.262	2	2.263		-0.490

Appendix A: Details of Anomaly Clusters

Cluster	Abbreviation	Description	Reference Paper
Accruals	*cowc_gr*1*a*	Change in current operating working capital	Richardson et al. (2005)
	oaccruals_at	Operating accruals	Sloan (1996)
Debt Issuance	*debt_gr*3	Growth in book debt (3 years)	Lyandres Sun and Zhang (2008)
	fnl_gr1a	Change in financial liabilities	Richardson et al. (2005)
Investment	*capx_gr*1	CAPEX growth (1 year)	Xie (2001)
	*inv_gr*1*a*	Inventory change	Thomas and Zhang (2002)
	*noa_gr*1*a*	Change in net operating assets	Hirshleifer et al. (2004)
	*seas*_2_5*na*	Years 2-5 lagged returns, nonannual	Heston and Sadka (2008)
Momentum	*resff*3_12_1	Residual momentum t-12 to t-1	Blitz Huij and Martens (2011)
	*resff*3_6_1	Residual momentum t-6 to t-1	Blitz Huij and Martens (2011)
	*ret*_12_1	Price momentum t-12 to t-1	Jegadeesh and Titman (1993)
	*ret*_6_1	Price momentum t-6 to t-1	Jegadeesh and Titman (1993)
	*ret*_9_1	Price momentum t-9 to t-1	Jegedeesh and Titman (1993)
	*seas*_1_1*na*	Year 1-lagged return, nonannual	Heston and Sadka (2008)
Profit Growth	*ret*_12_7	Price momentum t-12 to t-7	Novy-Marx (2012)
Profitability	*ebit_bev*	Return on net operating assets	Soliman (2008)
	niq_be	Quarterly return on equity	Hou Xue and Zhang (2015)
	ocf_at	Operating cash flow to assets	Bouchard, Krüger, Landier and Thesmar (2019)
Quality	*cop_at*	Cash-based operating profits-to-book assets	
	*cop_atl*1	Cash-based operating profits-to-lagged book assets	Ball et al. (2016)
	gp_at	Gross profits-to-assets	Novy-Marx (2013)
	*gp_atl*1	Gross profits-to-lagged assets	
	mispricing_perf	Mispricing factor: Performance	Stambaugh and Yuan (2016)
	niq_at	Quarterly return on assets	Balakrishnan Bartov and Faurel
	opex_at	Operating leverage	Novy-Marx (2011)
	qmj_prof	Quality minus Junk: Profitability	Assness, Frazzini and Pedersen
	sale_bev	Asset turnover	Soliman (2008)
Seasonality	*seas*_6_10*an*	Years 6-10 lagged returns, annual	Heston and Sadka (2008)
Short-Term Reversal	*rmax*5_*rvol*_21*d*	Highest 5 days of return scaled by volatility	Assness, Frazzini, Gormsen, Pedersen (2020)
Value	*fcf_me*	Free cash flow-to-price	Lakonishok Shleifer and Vishny
	netis_at	Net total issuance	Bradshaw Richardson and Sloan
	ni_me	Earnings-to-price	Basu (1983)
	ocf_me	Operating cash flow-to-price	Desai Rajgopal and

Appendix B. Valuation models

We use 4 popular valuation models to link each firm's earnings forecast with the stock prices. If both sides of the valuation model equal to each other, we can therefore get the corresponding ICC for each model specified. The four valuation models are as follows:

(1) Gebhardt, Lee, and Swaminathan (GLS 2001) model:

$$\mathrm{P}_t^* = B_t + \sum_{i=1}^{T-1} \frac{\left(FROE_{t+i} - R_{gls}\right) \times B_{t+i-1}}{\left(1 + R_{gls}\right)^i} + \frac{\left(FROE_{t+T} - R_{gls}\right) \times B_{i+T-1}}{\left(1 + R_{gls}\right)^{T-1} \times R_{gls}};$$

(2) Claus and Thomas (CT 2001):

$$\mathrm{P}_t^* = B_t + \sum_{i=1}^{5} \frac{\left(FEPS_{t+i} - R_{ct} \times B_{t+i-1}\right)}{\left(1 + R_{ct}\right)^i} + \frac{\left(FEPS_{t+5} - R_{ct} \times B_{t+4}\right) \times \left(1 + g_{lt}\right)}{\left(R_{ct} - g_{lt}\right) \times \left(1 + R_{ct}\right)^5}$$

(3) Ohlson and Juettner-Nauroth (OJ 2005) as implemented by Gode and Mohanram (2003):

$$\mathrm{P}_t^* = \frac{E(EPS_{t+1})}{R_{oj}} + \frac{E(EPS_{t+1}) \times E[g_{st} - R_{oj} \times (1 - POUT)]}{R_{oj} \times (R_{oj} - g_{lt})}$$

(4) the modified PEG ratio model of Easton (MPEG 2004):

$$\mathrm{P}_t^* = \frac{E(EPS_{t+1})}{R_{mpeg}} + \frac{E(EPS_{t+1}) \times E[g_{st} - R_{mpeg} \times (1 - POUT)]}{R_{mpeg}^2}$$

where $\mathrm{P}_t^* = P_t/\left(1 + R_{gls}\right)^{\frac{lag}{12}}$ is the adjusted stock price so that P_t^* is one year before the I/B/E/S one-year-ahead earnings forecast date (fpedats); P_t is the before-dividend price in month t; B_t is the book value of equity per share in month t; T is set at 12; and F ROE is the earnings per share forecast divided by the book value of equity per share for the first three years, declining linearly to an equilibrium return on equity from the fourth year to the 12th year. The equilibrium return on equity is calculated as the past 10year industry-level median return on equity. The industry level ROE is winsorized to a value between the risk-free rate and 0.3. The book value of equity is estimated using the clean-surplus condition $\mathrm{B}_{t+1} = \mathrm{B}_t + \mathrm{EPS}_{t+1} - \mathrm{DPS}_{t+1}$, where DPS_{t+i} is equal to EPS_{t+i} multiplied by POUT, POUT is the current dividend payout ratio, and FEPS_{t+i} is calculated using the long-term earnings growth rate from I/B/E/S or the growth rate implied by EPS_{t+2} and EPS_{t+3}. The longterm abnormal earnings growth rate, g_{lt}, is calculated using the contemporaneous risk-free rate minus 3%. The short-term earnings growth rate, g_{st}, is the average of the shortterm earnings growth rate implied by EPS_{t+1}, EPS_{t+2}, and analysts' long-term growth rate forecasts.

Appendix C: Results on country-level analysis for each anomaly

Table C1: Fama-MacBeth Regression results for each country

Figure C1: Return decomposition of anomalies for each country

Figure C2. Variance decomposition of stock anomaly 1-month returns by country

Table C1. Fama-MacBeth Regression results for each country

This table shows the regression results for future stock return, CF news and DR news on each anomaly characteristic. We run Fama-MacBeth regression in each market:

$$Y_{i,t+1} = a + b * Char_{i,t} + c * ME_{i,t} + d * BM_{i,t} + e * Beta_{i,t} + \epsilon_{i,t+1}$$

where $Y_{i,t+1}$ can be stock return, CF news, DR news for stock *i* in month *t+1*, $Char_{i,t}$ is the anomaly characteristic of stock *i* in month *t.* We control firm size (ME), book-to-market (BM) ratio and market Beta while examine the predictability of each anomaly characteristic on future stock return, CF news and DR news. Beta is estimated with 1-month daily stock return of stock *i* within month *t* with the market daily return. This table many shows coefficient *b* in each country. We show the t-statistic and coefficient on $Char_{i,t}$.

Panel A: Accruals

	Ret	CF	DR	Ret	CF	DR	RET	CF	DR
	AUS	AUS	AUS	HKG	HKG	HKG	SGP	SGP	SGP
cowc_gr1a	**-0.024**	0.019	**-0.043**	**-0.038**	-0.019	**-0.023**	-0.014	0.011	-0.03
	(-3.74)	(1.39)	**(-3.17)**	**(-4.26)**	(-1.40)	**(-1.69)**	(-1.31)	(0.59)	(-1.59)

	RET	CF	DR	RET	CF	DR	RET	CF	DR	RET	CF	DR	RET	CF	DR
	AUS	AUS	AUS	GBR	GBR	GBR	HKG	HKG	HKG	SGP	SGP	SGP	TWN	TWN	TWN
oaccruals_at	**-0.011**	-0.006	-0.003	**-0.011**	-0.011	-0.009	**-0.037**	**-0.022**	**-0.016**	-0.013	0.012	**-0.033**	-0.012	0.03	-0.045
	(-2.12)	(-0.75)	(-0.43)	**(-2.59)**	(-1.15)	(-0.95)	**(-5.69)**	**(-2.38)**	**(-1.69)**	(-1.35)	(0.75)	**(-1.95)**	(-1.14)	(1.10)	(-1.46)

Panel B: Debt Issuance

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	HKG	HKG	HKG	SGP	SGP	SGP	SWE	SWE	SWE
*debt_gr*3	-0.001	-0.001	0.000	0.000	**-0.001**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000
	(-1.05)	(-0.22)	(-0.04)	(-1.26)	**(-2.09)**	(1.35)	(-1.29)	(-0.92)	(0.43)	**(-2.26)**	(-1.16)	(0.61)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	DEU	DEU	DEU	HKG	HKG	HKG
*fnl_gr*1*a*	**-0.024**	-0.018	-0.004	**-0.018**	-0.016	-0.002	**-0.02**	**-0.019**	-0.003
	(-3.06)	(-1.53)	(-0.38)	**(-2.12)**	(-0.85)	(-0.11)	**(-3.80)**	**(-2.47)**	(-0.45)

Panel C: Investment

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	DEU	DEU	DEU	HKG	HKG	HKG
*capx_gr*1	-0.022	0.117	-0.136	-0.001	0.001	-0.002	0.000	-0.001	0.000
	(-0.78)	(0.91)	(-0.89)	(-1.00)	(0.52)	(-0.86)	(-1.64)	(-1.71)	(0.69)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	GBR	GBR	GBR	JPN	JPN	JPN	THA	THA	THA	TWN	TWN	TWN
*inv_gr*1*a*	**-0.024**	-0.028	-0.001	**-0.031**	**-0.041**	0.005	-0.054	-0.061	0.000	-0.021	0.054	**-0.081**
	(-2.46)	(-1.42)	(-0.08)	**(-2.49)**	**(-3.00)**	(0.32)	(-1.42)	(-1.25)	(0.01)	(-1.63)	(1.41)	**(-1.86)**

Panel C: Investment (continue)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHE	CHE	CHE	CHN	CHN	CHN	DEU	DEU	DEU	GBR	GBR	GBR
noa_gr1a	**-0.004**	0.000	-0.003	**-0.014**	**-0.017**	0.002	-0.001	**-0.003**	0.001	**-0.007**	**-0.011**	0.003	**-0.005**	-0.006	0.002
	(-1.76)	(-0.12)	(-0.89)	**(-3.01)**	**(-1.78)**	(0.24)	(-0.93)	**(-1.72)**	(0.42)	**(-3.04)**	**(-2.12)**	(0.55)	**(-2.40)**	(-1.00)	(0.38)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	KOR	KOR	KOR	NOR	NOR	NOR	SGP	SGP	SGP	THA	THA	THA
noa_gr1a	**-0.019**	**-0.017**	-0.002	-0.007	**-0.013**	0.007	-0.007	-0.010	0.000	**-0.009**	-0.005	-0.005
	(-3.18)	**(-1.99)**	(-0.22)	(-1.50)	**(-1.96)**	(1.07)	(-1.59)	(-1.15)	(0.05)	**(-1.75)**	(-0.56)	(-0.63)

	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	JPN	JPN	JPN
seas_2_5na	**-0.195**	**-0.149**	-0.04	**-0.124**	**-0.224**	**0.091**
	(-4.27)	**(-1.86)**	(-0.51)	**(-3.36)**	**(-4.92)**	**(1.86)**

Panel D: Momentum

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	BRA	BRA	BRA	CHN	CHN	CHN	FRA	FRA	FRA	GBR	GBR	GBR
*resff*3_12_1	**0.018**	**0.027**	**-0.008**	**0.014**	**0.024**	-0.009	**0.009**	**0.018**	**-0.009**	**0.012**	**0.015**	-0.003	**0.015**	**0.017**	-0.002
	(9.21)	**(9.58)**	**(-2.43)**	**(3.70)**	**(3.21)**	(-1.14)	**(3.65)**	**(7.10)**	**(-2.57)**	**(7.21)**	**(6.06)**	(-0.97)	**(8.20)**	**(5.50)**	(-0.56)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	HKG	HKG	HKG	JPN	JPN	JPN	THA	THA	THA	TWN	TWN	TWN	ZAF	ZAF	ZAF
*resff*3_12_1	**0.019**	**0.024**	-0.004	**0.006**	**0.011**	**-0.005**	**0.008**	**0.02**	**-0.012**	**0.011**	**0.011**	-0.001	**0.016**	**0.023**	-0.006
	(8.68)	**(9.27)**	(-1.33)	**(3.96)**	**(6.62)**	**(-2.72)**	**(3.11)**	**(4.89)**	**(-2.99)**	**(4.34)**	**(3.28)**	(-0.20)	**(4.99)**	**(5.59)**	(-1.43)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	HKG	HKG	HKG	JPN	JPN	JPN	MYS	MYS	MYS	NLD	NLD	NLD
*resff*3_6_1	**0.006**	**0.013**	**-0.006**	**0.005**	**0.012**	**-0.006**	**0.003**	**0.007**	**-0.005**	**0.005**	**0.009**	**-0.003**	0.001	**0.006**	**-0.005**
	(6.51)	**(7.90)**	**(-3.83)**	**(4.10)**	**(9.13)**	**(-4.40)**	**(3.93)**	**(10.38)**	**(-5.18)**	**(4.63)**	**(5.66)**	**(-2.12)**	(0.45)	**(2.25)**	**(-1.70)**

	Ret	CF	DR	Ret	CF	DR
	POL	POL	POL	THA	THA	THA
*resff*3_6_1	**0.003**	**0.01**	**-0.006**	**0.005**	**0.01**	**-0.005**
	(1.83)	**(3.10)**	**(-1.65)**	**(3.74)**	**(4.68)**	**(-2.40)**

Panel D: Momentum (continue)															
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHE	CHE	CHE	DEU	DEU	DEU	GBR	GBR	GBR	HKG	HKG	HKG
*ret*_12_1	**0.015**	**0.021**	**-0.007**	**0.011**	**0.032**	**-0.02**	**0.017**	**0.027**	**-0.01**	**0.011**	**0.019**	**-0.008**	**0.007**	**0.017**	**-0.008**
	(7.66)	**(6.26)**	**(-1.94)**	**(3.72)**	**(8.11)**	**(-4.26)**	**(6.29)**	**(8.17)**	**(-3.24)**	**(4.85)**	**(6.92)**	**(-3.33)**	**(2.66)**	**(6.48)**	**(-3.16)**
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	IND	IND	IND	SWE	SWE	SWE	THA	THA	THA	ZAF	ZAF	ZAF			
*ret*_12_1	0.008	0.01	-0.002	**0.011**	**0.017**	-0.005	0.005	**0.039**	-0.033	**0.024**	**0.058**	**-0.032**			
	(1.14)	(1.02)	(-0.15)	**(3.94)**	**(5.72)**	(-1.51)	(1.12)	**(1.83)**	(-1.44)	**(3.75)**	**(2.20)**	**(-1.34)**			
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	BRA	BRA	BRA	CHE	CHE	CHE	HKG	HKG	HKG	IND	IND	IND
*ret*_6_1	**0.025**	**0.051**	**-0.026**	**0.022**	**0.039**	**-0.016**	**0.026**	**0.051**	**-0.024**	**0.013**	**0.038**	**-0.022**	**0.016**	0.016	0.000
	(7.37)	**(7.14)**	**(-3.64)**	**(3.66)**	**(4.54)**	**(-1.82)**	**(6.05)**	**(7.79)**	**(-3.23)**	**(3.21)**	**(9.61)**	**(-5.25)**	**(1.72)**	(1.33)	(0.04)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR						
	POL	POL	POL	THA	THA	THA	ZAF	ZAF	ZAF						
*ret*_6_1	**0.022**	**0.049**	**-0.025**	**0.017**	**0.024**	-0.007	**0.027**	**0.075**	**-0.047**						
	(3.22)	**(5.51)**	**(-2.36)**	**(3.10)**	**(2.98)**	(-0.92)	**(4.01)**	**(4.18)**	**(-2.82)**						
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	DEU	DEU	DEU	HKG	HKG	HKG	IND	IND	IND	MYS	MYS	MYS
*ret*_9_1	**0.018**	**0.031**	**-0.012**	**0.019**	**0.035**	**-0.015**	**0.011**	**0.025**	**-0.012**	**0.015**	0.007	0.007	**0.012**	**0.027**	**-0.015**
	(7.29)	**(7.53)**	**(-2.83)**	**(5.81)**	**(8.51)**	**(-3.93)**	**(3.63)**	**(8.28)**	**(-3.65)**	**(2.32)**	(0.78)	(0.70)	**(3.52)**	**(7.12)**	**(-3.32)**
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	NLD	NLD	NLD	POL	POL	POL	THA	THA	THA	ZAF	ZAF	ZAF			
*ret*_9_1	**0.011**	**0.024**	**-0.012**	**0.017**	**0.041**	**-0.023**	**0.012**	**0.033**	-0.02	**0.024**	**0.044**	**-0.018**			
	(2.93)	**(3.94)**	**(-1.87)**	**(3.38)**	**(5.20)**	**(-2.60)**	**(2.51)**	**(2.65)**	(-1.52)	**(4.56)**	**(4.42)**	**(-1.81)**			
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	AUS	AUS	AUS	BRA	BRA	BRA	IND	IND	IND	NOR	NOR	NOR			
*seas*_1_1*na*	**0.198**	**0.372**	**-0.171**	**0.206**	**0.385**	**-0.174**	0.084	**0.251**	-0.166	**0.162**	**0.277**	**-0.117**			
	(7.77)	**(8.52)**	**(-3.90)**	**(4.44)**	**(5.62)**	**(-2.61)**	(1.23)	**(2.67)**	(-1.58)	**(3.62)**	**(5.78)**	**(-2.19)**			
	Ret	CF	DR	Ret	CF	DR									
	THA	THA	THA	ZAF	ZAF	ZAF									
*seas*_1_1*na*	**0.091**	**0.516**	-0.412	**0.198**	**0.622**	**-0.403**									
	(1.87)	**(2.10)**	(-1.59)	**(3.84)**	**(3.80)**	**(-2.64)**									

Panel E: Profit Growth

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHN	CHN	CHN	FRA	FRA	FRA	IND	IND	IND
*ret*_12_7	**0.016**	0.007	0.009	**0.008**	**0.008**	0.000	**0.015**	**0.008**	**0.007**	0.013	0.019	-0.005
	(6.11)	(1.27)	(1.54)	**(2.12)**	**(2.62)**	(-0.07)	**(4.91)**	**(2.12)**	**(1.70)**	(1.34)	(0.99)	(-0.24)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	ITA	ITA	ITA	THA	THA	THA	ZAF	ZAF	ZAF			
*ret*_12_7	0.962	0.234	0.705	0.000	**0.021**	**-0.02**	**0.035**	0.008	0.028			
	(1.51)	(0.50)	(0.98)	(0.07)	**(1.82)**	**(-1.95)**	**(3.29)**	(0.45)	(1.56)			

Panel F: Profitability

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	FRA	FRA	FRA	GBR	GBR	GBR	HKG	HKG	HKG	ITA	ITA	ITA			
ebit_bev	**0.003**	-0.001	**0.005**	0.001	0.002	-0.001	0.002	0.001	0.002	0.009	-0.002	0.013			
	(2.61)	(-0.50)	**(2.49)**	(1.59)	(1.20)	(-0.60)	(1.00)	(0.43)	(0.60)	(2.02)	(-0.21)	(1.61)			
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	FRA	FRA	FRA	HKG	HKG	HKG	TWN	TWN	TWN	ZAF	ZAF	ZAF
niq_be	**0.075**	0.116	-0.038	0.057	-0.034	0.097	0.517	0.118	0.396	**0.068**	0.013	0.044	0.311	**0.126**	0.187
	(2.88)	(1.15)	(-0.42)	(0.47)	(-0.32)	(1.04)	(1.20)	(0.61)	(1.34)	**(1.93)**	(0.22)	(0.87)	(1.33)	**(1.66)**	(0.95)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	DEU	DEU	DEU	FRA	FRA	FRA	HKG	HKG	HKG	ITA	ITA	ITA	KOR	KOR	KOR
ocf_at	**0.027**	0.01	**0.019**	**0.034**	**0.02**	**0.021**	**0.024**	**0.014**	0.014	**0.034**	0.009	0.026	**0.033**	**-0.039**	**0.065**
	(5.57)	(1.27)	**(2.22)**	**(5.32)**	**(2.13)**	**(2.12)**	**(3.61)**	**(1.80)**	(1.64)	**(4.26)**	(0.52)	(1.43)	**(1.98)**	**(-1.75)**	**(2.45)**
	Ret	CF	DR	Ret	CF	DR									
	SWE	SWE	SWE	TWN	TWN	TWN									
ocf_at	**0.031**	0.011	**0.025**	**0.023**	0.014	0.017									
	(4.84)	(1.16)	**(2.64)**	**(2.31)**	(0.44)	(0.48)									

Panel G: Quality

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	AUS	AUS	AUS	DEU	DEU	DEU	GBR	GBR	GBR	HKG	HKG	HKG			
cop_at	**0.007**	-0.003	**0.013**	**0.019**	**0.011**	0.01	**0.012**	0.001	0.011	**0.024**	0.01	**0.014**			
	(1.98)	(-0.59)	**(2.43)**	**(5.86)**	**(1.94)**	(1.61)	**(4.10)**	(0.11)	(1.58)	**(5.24)**	(1.59)	**(2.09)**			
	Ret	CF	DR	Ret	CF	DR									
	SGP	SGP	SGP	TWN	TWN	TWN									
cop_at	**0.022**	-0.002	**0.026**	**0.016**	-0.017	**0.037**									
	(3.59)	(-0.22)	**(2.20)**	**(1.89)**	(-0.90)	**(1.80)**									
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	DEU	DEU	DEU	HKG	HKG	HKG	MYS	MYS	MYS	TWN	TWN	TWN			
*cop_atl*1	**0.010**	0.004	0.006	**0.013**	0.005	0.008	**0.013**	-0.003	**0.017**	0.009	-0.015	**0.028**			
	(4.22)	(0.97)	(1.46)	**(3.51)**	(1.11)	(1.53)	**(4.15)**	(-0.58)	**(2.99)**	(1.57)	(-1.09)	**(1.86)**			
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	FRA	FRA	FRA	HKG	HKG	HKG	IND	IND	IND	ITA	ITA	ITA	KOR	KOR	KOR
gp_at	**0.004**	0.005	0.001	0.004	0.021	-0.017	0.008	0.05	-0.019	**0.007**	**-0.013**	**0.022**	**0.022**	0.006	0.014
	(2.60)	(1.61)	(0.17)	(0.41)	(0.54)	(-0.46)	(1.10)	(1.00)	(-0.60)	**(2.30)**	**(-2.16)**	**(3.40)**	**(2.54)**	(0.58)	(1.38)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	HKG	HKG	HKG	ITA	ITA	ITA	KOR	KOR	KOR	TWN	TWN	TWN			
*gp_atl*1	0.01	-0.015	**0.026**	0.004	-0.006	**0.011**	0.003	-0.007	0.009	**0.010**	-0.017	**0.028**			
	(1.23)	(-1.29)	**(2.06)**	(1.34)	(-1.20)	**(1.99)**	(0.40)	(-0.83)	(0.97)	**(1.85)**	(-1.27)	**(2.13)**			
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHE	CHE	CHE	DEU	DEU	DEU	GBR	GBR	GBR	HKG	HKG	HKG
mispricing_perf	**0.034**	**0.04**	-0.002	**0.022**	**0.037**	**-0.012**	**0.031**	**0.03**	0.003	**0.032**	**0.039**	**-0.014**	**0.023**	**0.033**	-0.005
	(7.19)	**(5.98)**	(-0.26)	**(5.44)**	**(6.28)**	**(-1.75)**	**(6.72)**	**(5.78)**	(0.65)	**(8.43)**	**(7.98)**	**(-3.08)**	**(4.91)**	**(6.72)**	(-1.09)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	IND	IND	IND	NLD	NLD	NLD	POL	POL	POL	THA	THA	THA	ZAF	ZAF	ZAF
mispricing_perf	0.092	0.003	0.096	**0.021**	**0.016**	0.007	**0.03**	**0.049**	-0.015	**0.022**	**0.024**	-0.004	0.012	0.02	-0.005
	(0.55)	(0.04)	(0.90)	**(4.80)**	**(2.34)**	(0.88)	**(3.32)**	**(3.27)**	(-0.94)	**(3.11)**	**(2.32)**	(-0.49)	(0.75)	(1.27)	(-0.58)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR						
	AUS	AUS	AUS	ITA	ITA	ITA	TWN	TWN	TWN						
niq_at	**0.105**	0.072	0.049	**0.305**	-0.062	**0.338**	**0.108**	0.008	0.104						
	(3.12)	(1.19)	(0.90)	**(1.76)**	(-0.79)	**(2.04)**	**(1.80)**	(0.09)	(1.27)						

Panel G: Quality (continues)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	IND	IND	IND	MYS	MYS	MYS	SGP	SGP	SGP
opex_at	**0.002**	-0.002	**0.004**	0.011	0.005	0.005	**0.004**	-0.001	**0.004**	**0.004**	**0.004**	0.000
	(2.66)	(-1.64)	**(2.92)**	(1.18)	(0.81)	(0.52)	**(3.46)**	(-0.27)	**(2.24)**	**(3.02)**	**(1.92)**	(-0.15)

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	CHE	CHE	CHE	DEU	DEU	DEU	FRA	FRA	FRA	GBR	GBR	GBR
qmj_prof	**0.003**	0.001	**0.002**	**0.004**	0.001	**0.002**	**0.004**	0.001	**0.003**	**0.003**	0.000	**0.002**
	(4.00)	(0.54)	**(1.89)**	**(4.85)**	(1.60)	**(2.35)**	**(6.67)**	(0.94)	**(4.09)**	**(6.55)**	(0.39)	**(1.87)**

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	HKG	HKG	HKG	ITA	ITA	ITA	KOR	KOR	KOR
qmj_prof	**0.003**	0.001	**0.002**	**0.003**	0.000	**0.003**	**0.003**	-0.002	**0.005**
	(3.58)	(1.15)	**(1.88)**	**(4.64)**	(0.36)	**(2.64)**	**(3.04)**	(-1.62)	**(3.35)**

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHN	CHN	CHN	FRA	FRA	FRA	HKG	HKG	HKG
sale_bev	**0.001**	-0.001	**0.001**	**0.000**	0.000	0.000	**0.000**	0.000	**0.000**	0.000	0.000	0.000
	(2.51)	(-1.15)	**(2.18)**	**(1.65)**	(-0.65)	(1.44)	**(4.22)**	(-0.36)	**(1.91)**	(1.34)	(0.59)	(0.28)

	Ret	CF	DR	Ret	CF	DR
	IDN	IDN	IDN	MYS	MYS	MYS
sale_bev	**0.002**	0.001	0.001	**0.001**	0.000	0.000
	(2.15)	(0.86)	(0.58)	**(1.81)**	(-0.58)	(1.61)

Panel H: Seasonality

	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	DEU	DEU	DEU	GBR	GBR	GBR	HKG	HKG	HKG	JPN	JPN	JPN
*seas*_6_10*an*	**0.076**	-0.019	**0.097**	**0.045**	**0.065**	-0.017	0.027	-0.034	0.063	**0.048**	0.014	**0.034**
	(4.27)	(-0.61)	**(2.81)**	**(4.77)**	**(3.34)**	(-0.93)	(1.35)	(-0.93)	(1.57)	**(5.28)**	(1.34)	**(2.63)**

Panel I: Short-term reversal												
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	DEU	DEU	DEU	JPN	JPN	JPN	SWE	SWE	SWE
*rmax*5_*rvol*_21*d*	**-0.004**	0.003	**-0.007**	**-0.007**	**0.005**	**-0.012**	**-0.003**	**0.006**	**-0.009**	**-0.006**	**0.008**	**-0.014**
	(-3.14)	(1.19)	**(-2.88)**	**(-4.86)**	**(3.03)**	**(-6.67)**	**(-2.77)**	**(5.76)**	**(-7.15)**	**(-3.86)**	**(3.41)**	**(-5.42)**

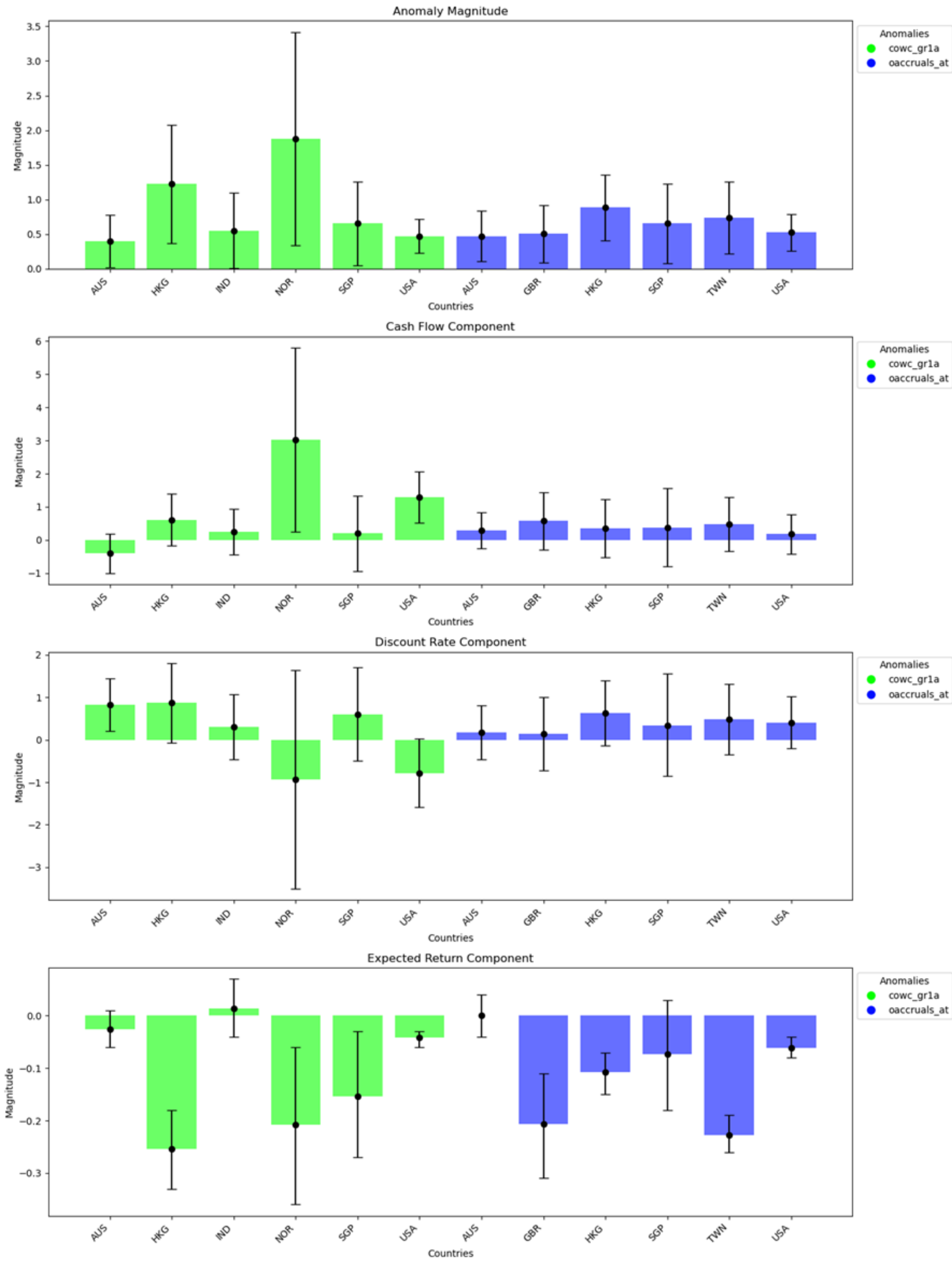
Panel J: Value												
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	CHE	CHE	CHE	DEU	DEU	DEU	GBR	GBR	GBR	HKG	HKG	HKG
fcf_me	**0.021**	0.004	0.023	**0.009**	**0.008**	0.002	**0.032**	-0.017	**0.047**	**0.004**	-0.003	**0.007**
	(3.01)	(0.26)	(1.52)	**(3.28)**	**(1.92)**	(0.39)	**(1.76)**	(-1.34)	**(1.68)**	**(2.52)**	(-1.16)	**(2.83)**
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	JPN	JPN	JPN	MYS	MYS	MYS	SGP	SGP	SGP	TWN	TWN	TWN
fcf_me	0.009	0.027	-0.018	0.012	-0.036	0.048	0.002	0.002	0.002	0.034	0.105	-0.063
	(1.09)	(1.41)	(-0.88)	(0.25)	(-1.03)	(0.98)	(0.95)	(0.38)	(0.37)	(1.03)	(0.94)	(-0.78)
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	AUS	AUS	AUS	CHE	CHE	CHE	CHN	CHN	CHN	DEU	DEU	DEU
netis_at	-0.004	-0.004	-0.001	**-0.033**	**-0.036**	-0.001	**-0.009**	**-0.016**	0.005	**-0.024**	**-0.015**	-0.012
	(-0.83)	(-0.57)	(-0.11)	**(-4.80)**	**(-2.15)**	(-0.07)	**(-2.58)**	**(-3.23)**	(1.00)	**(-5.15)**	**(-1.83)**	(-1.53)
	Ret	CF	DR	Ret	CF	DR						
	FRA	FRA	FRA	HKG	HKG	HKG						
netis_at	**-0.014**	0.01	-0.028	**-0.022**	**-0.018**	-0.008						
	(-1.98)	(0.44)	(-1.14)	**(-4.32)**	**(-2.03)**	(-0.79)						

Panel J: Value (continue)

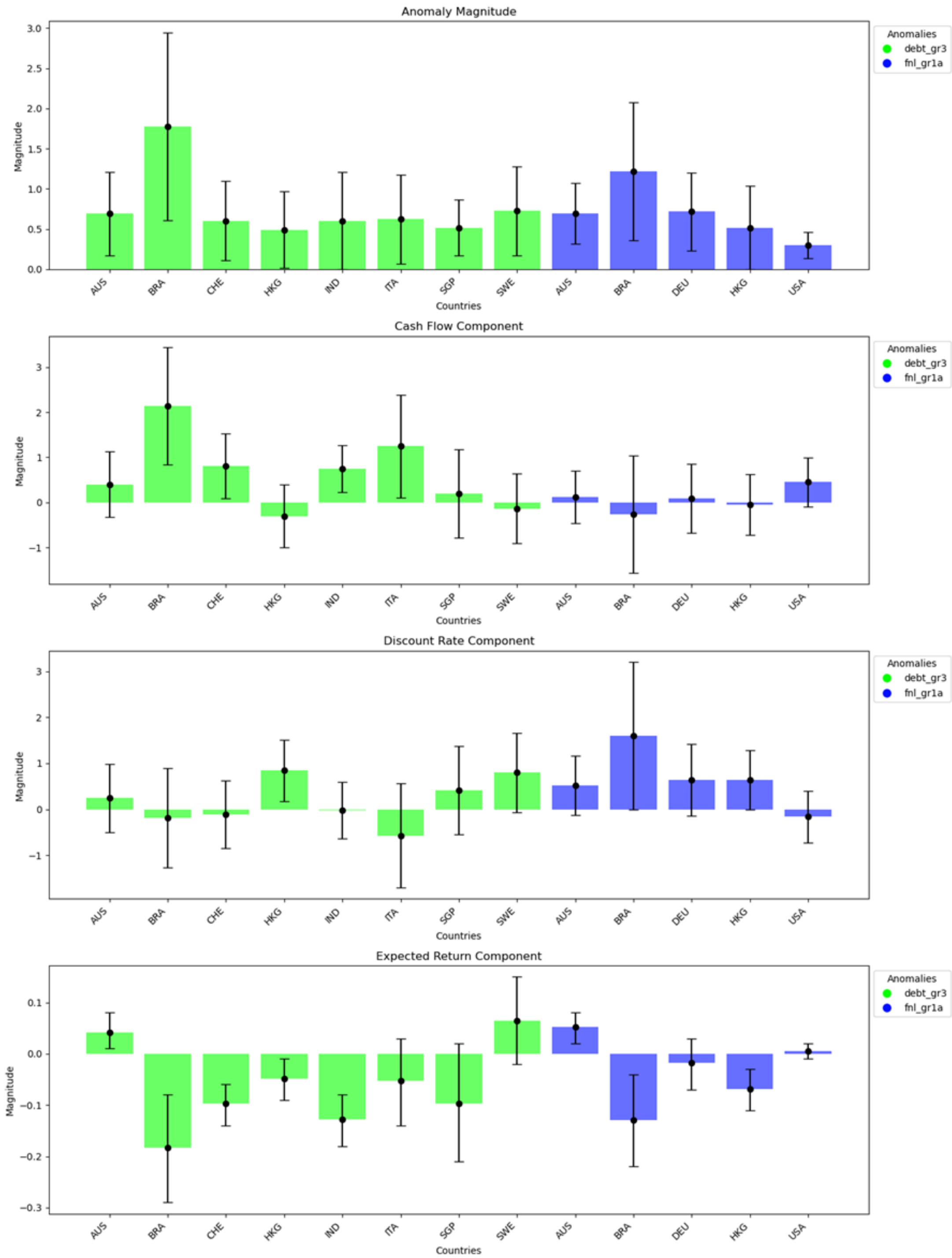
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR			
	CHE	CHE	CHE	HKG	HKG	HKG	IDN	IDN	IDN	MYS	MYS	MYS			
ni_me	**0.014**	**0.028**	-0.011	0.003	0.004	-0.006	0.403	-0.59	0.98	0.005	-0.012	0.01			
	(2.42)	**(2.36)**	(-0.85)	(0.71)	(0.39)	(-0.58)	(1.12)	(-1.04)	(1.07)	(0.56)	(-0.84)	(0.65)			
	Ret	CF	DR	Ret	CF	DR									
	SGP	SGP	SGP	TWN	TWN	TWN									
ni_me	0.001	-0.007	0.001	**0.028**	0.007	0.017									
	(0.06)	(-0.39)	(0.04)	**(2.41)**	(0.22)	(0.48)									
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	DEU	DEU	DEU	FRA	FRA	FRA	GBR	GBR	GBR	HKG	HKG	HKG	IDN	IDN	IDN
ocf_me	**0.011**	**0.010**	0.000	**0.008**	0.002	0.007	0.005	**-0.015**	**0.018**	**0.005**	0.004	0.000	**0.029**	-0.018	**0.050**
	(3.91)	**(2.06)**	(0.04)	**(2.56)**	(0.34)	(1.42)	(1.57)	**(-2.50)**	**(3.26)**	**(3.00)**	(1.45)	(0.14)	**(2.88)**	(-1.00)	**(2.85)**
	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR	Ret	CF	DR
	JPN	JPN	JPN	KOR	KOR	KOR	MYS	MYS	MYS	SGP	SGP	SGP	TWN	TWN	TWN
ocf_me	0.001	**-0.010**	**0.010**	**0.011**	**-0.015**	**0.023**	**0.014**	0.003	**0.012**	**0.005**	0.003	0.002	**0.014**	-0.032	**0.05**
	(0.75)	**(-3.01)**	**(3.20)**	**(2.30)**	**(-1.65)**	**(2.76)**	**(5.72)**	(0.56)	**(1.90)**	**(2.19)**	(0.65)	(0.32)	**(1.67)**	(-1.30)	**(1.96)**

Figure C1. Return decomposition of anomalies for each country

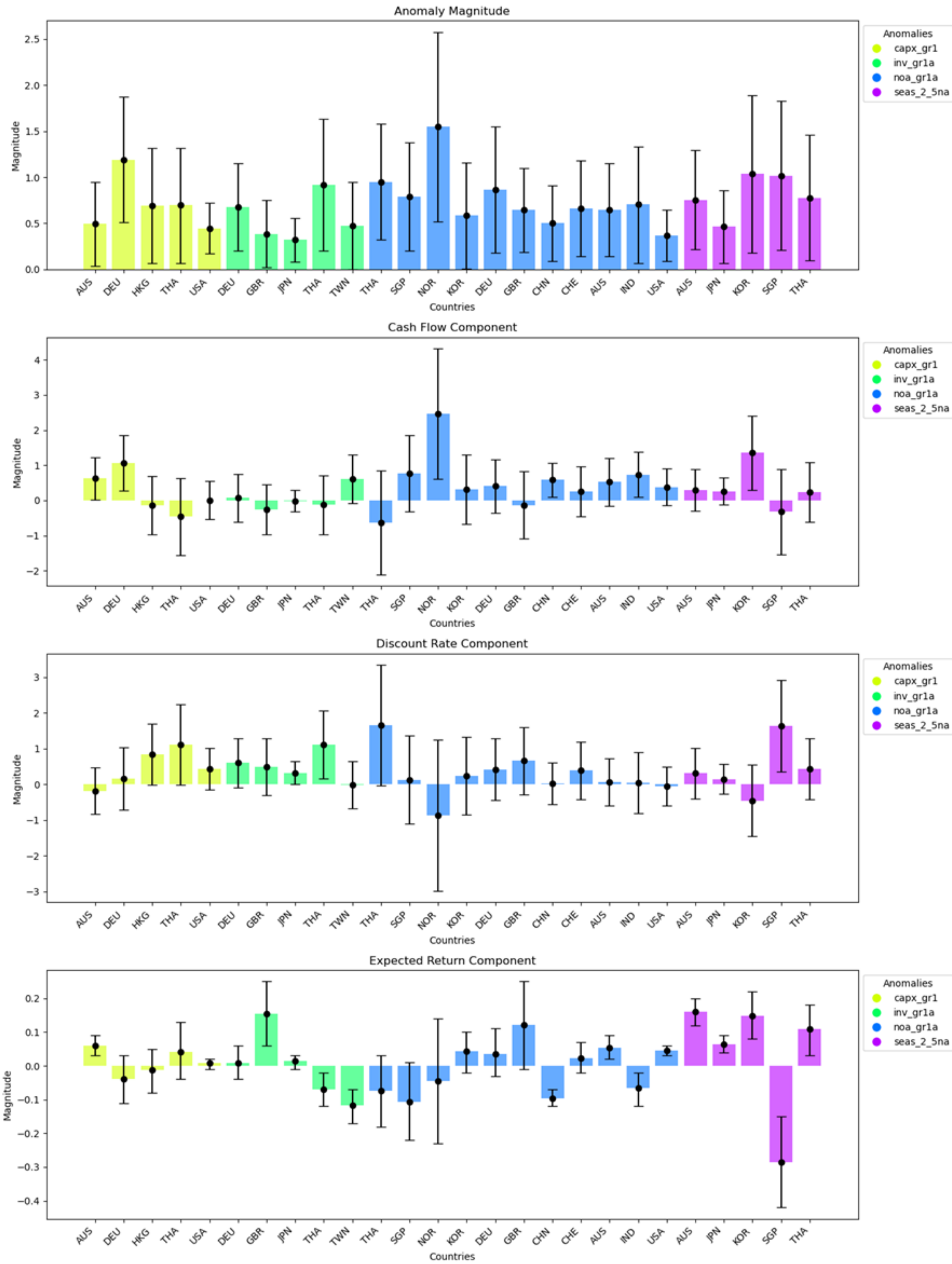
Accruals: Components with *t*-stat



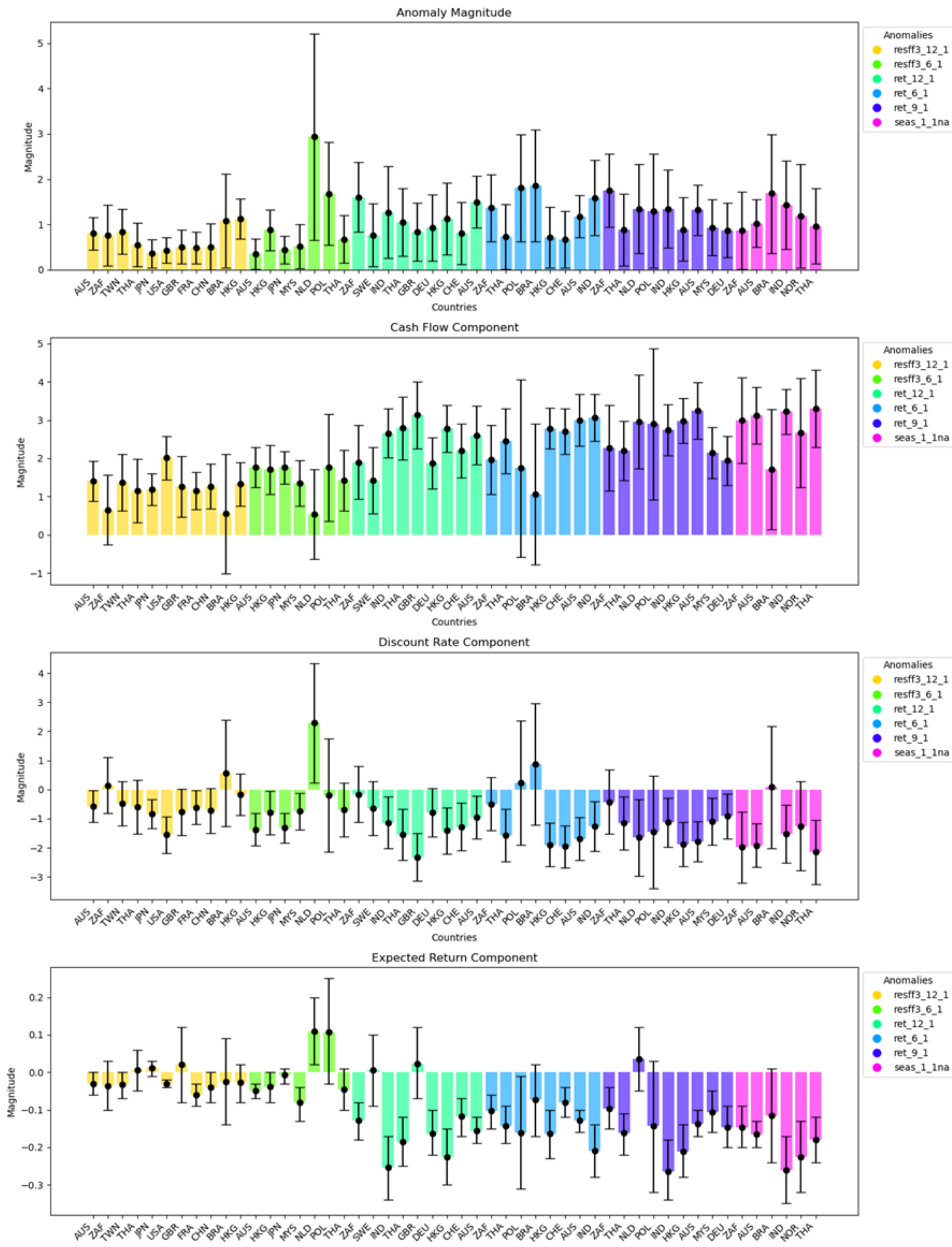
Debt issuance: Components with t-stat



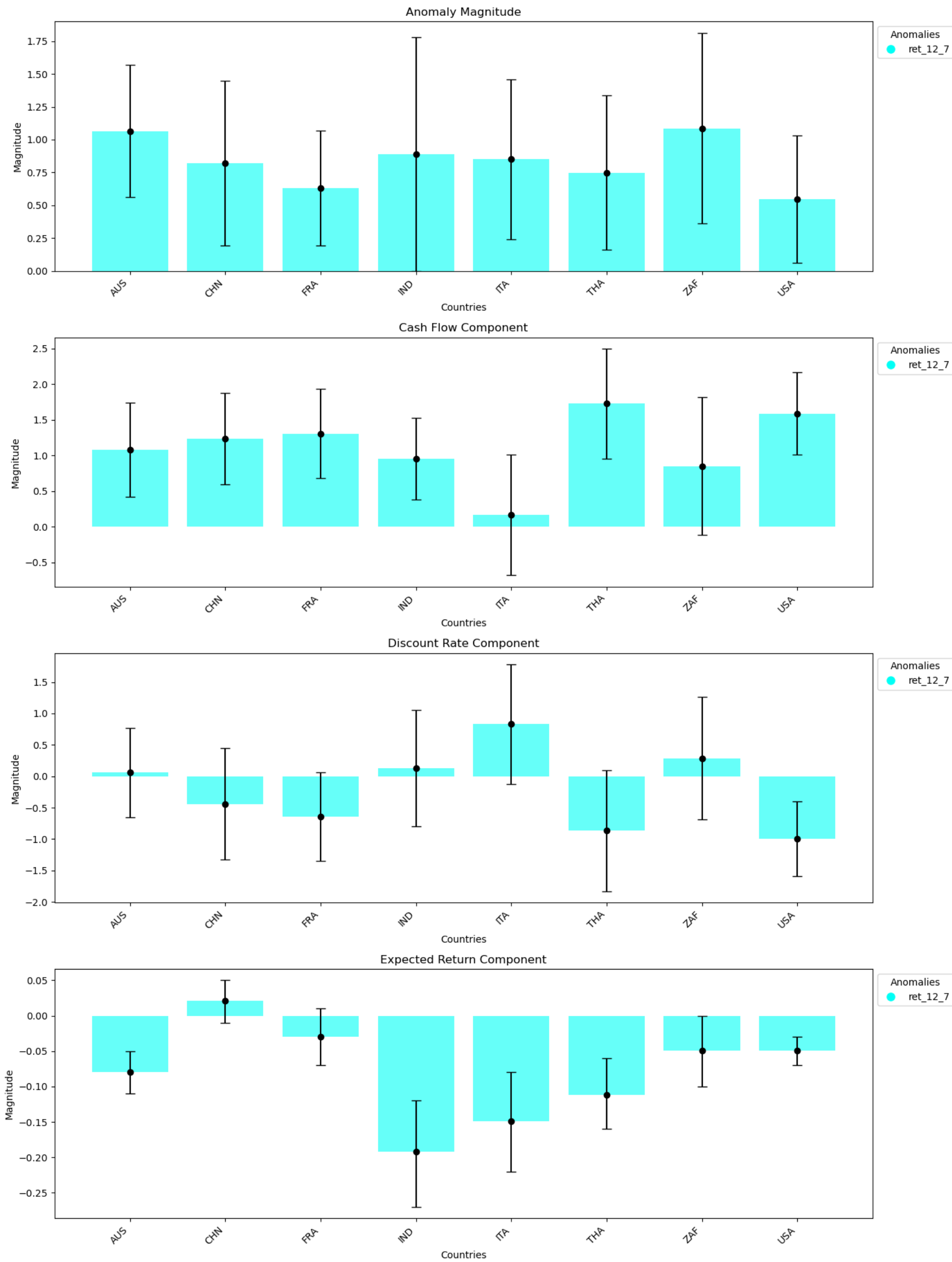
Investment: Components with t-stat



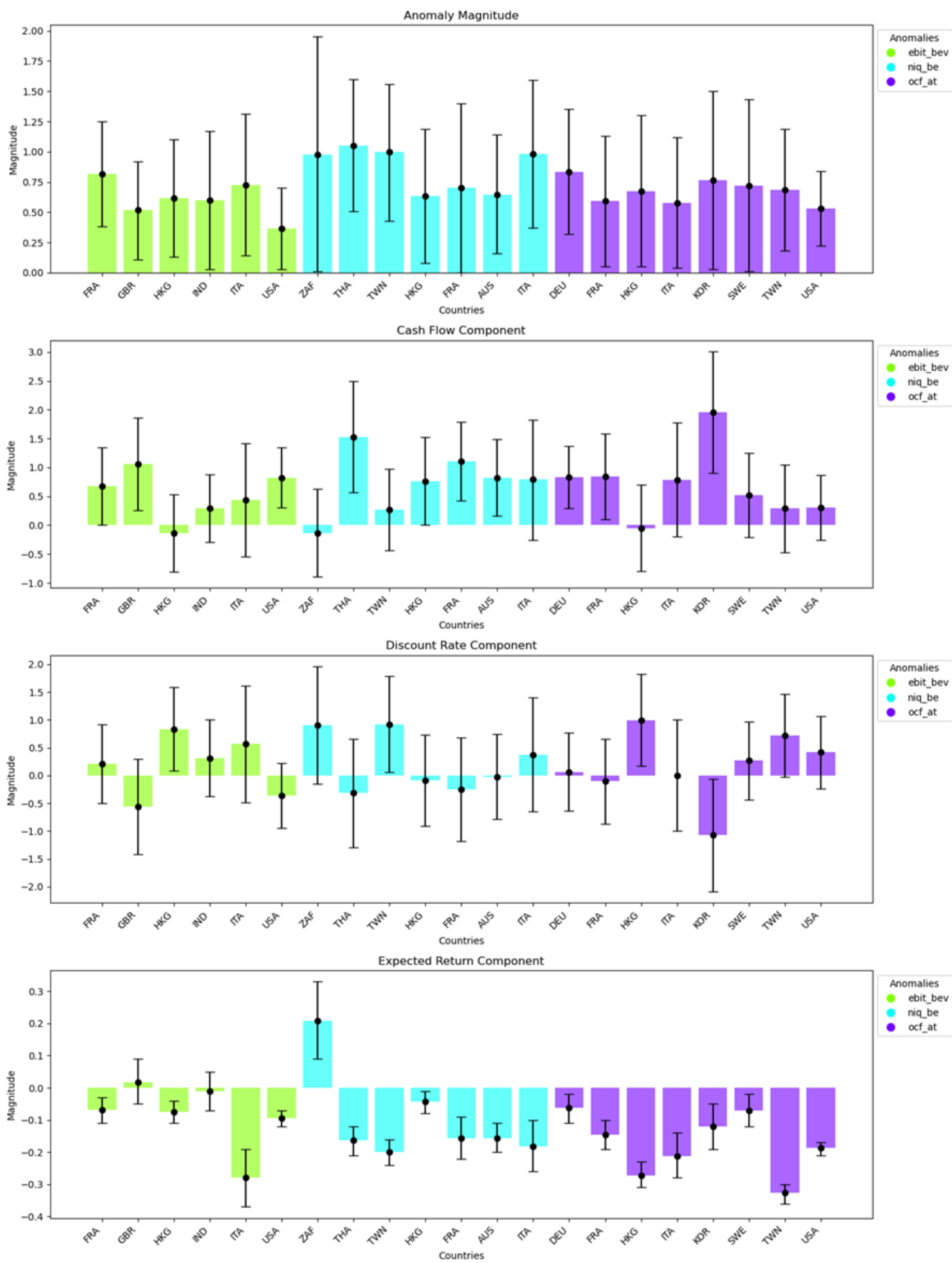
Momentum: Components with *t*-stat



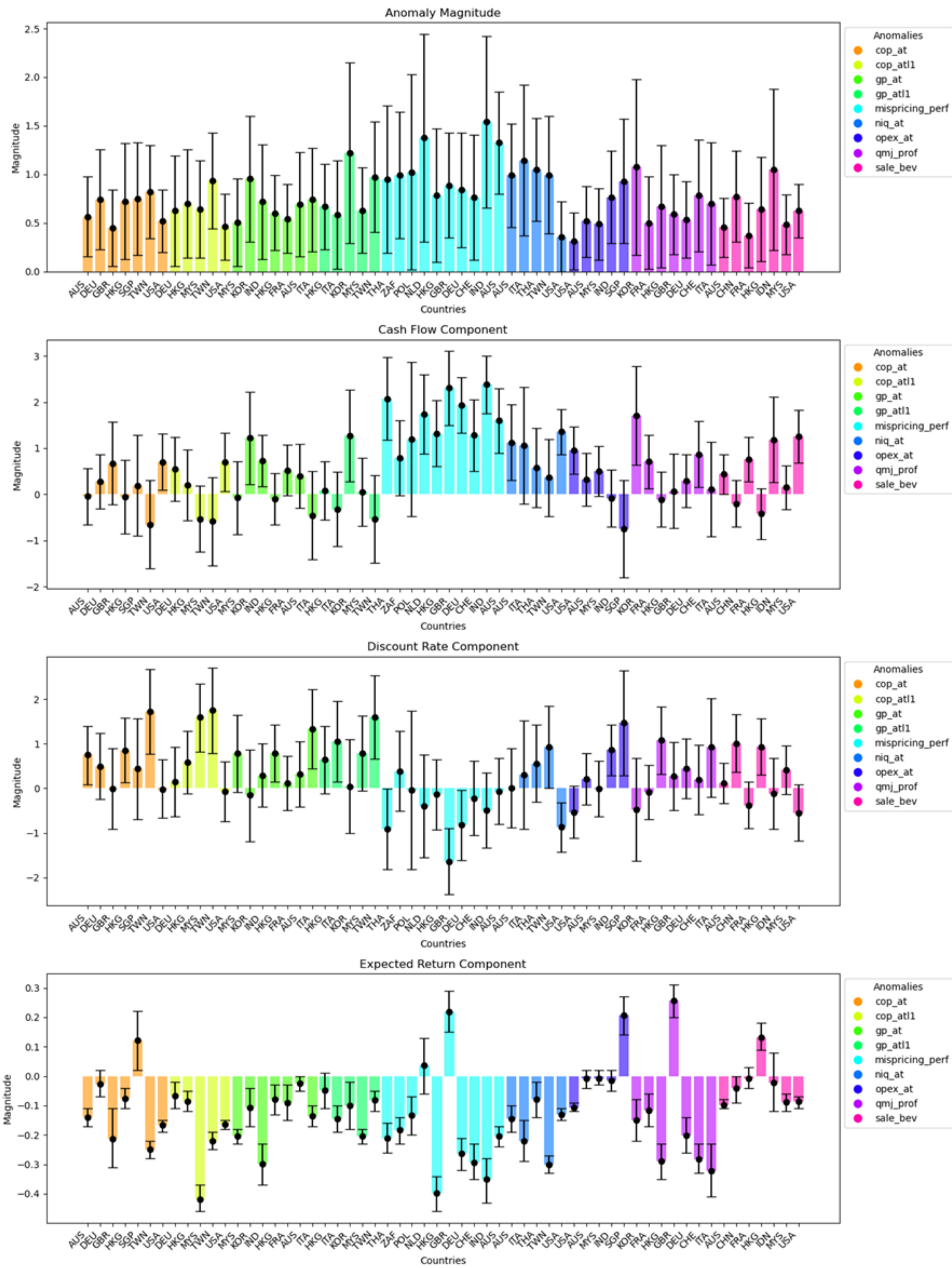
Profit Growth: Components with t-stat



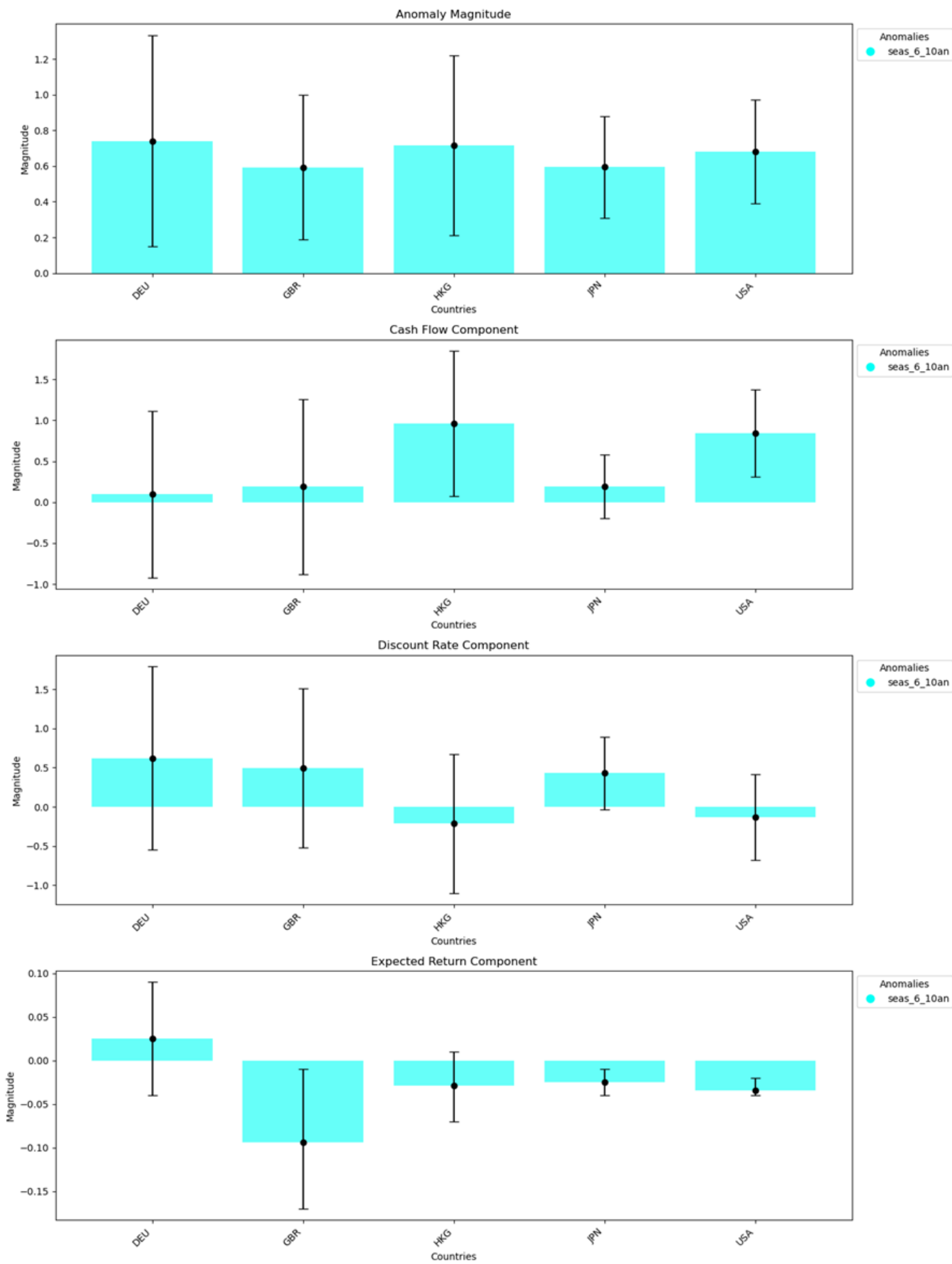
Profitability: Components with *t*-stat



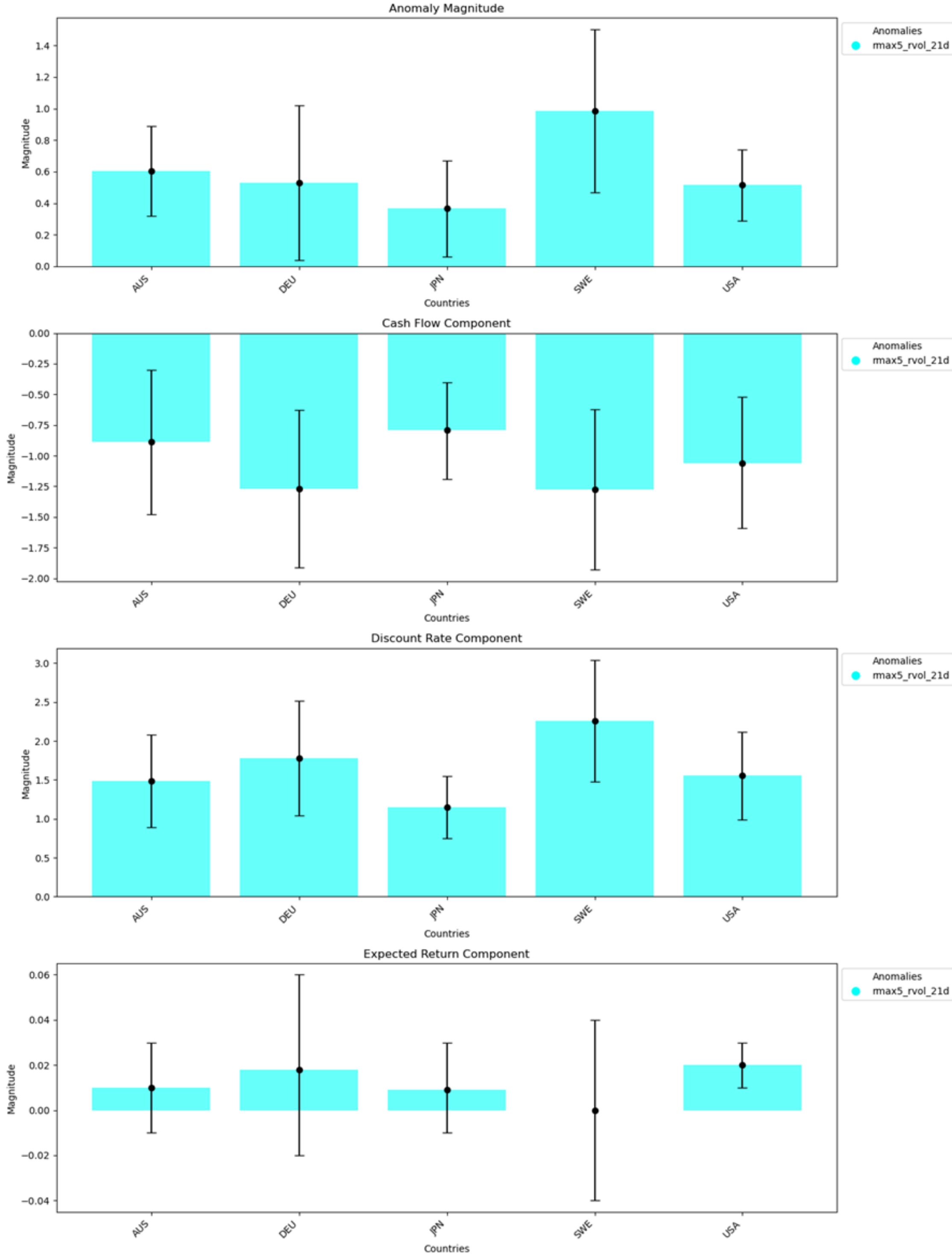
Quality: Components with *t*-stat



Seasonality: Components with *t*-stat



Short-Term Reversal: Components with *t*-stat



Value: Components with *t*-stat

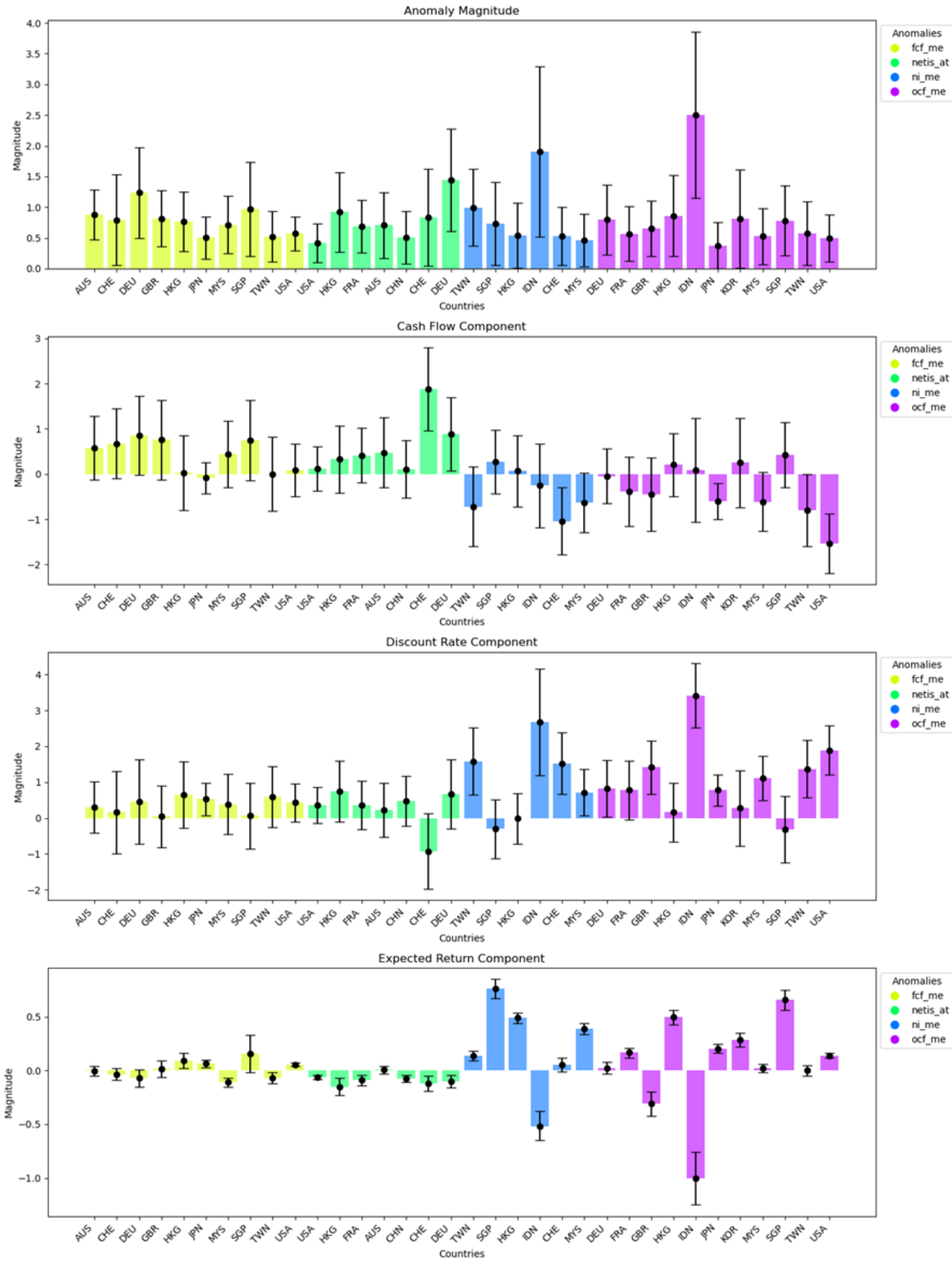
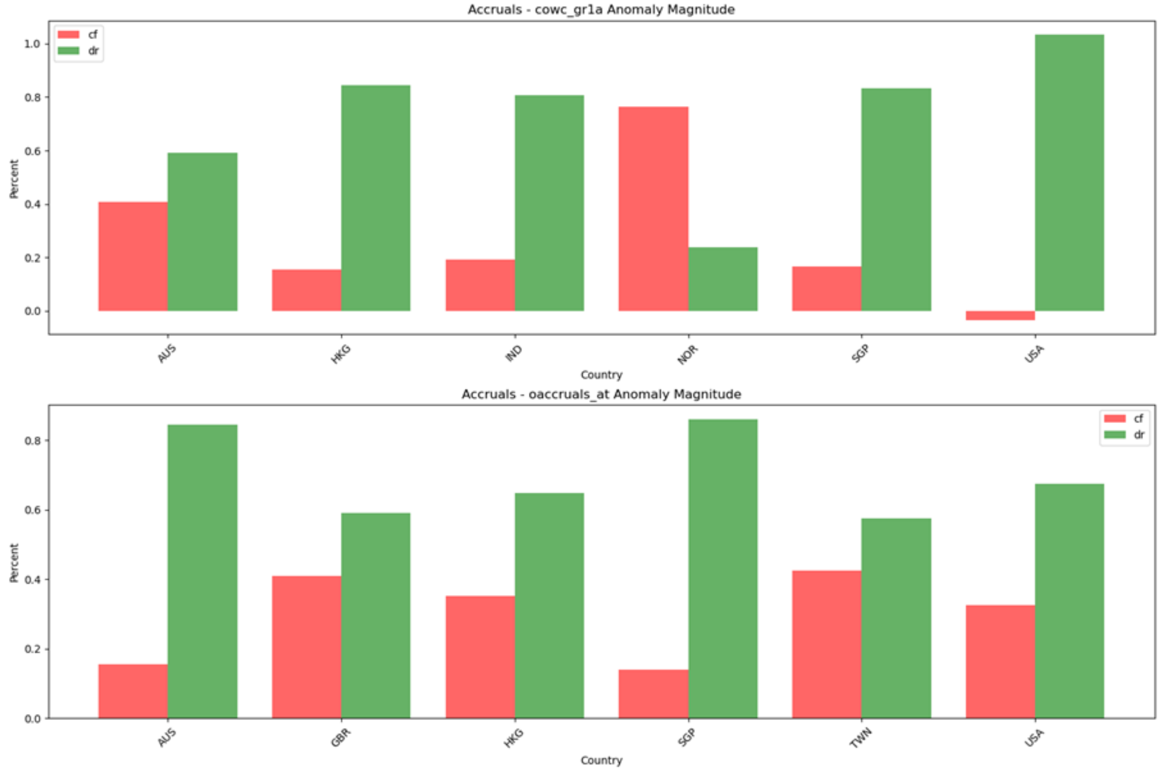
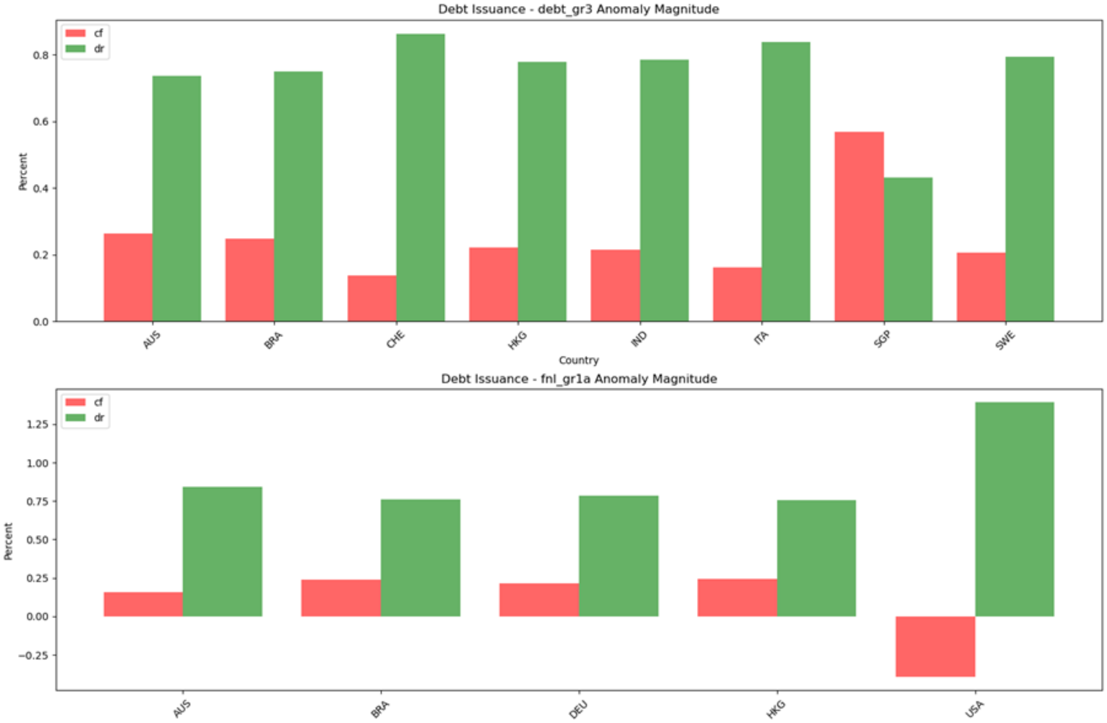


Figure C2. Variance decomposition of stock anomaly 1-month returns by country

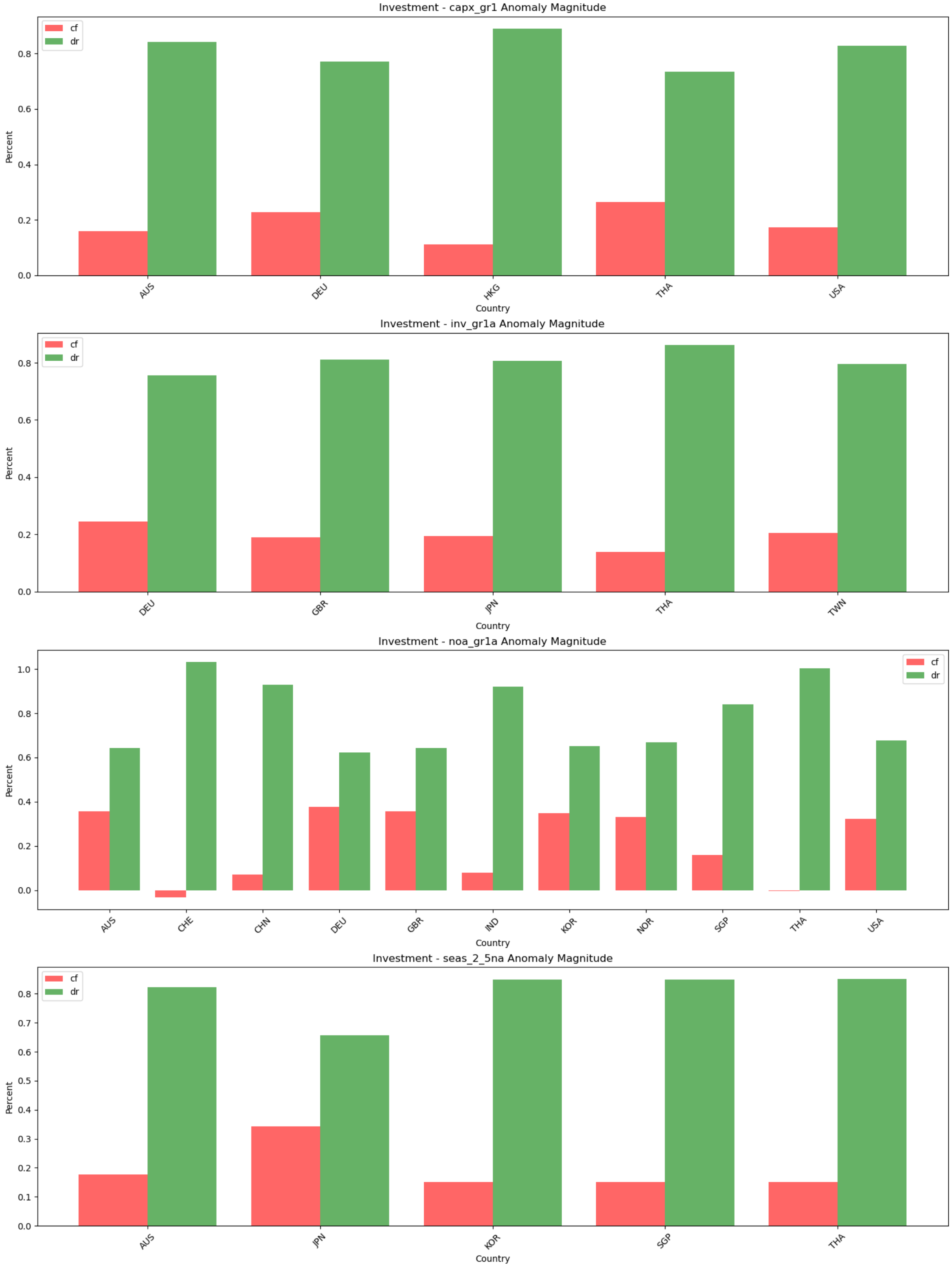
Accruals anomalies



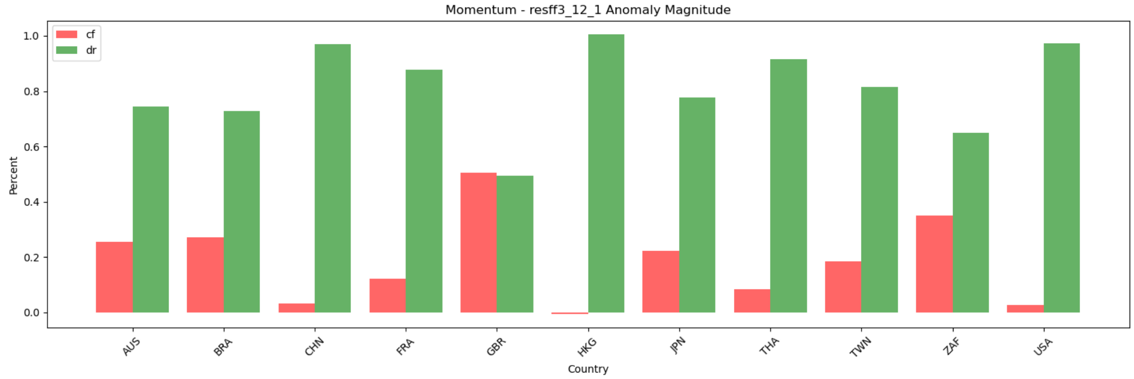
Debt issuance anomalies

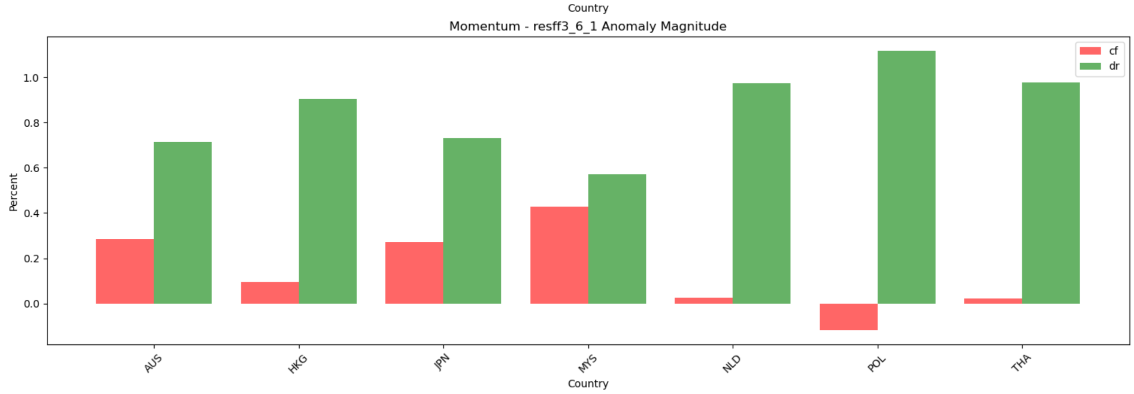


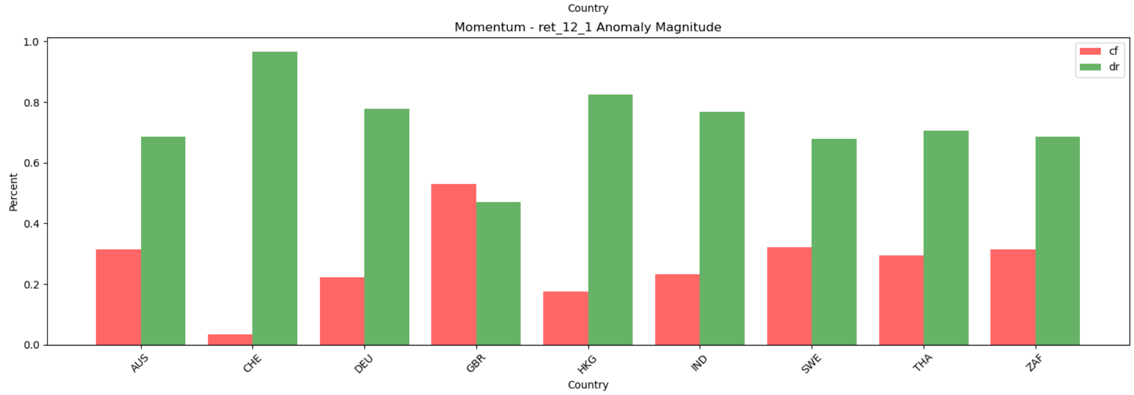
Investment anomalies



Momentum anomalies







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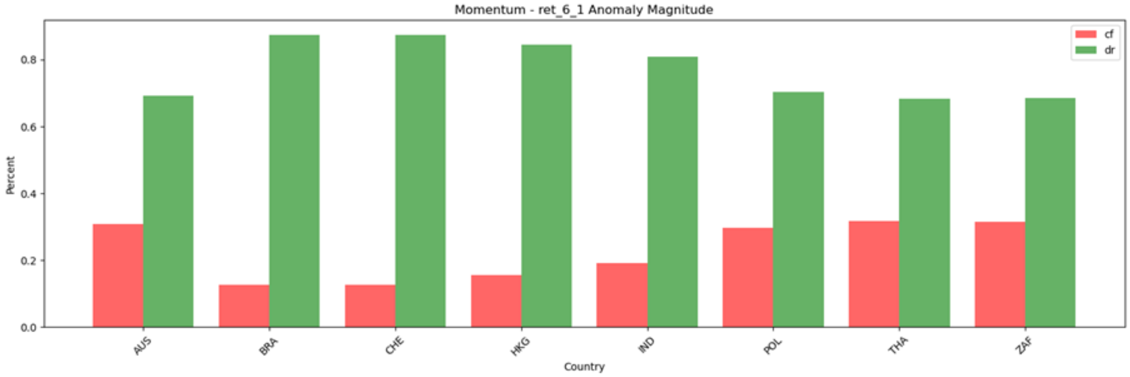
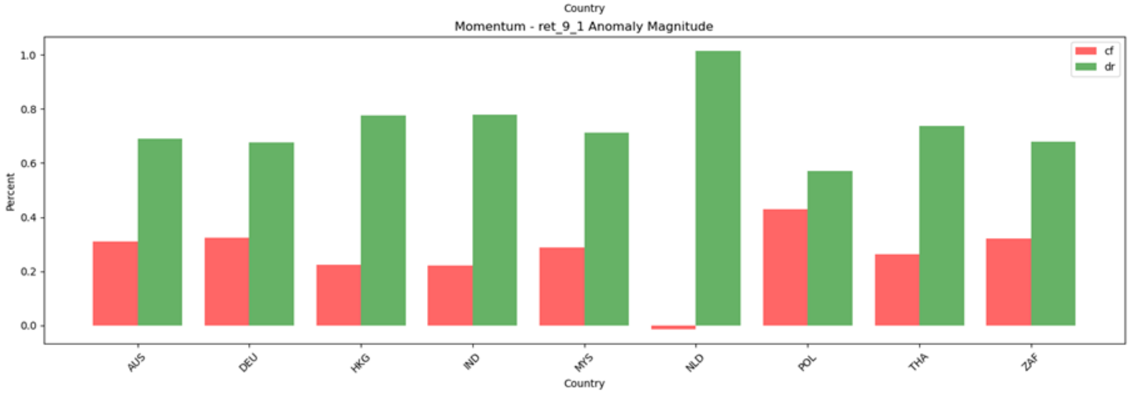
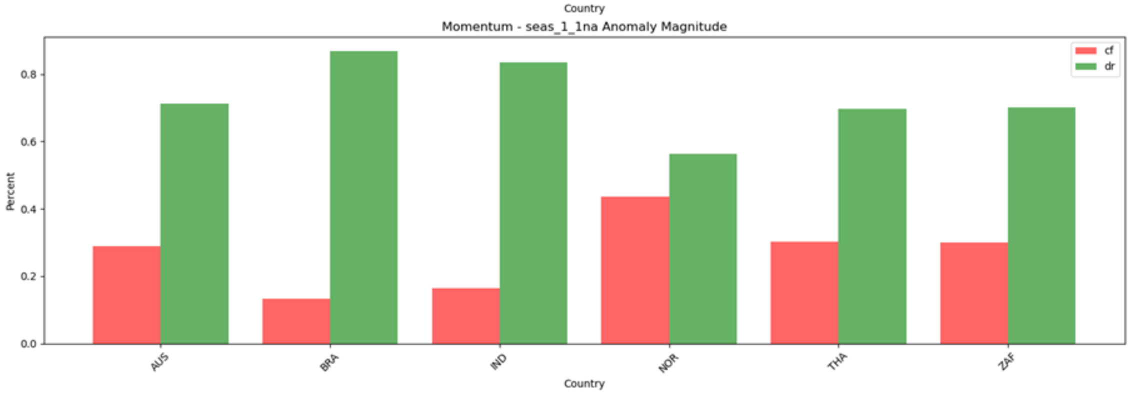
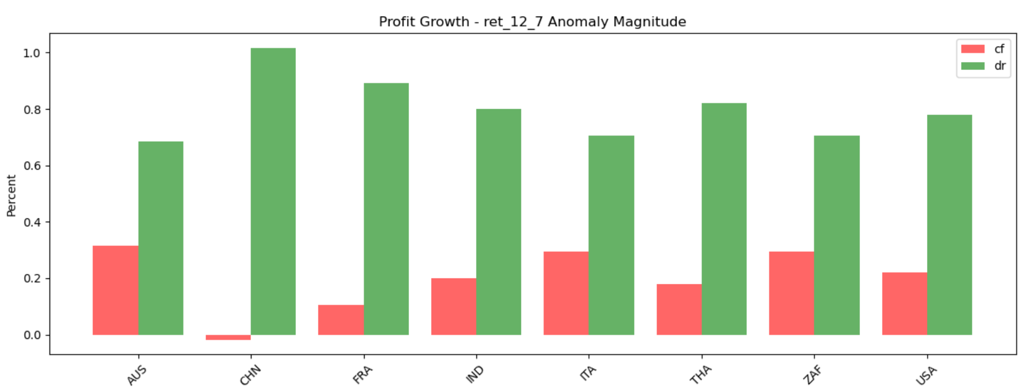






Profit Growth anomalies



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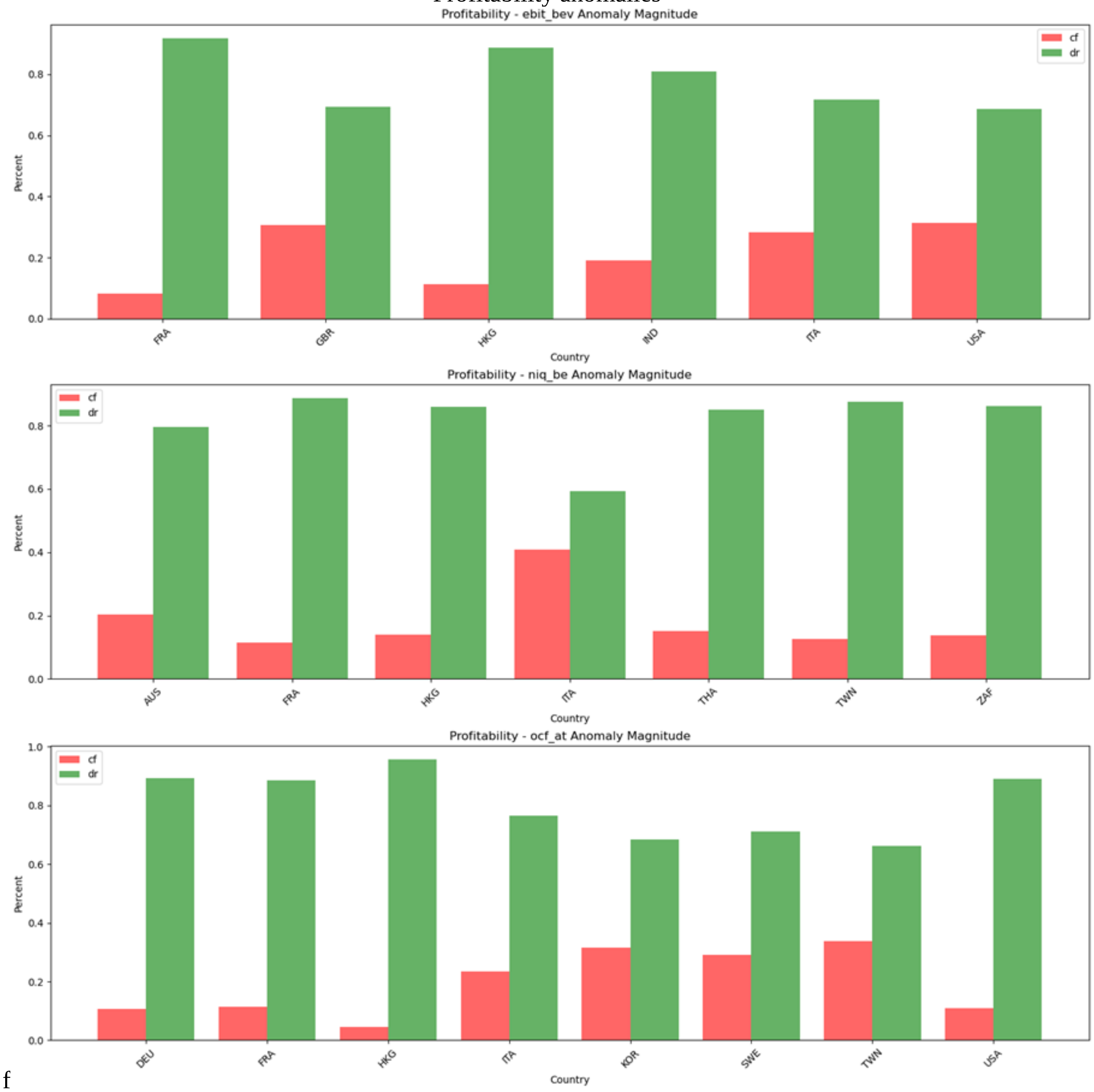

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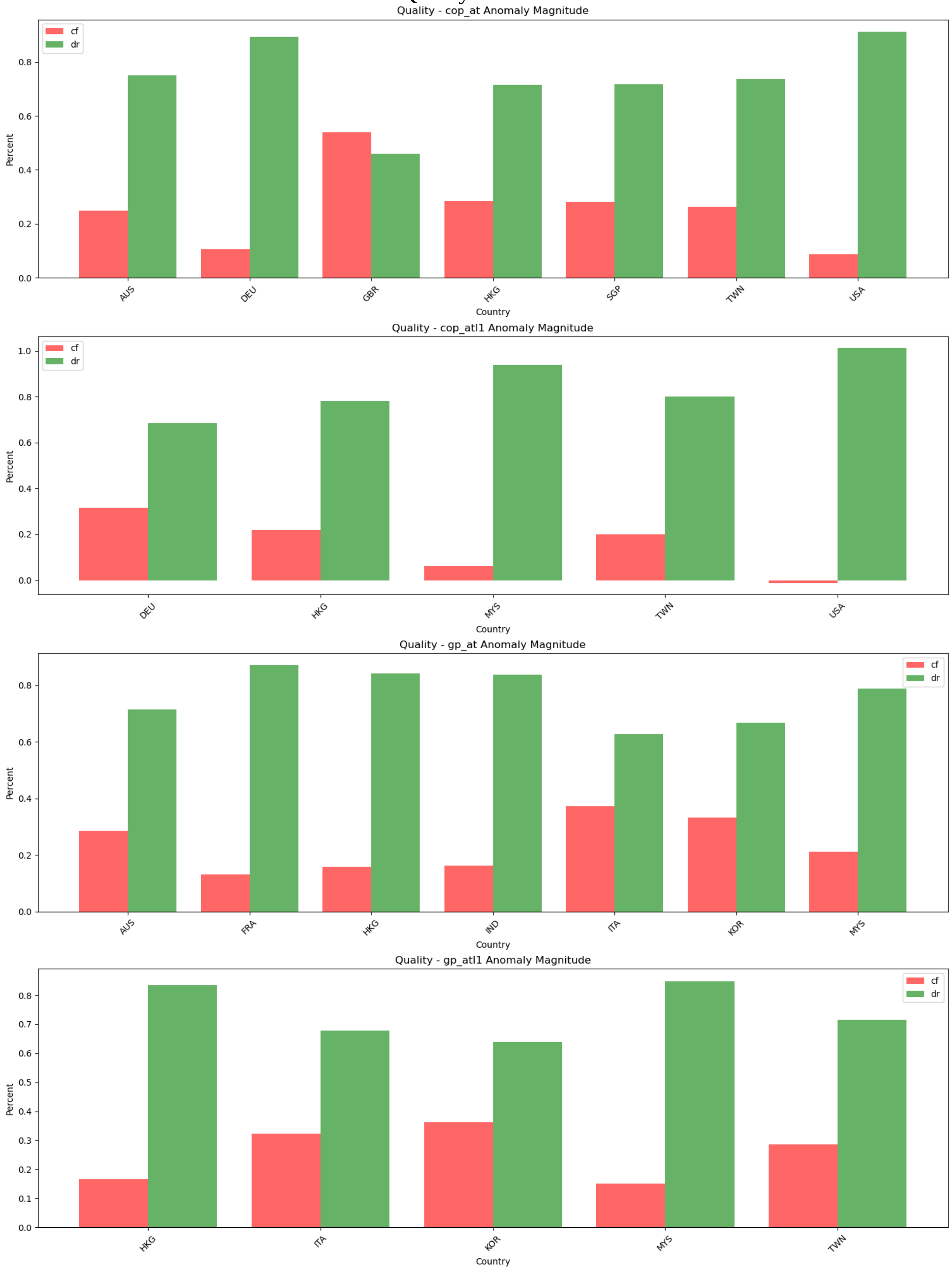
Quality anomalies



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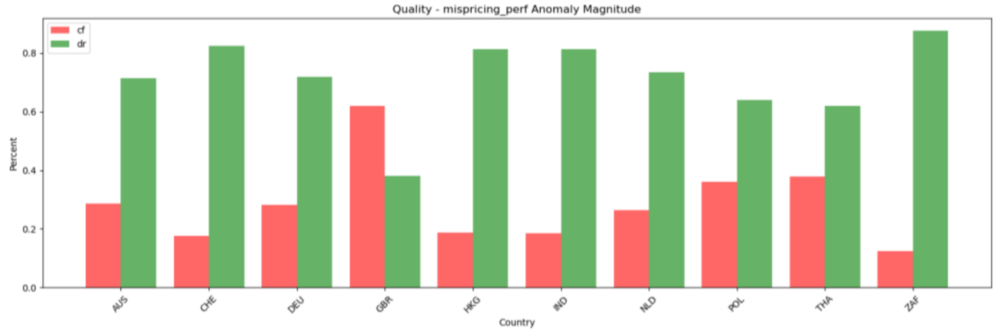
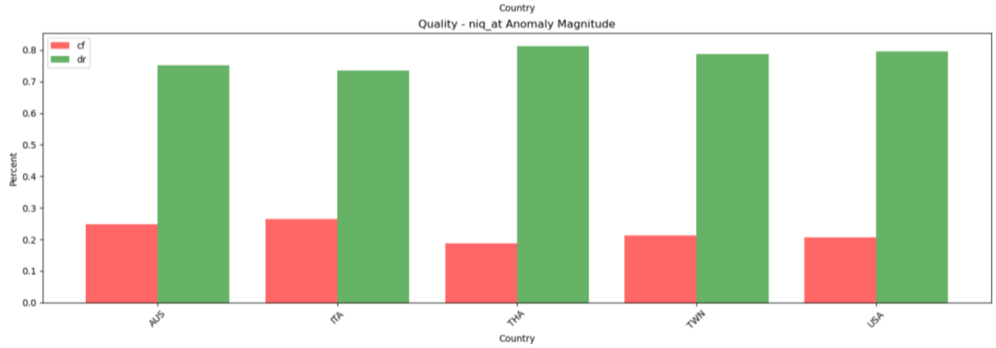
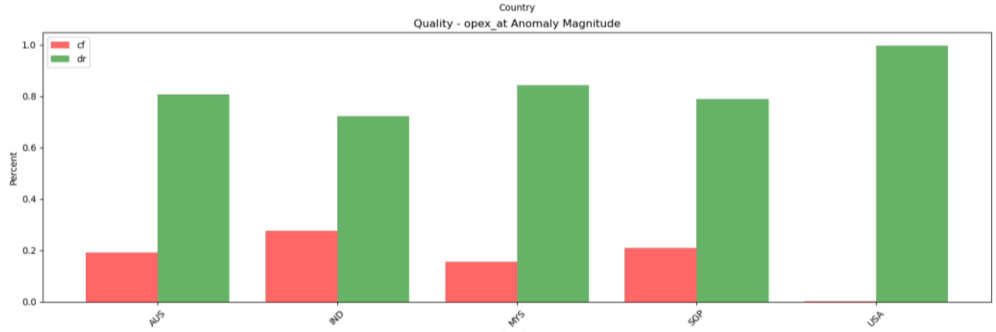
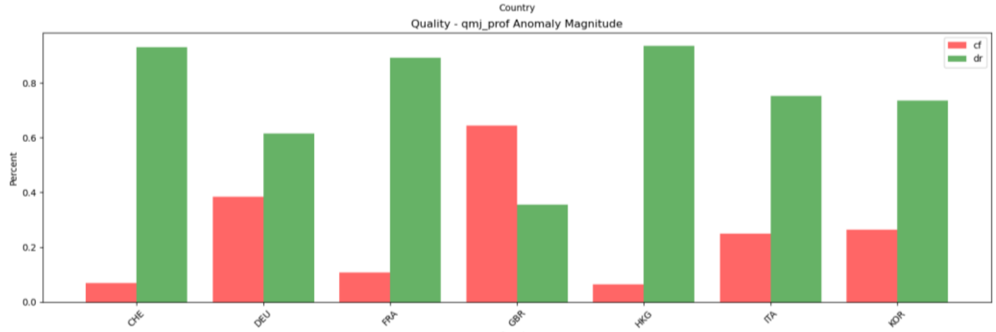
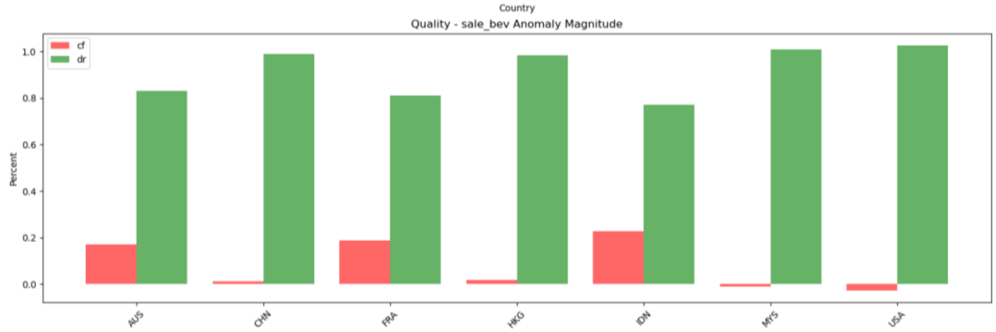


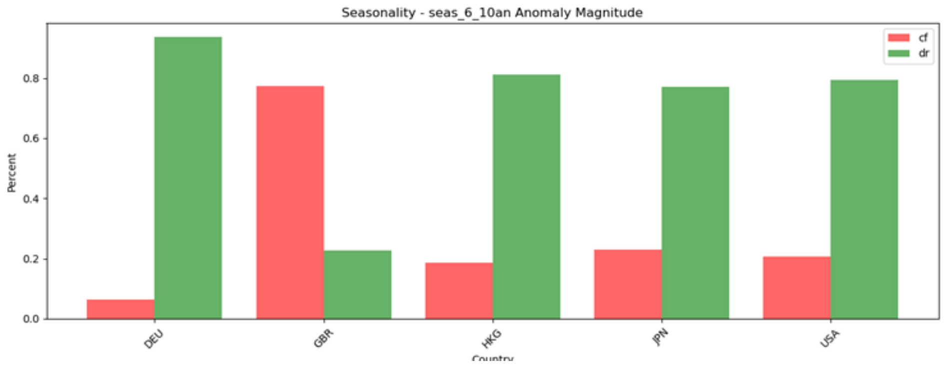




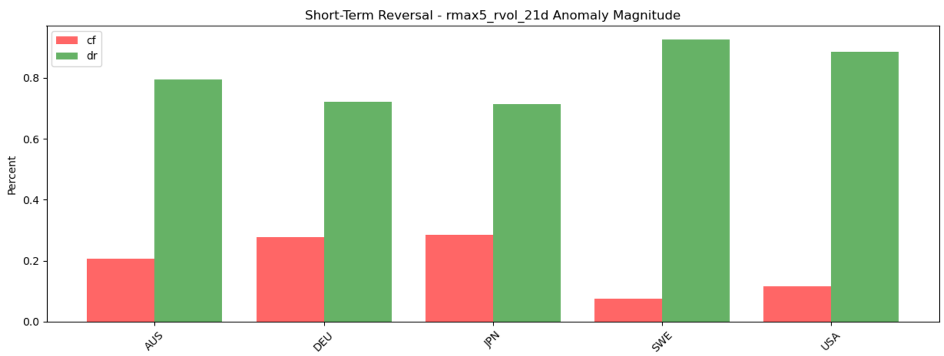




Seasonality anomalies



Short-Term Reversal anomalies



Value anomalies

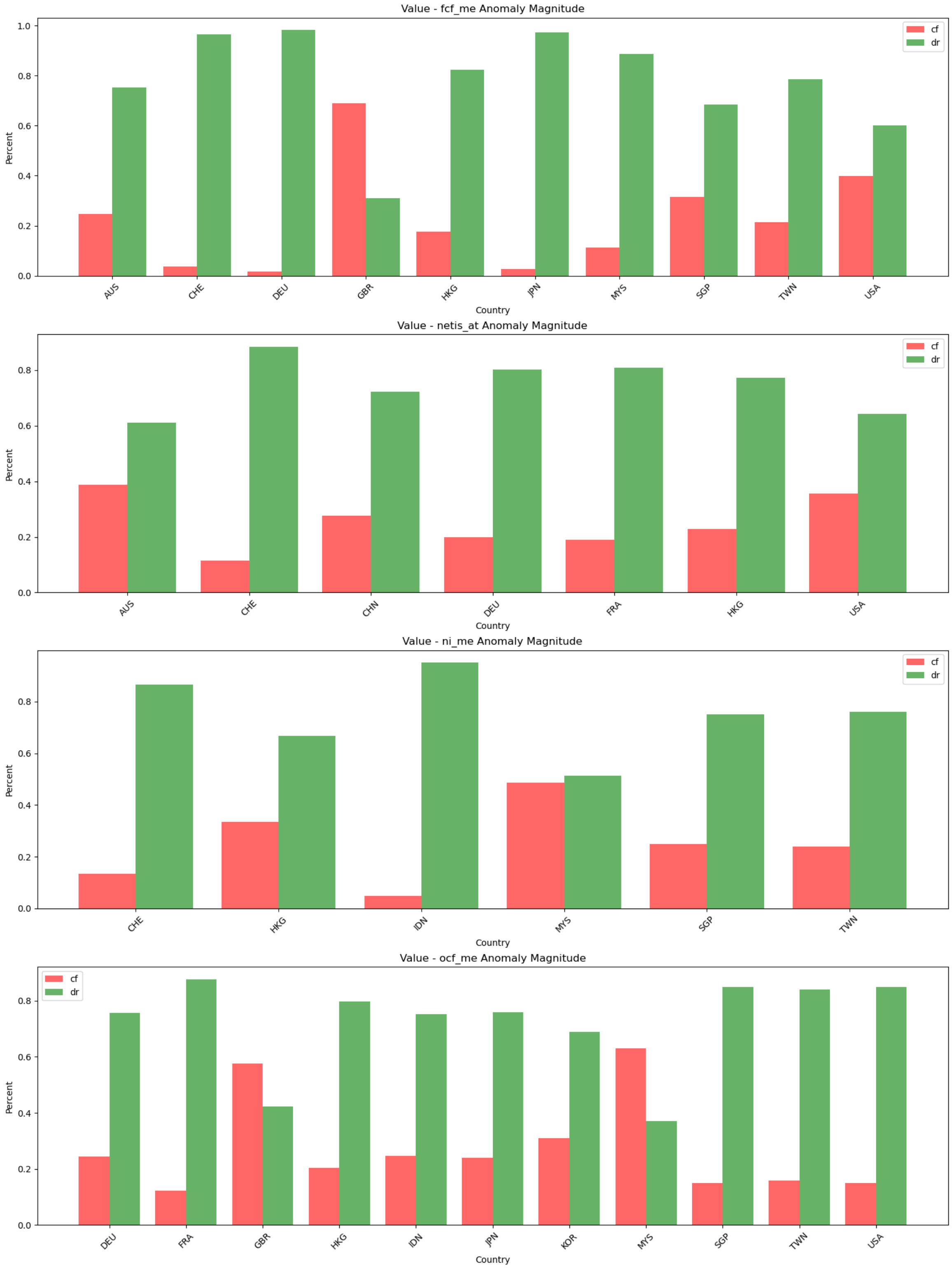
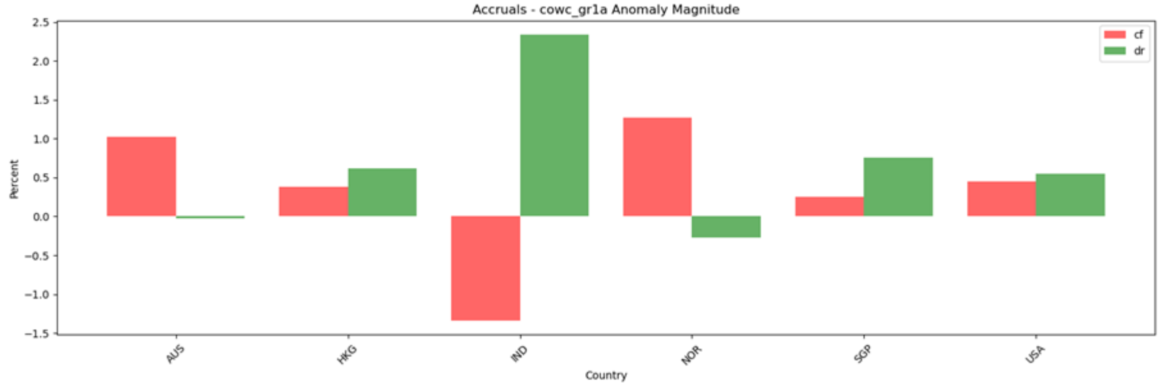
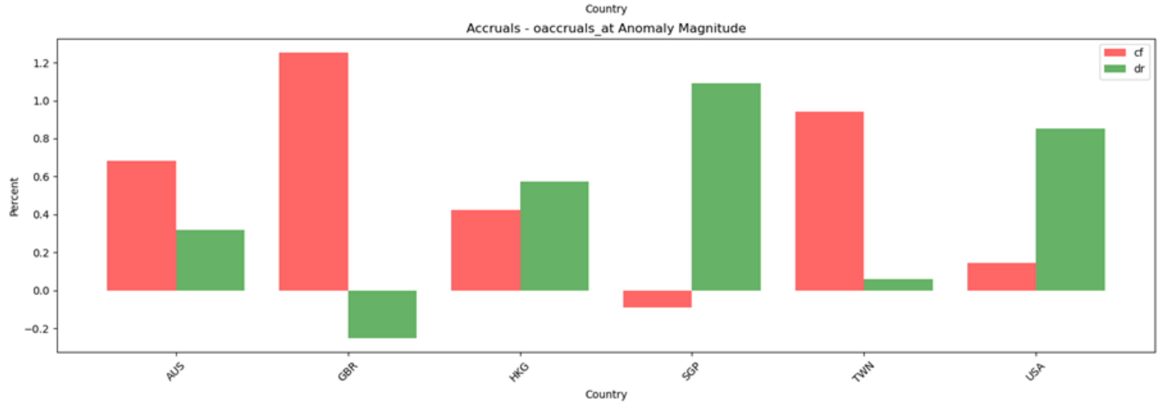


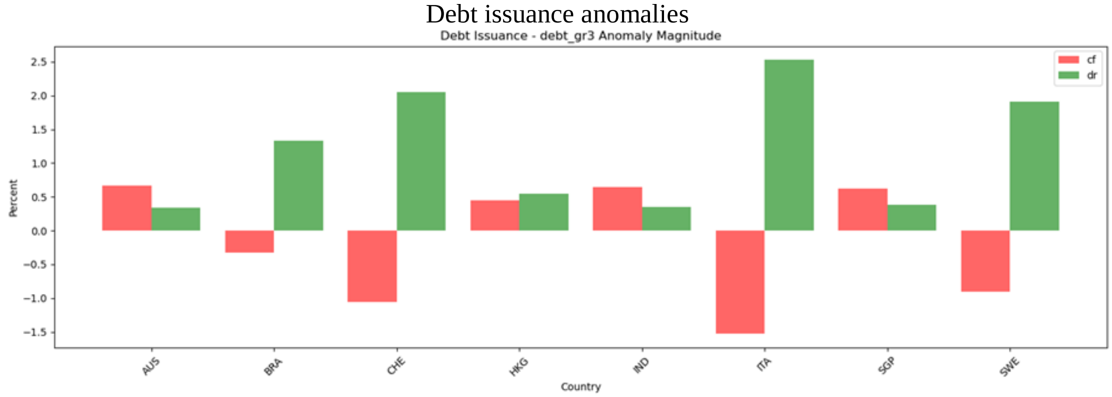
Figure C3. Variance decomposition of stock anomaly 1-year returns by country

Accruals anomalies

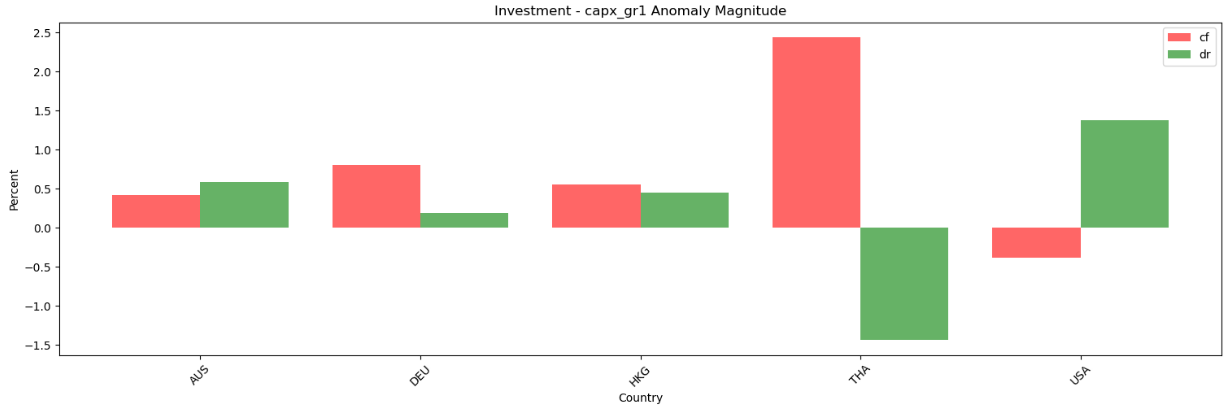


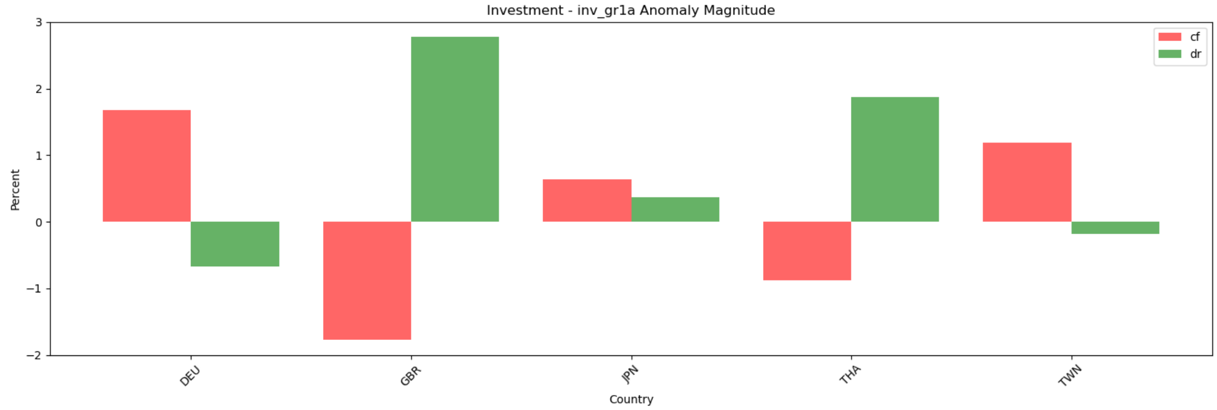


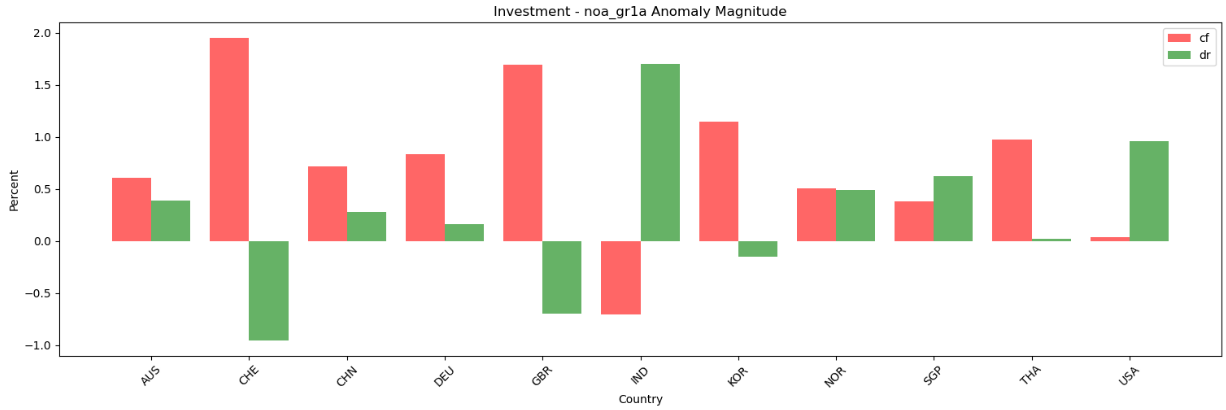
Debt issuance anomalies

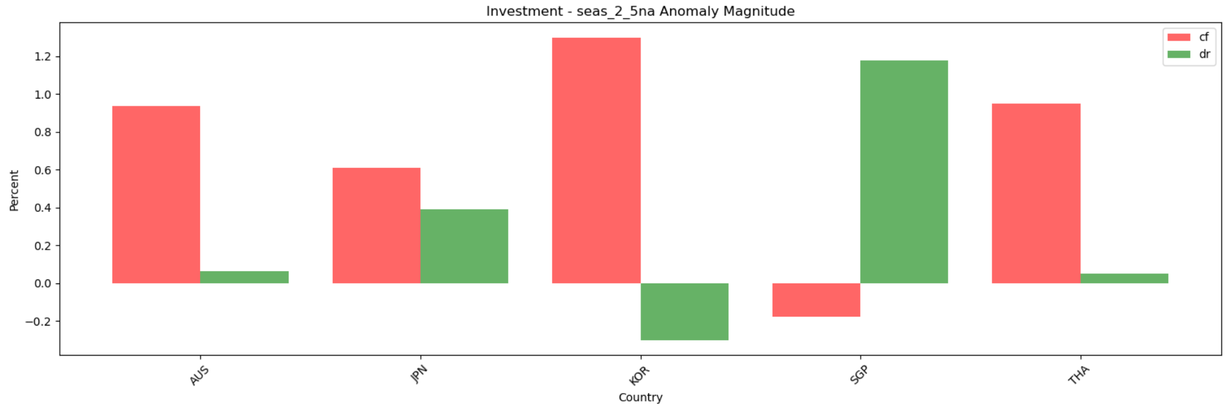


Investment anomalies









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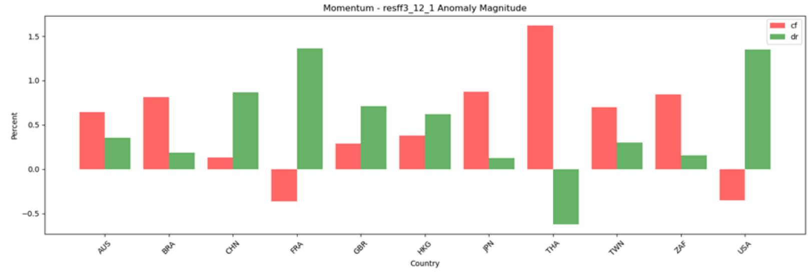
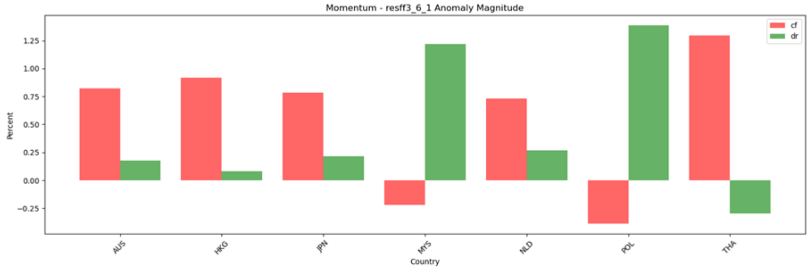
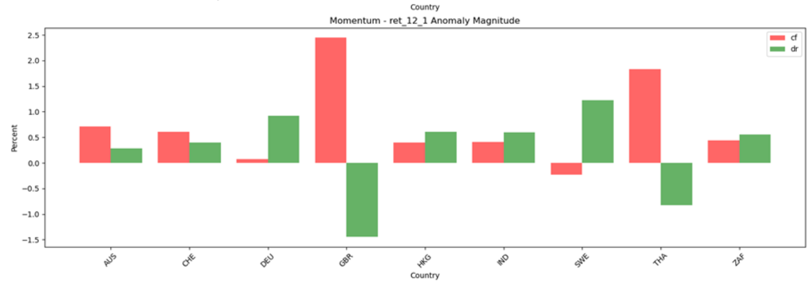
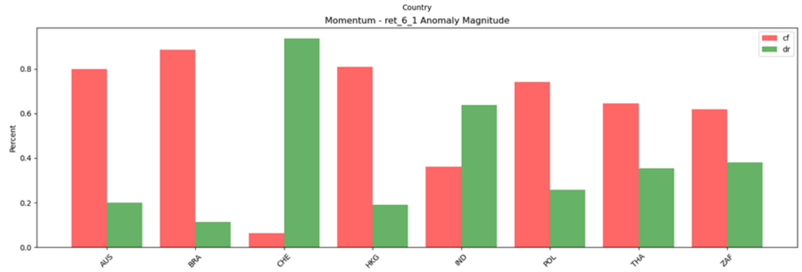
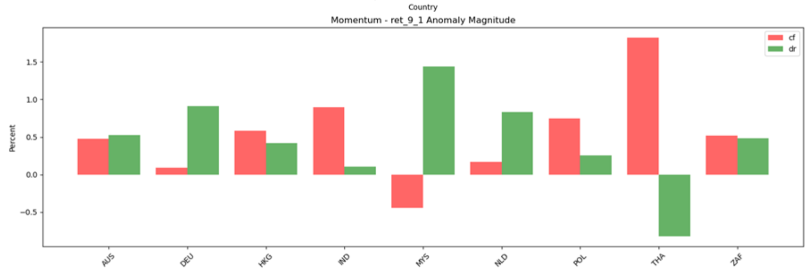
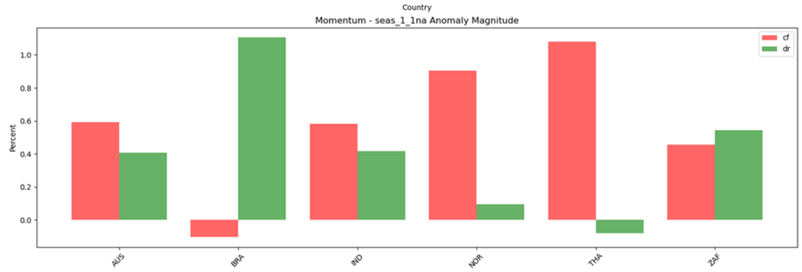




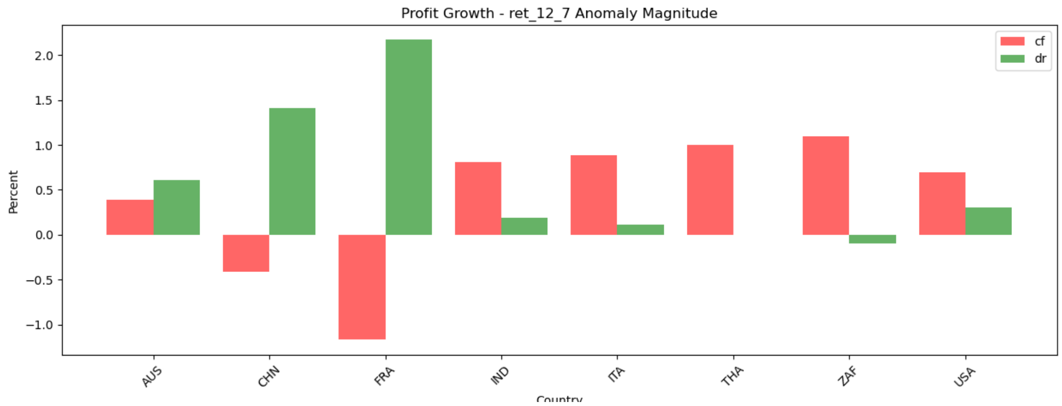








Profit Growth anomalies



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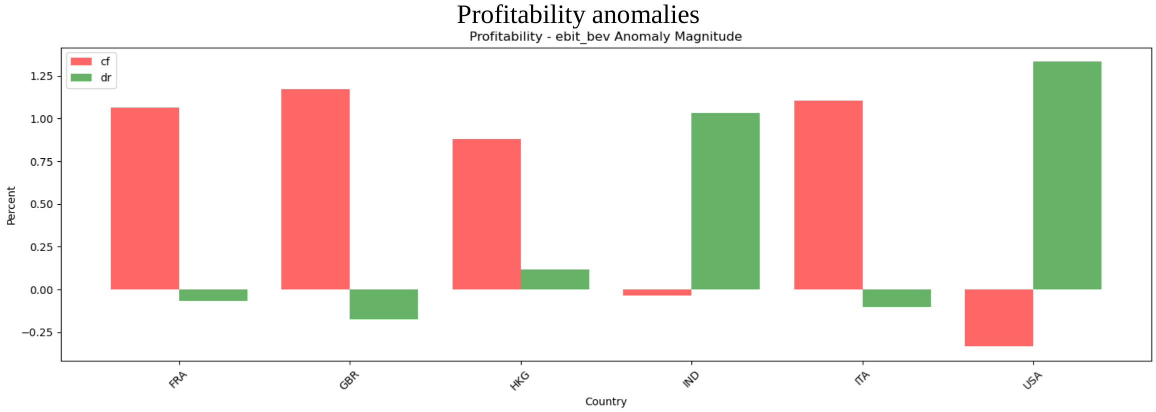
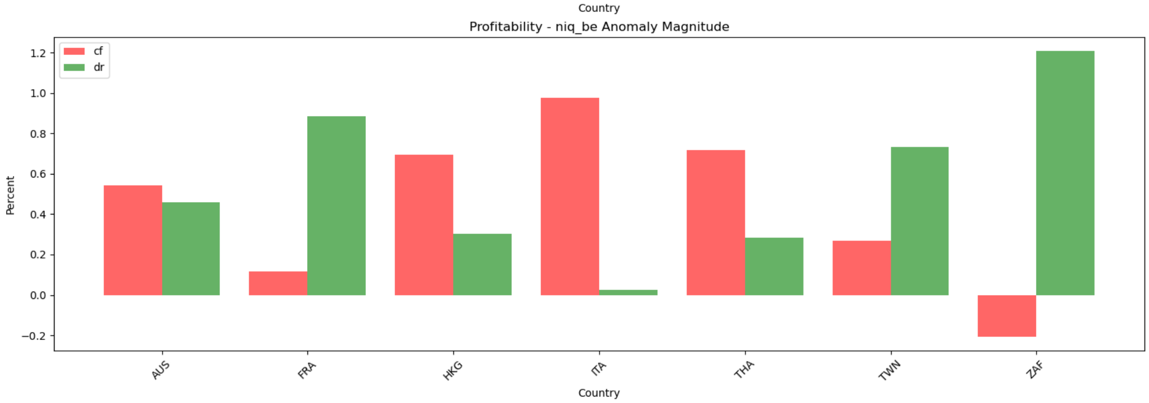
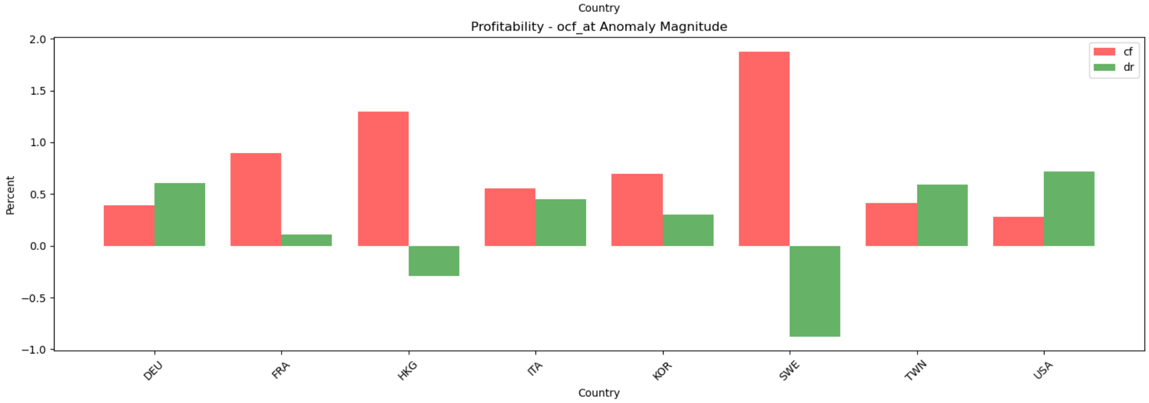
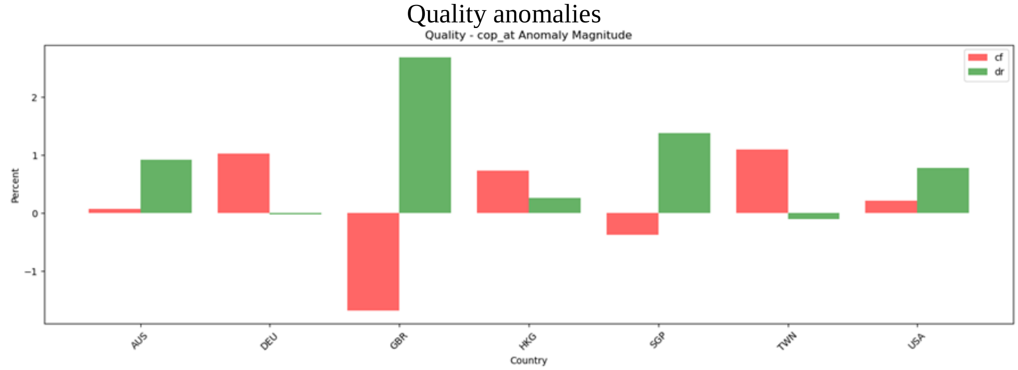
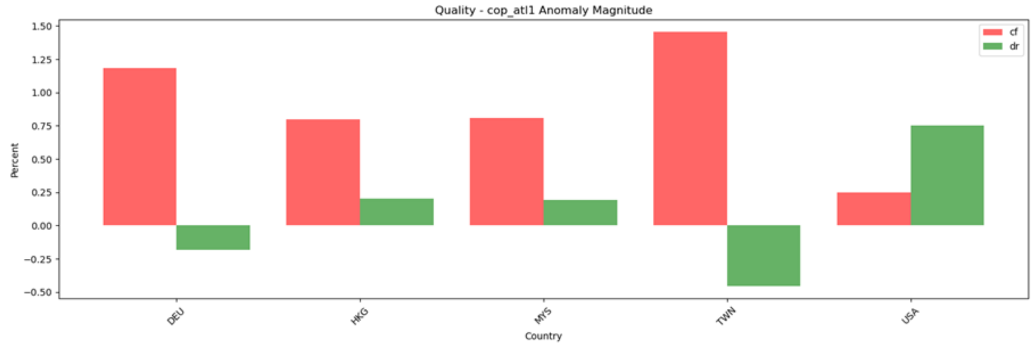


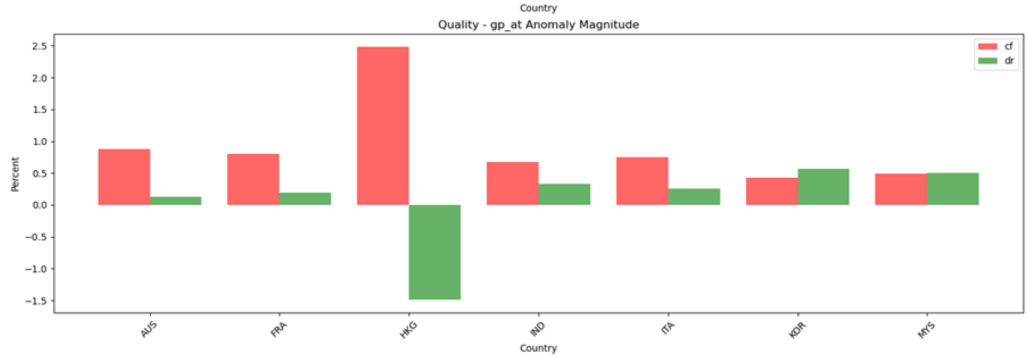


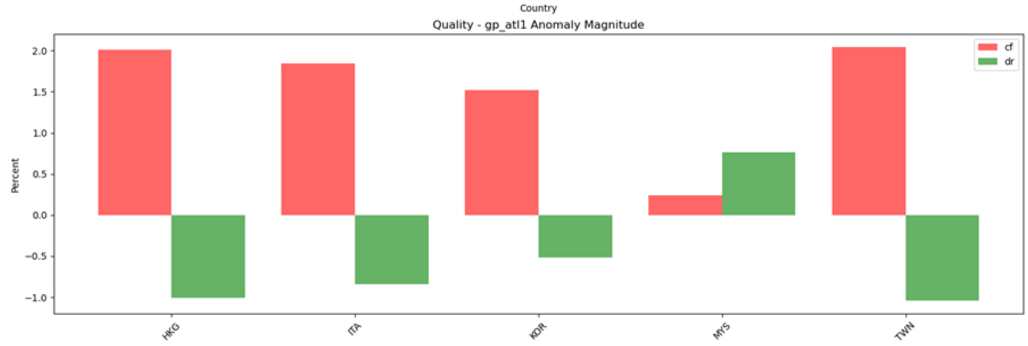


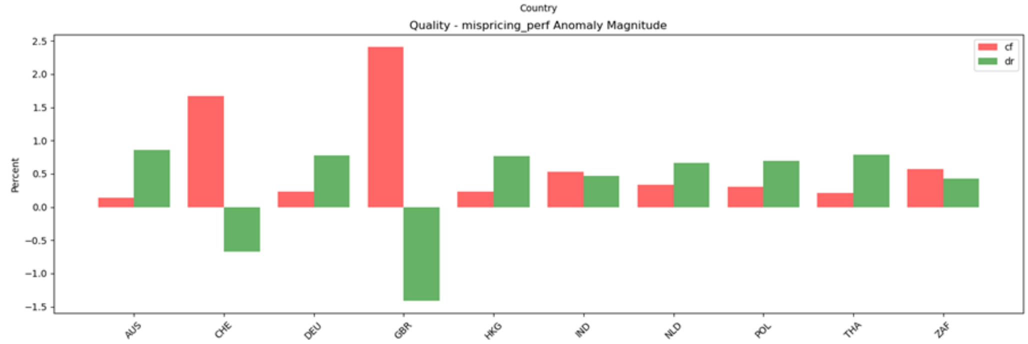
Quality anomalies



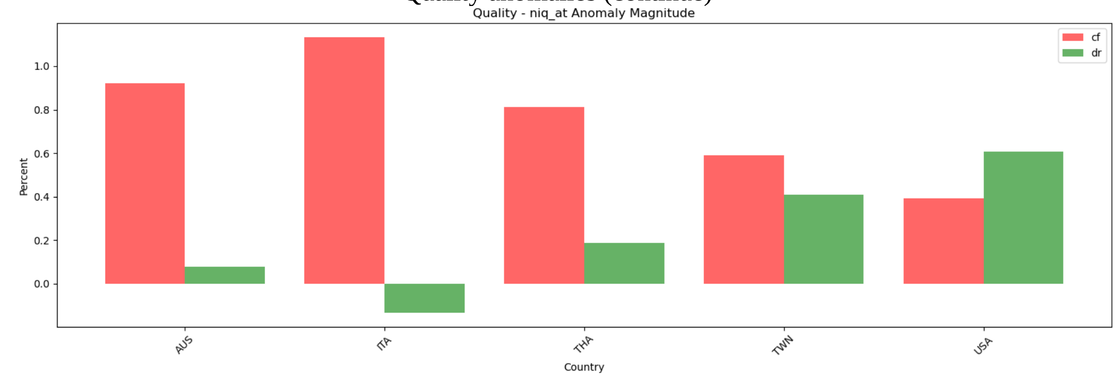


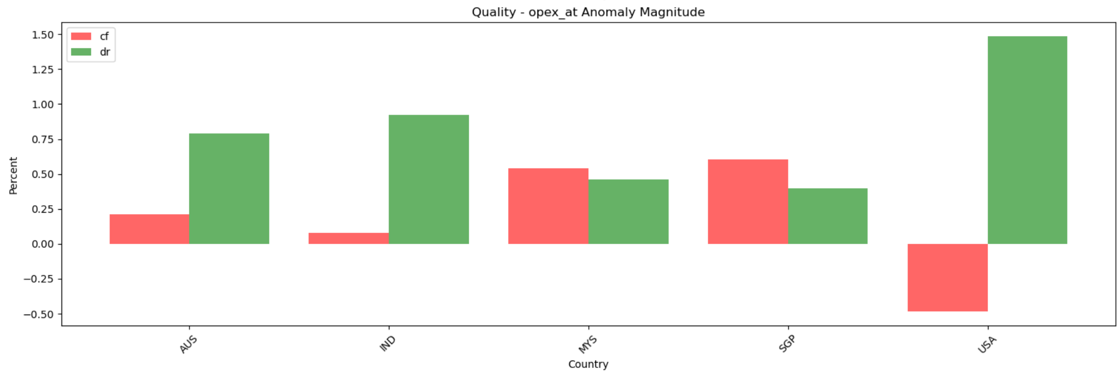


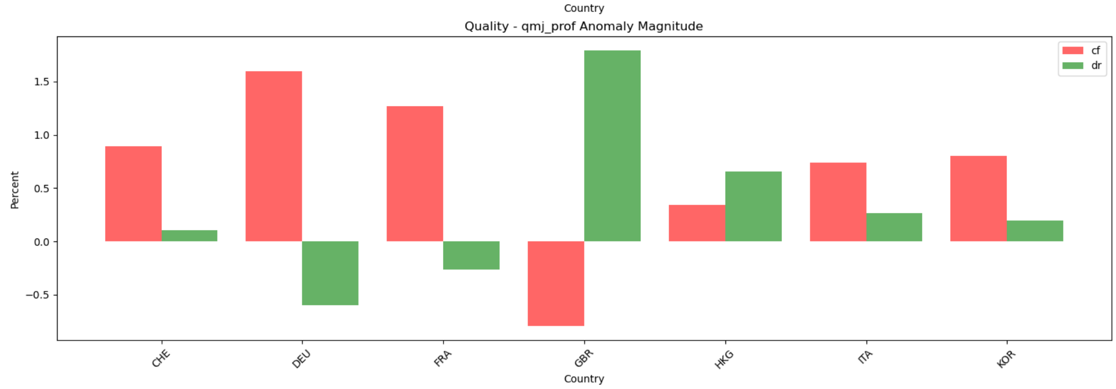


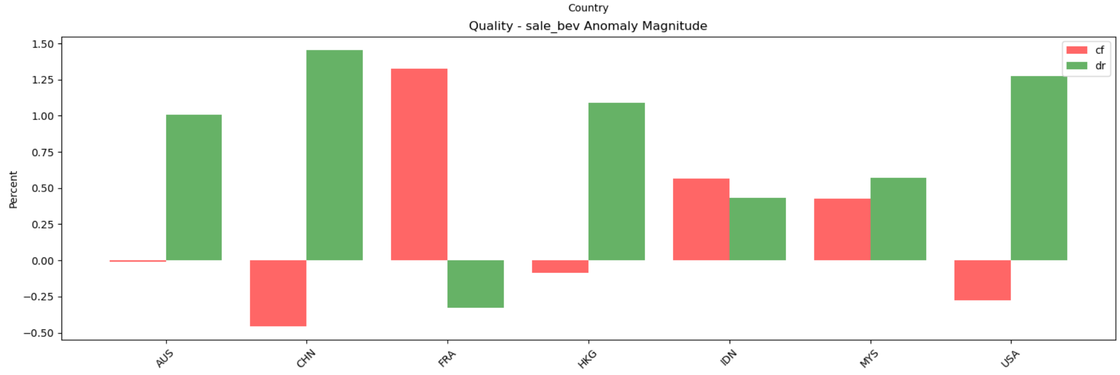


Quality anomalies (continue)

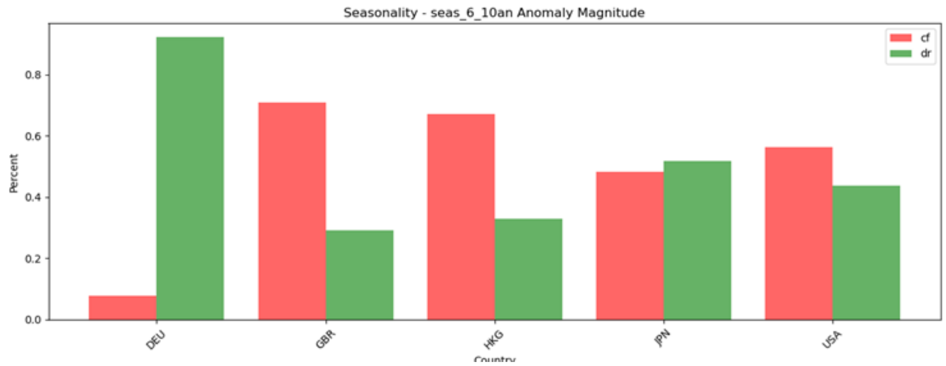




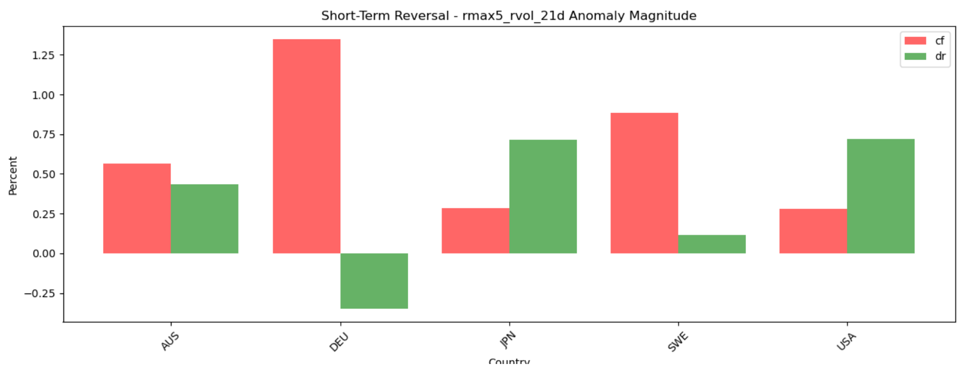




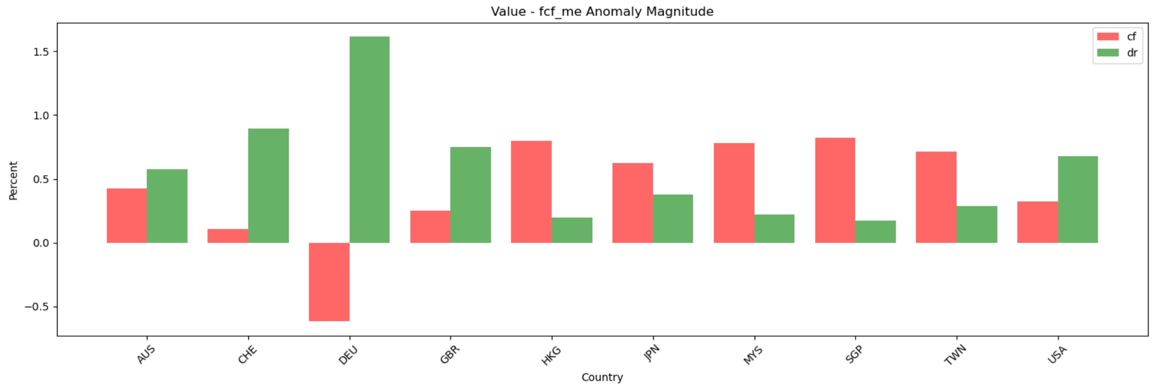
Seasonality anomalies

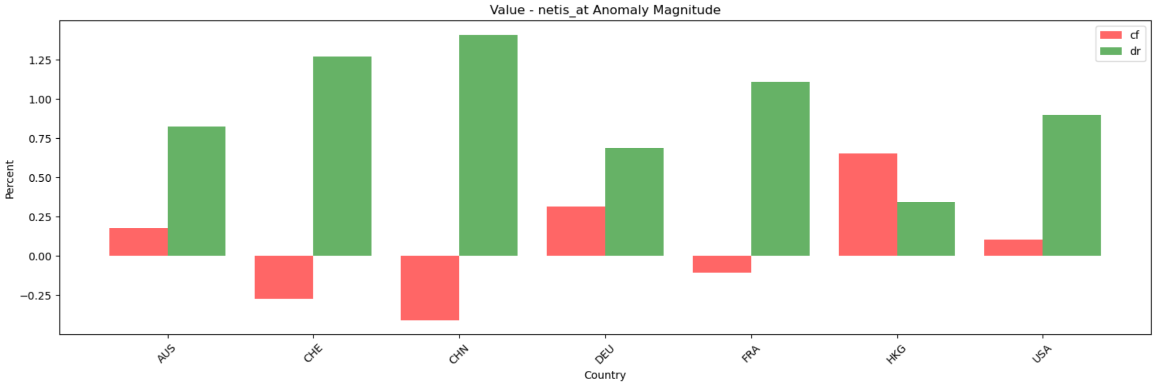


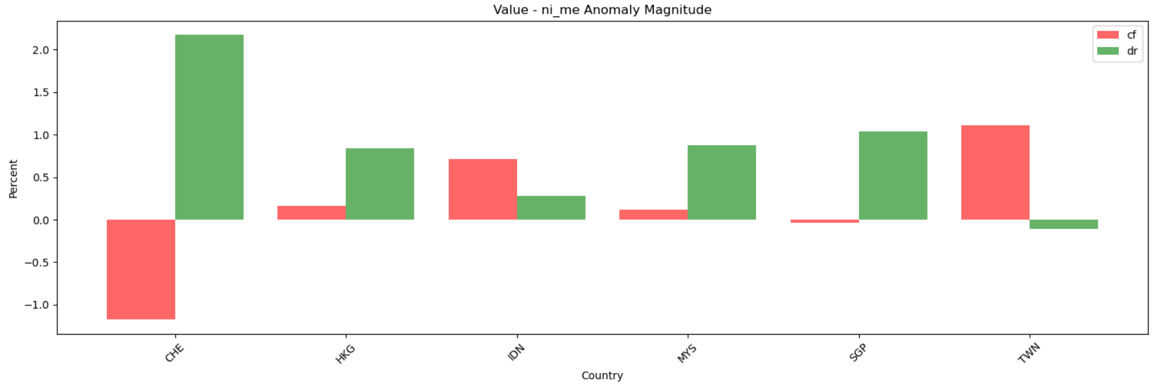
Short-term Reversal anomalies

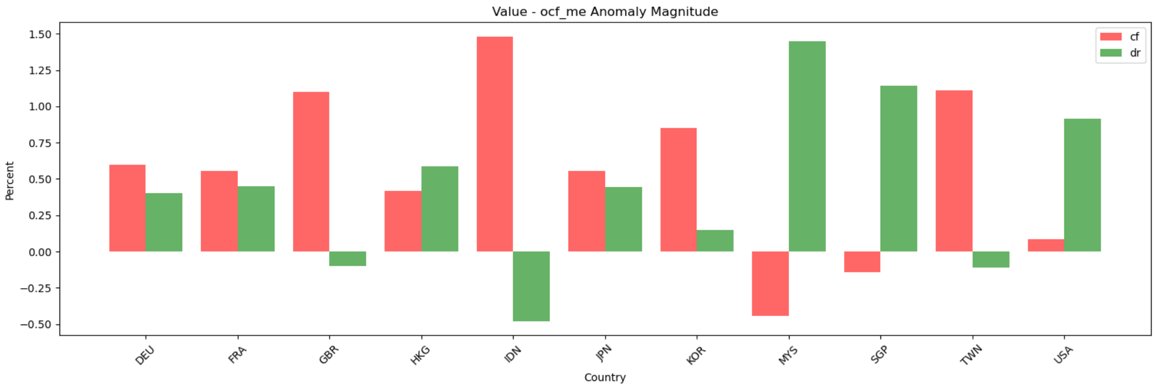


Value anomalies









Chapter 2: Interpretable Risk Perceptions in Equity Investments

2.1 Introduction

The risk-centric view of business cycles posits that fluctuations in financial market risk perceptions are a determinant of asset prices and a key driver of macroeconomic activity (Cochrane (2017), Pflueger, Siriwardane, and Sunderam (2020), Caballero and Simsek (2020)). Shifts in financial market risk perceptions can be implicitly embedded within the risky asset's risk premium. Furthermore, as risk perception drives important state variables' dynamics and future business cycles, it may also be relevant in the risk premiums of various factors. The time-varying risk premiums as well as those of prominent risk factors are known to be closely related to state variables and macroeconomic conditions (Chordia and Shivakumar (2002), Bansal, Dittmar, and Lundblad (2005), Cooper and Priestley (2009), Gormsen and Jensen (2024)). We seek to explore how risk perceptions influence the conditional risk premiums and factor performance.

We first find both in-sample and out-of-sample evidence of the predictive power of risk perception on future market return, size, profitability and momentum risk premia. Risk perception is measured by the price of volatile stocks (PVS) by Pflueger, Siriwardane, and Sunderam (2020). The predictive power of PVS on market return demonstrates its impact on future investment opportunity sets (Merton (1973), Brennan, Wang, and Xia (2004)). PVS negatively predicts the market return and size factor premium, but positively on the profitability and momentum factor premiums. The magnitude and stability of these factor premiums have been documented to vary over time with specific moments (Daniel and Moskowitz (2016), Barroso and Santa-Clara (2015), Fama and French (2021), Smith and Timmermann (2022)). Our predictive analyses support that risk perceptions drive the return performance of various factors.

Investors' risk perceptions can behave as a latent factor that lies in asset prices and investors investment decisions. To further investigate how equity investments are subject to risk perceptions, we employ the instrumented principle analysis (IPCA) proposed by Kelly, Pruitt, and Su (2019) to mimic risk perceptions with tradable assets. Specifically, IPCA maps firm characteristics onto each individual firm's dynamic exposure to risk perceptions. This approach enables us to identify the characteristics that contribute most to the exposure of PVS with which we can explicitly assess how equity investors assess risk perceptions through the observable characteristics while making investment decisions. Moreover, the time-varying risk exposures delivered by IPCA estimation also enable us to evaluate the time-varying risk perceptions. Mimicking PVS with IPCA sheds light on our understanding using observable characteristics to project on the unobservable investor risk perceptions.

We obtain each individual stock's beta to PVS (β^{pvs}) from the above IPCA approach. Stocks with high asset-to-me value, low past return, and low sales are likely to be more sensitive to market risk perceptions. Then, we examine the predictive power of the monthly β^{pvs} in the cross-section difference of future stock returns to see if risk perception is priced in the cross-sectional of stocks. We first sort stocks into deciles based on their β^{pvs} and examine the significance of the corresponding portfolios in the following month. Stocks in the highest PVS beta β^{pvs} decile underperform the stocks in the lowest β^{pvs} decile by on average 2.614% than in an equal-weighted scheme and 0.976% in terms of value-weighted average. The results are statistically significant in the time series at the 99% confidence level. Moreover, the alphas adjusted for the Fama and French (1993; 2015) three-factor, five-factor, and six-factor models continue to be statistically significant.

Following the spirit of Kelly et al. (2019) and Fama and French (2020), the cross-sectional regression of stock's excess return $xret_{i,t}$ on the standardized β^{pvs} can generate the monthly mimicking factor of PVS ($fPVS$). Consistent with Fama and French (2020), $fPVS$ is a cross-sectional factor and is readily available at each month. We show that the mimicking factor *fPVS* has an average monthly return of -0.709% and is significantly different from 0 even after controlling for other cross-sectional risk factors. The mimicking factor *fPVS* has a correlation of 0.24 with PVS, and its significance persists in the out-of-sample estimation. The parametric approach confirms the univariate sorting results. The risk price of PVS is indeed significantly negative and it survives in an array of robustness tests. The results support that risk perception is indeed a latent factor in the cross-section of stock returns.

We continue to explore the roles of PVS in different aspects and periods of the equity investments. In different industries, the magnitude of PVS premium seems to vary. Moreover, with firm-level exposure to PVS, we can explicitly observe how each investment style incorporates risk perception from a holding-based perspective. With each stock's dynamic exposure to PVS (β_{t-1}^{PVS}) each month, we can know the ex-ante exposure of trading strategies or representative investment styles to PVS risks once we know the holdings. We call the cross-sectional constructed beta (CS beta) as opposed to the traditional time-series beta (TS beta) by regressing two-factor returns together. Our CS beta enables us to see the dynamic performance of each factor's exposure to PVS at different states of the economy. Along with the mimicking factor *fPVS*, we can further obtain the realized return as exposed to PVS. We correspondingly partition our sample period to analyze each factor's time-varying PVS exposure and PVS's risk premium. In months that have varying levels of factor premiums, their realized return on PVS is also significantly different. Except for the market factor, all other five factors have higher PVS realized returns during the corresponding high factor premium months. Factor's exposure to PVS also varies during different market conditions. Smith and Timmerman (2022) identify "breaks" for each risk factor. Our results here also imply risk perceptions capture those related dynamics.

Recent literature in behavior finance using survey data (Greenwood and Shleifer (2014), Holzmeister et al. (2020), Adam and Nagel (2023), Nagel and Xu (2023), De la O and Myers (2024)), laboratory experiments (Huber, Panaln and Zeisberger (2019), Charles, Frydman, and Kilic (2024)) and statistical methods (Cassella et al. (2025)) to highlight how the subjective risk might deviate from the realized returns. They also explore how investors' subjective expectations of volatility influence their risk-return trade-offs (Moreira and Muir (2017), Lochstoer and Muir (2022)). While our paper is motivated by the risk-centric theories, where the risk perceptions reflect on the price of risky assets, we focus more on how risk perceptions are projected into risk factor performance and investment decisions.

Lastly, we conduct textual analyses with the state-of-the-art LLM model Gemini 2.0 Flash to understand how investors express their subjective risk through text messages. Gemini model identifies the StockTwits messages expressing increased level of risk perception on the financial market. We compute an LLM-based risk perception ratio and find it positively correlated with PVS and can predict PVS in univariate regressions. The text-based contents provide more straightforward illustrations of how investors express their perceived risks. We find that investors talk about the market more and express more pessimistic opinions. Market participants explicitly show their perceived risk textually.

Our paper is associated with the asset pricing literature that relates to the risk and risk perceptions. Indeed, risk perception stems from people's evaluation of their surrounding financial markets, regardless rational or subjective. We find supporting evidence that prominent risk factor premiums, such as momentum, are driven by investor risk perceptions. Related research explores how investors' subjective expectations of volatility influence their risk-return trade-offs (Moreira and Muir (2017), Lochstoer and Muir (2022)). In finance literature, Lewellena and Nagel (2006) and Gormsen and Jensen (2024) seek to identify the time-varying risks to explain the cross-sectional stock returns. Conditional tests for varying risks (such as Campbell and Cochrane (2000), Nagel and Singleton (2011)) also examine conditional models' statistical explanatory power. Also, the Merton (1973) ICAPM literature states that an asset's expected return depends on its covariance with the market portfolio and with other state variables that proxy for changes in the future investment opportunity set (Shanken (1990), Brennan, Wang, and Xia (2004), Ang, Hodrick, Xing, and Zhang (2006), Bali (2008)). Recently, Barroso, Boons, and Karehnke (2021) show that the cross-section of stock exposure to a state variable is time-varying and the findings still fit in the ICAPM framework. Our paper tries to provide evidence that not only the risk itself, but the time-varying perceptions of risk have effects on the risk premiums and risk factors. We show that the time-varying risk perceptions are priced in the cross-section of stocks. Factors like size, momentum, and profitability are also exposed to risk perceptions.

Our paper provides a framework on how to assess investor risk perception in the context of equity investing. Risk perception can refer to people's subjective and unobservable expectations about future risk. Previous literature in experimental finance and decision science tried to capture risk perception and its role in investment decisions with survey and laboratory experiments (Weber and Hsee (1998), Holzmeister et al. (2020)). They mainly focus on investor actions when they face the same level of risk, but also consider other factors that might affect their perceptions of the future risk. Investors' subjective risks have been addressed by recent behavior finance research using survey data (Greenwood and Shleifer (2014), Holzmeister et al. (2020), Adam and Nagel (2023), Nagel and Xu (2023)), laboratory experiments (Huber, Panaln and Zeisberger (2019), De la O and Myers (2024), Charles, Frydman, and Kilic (2024)) and statistical methods (Cassella et al. (2025)). They also argue that investor subjective assessment of risks will directly shape their perceived future investment opportunity set and investment decisions (Giglio et al. (2021), Dahlquist and Ibert (2024), Couts, Gonçalves, and Loudis (2024)). Gormsen and Huber (2024) use conference call texts data to extract the perceived cost of capital data from managers and find its relation to risk factors. They focus on the behavior biases and how the subjective expectations deviate from the realized ones. Our paper parallels to these papers as we do not argue whether it is rational or irrational, but quantify investor's risk perception as an outcome from the equity prices. Leveraging on IPCA, our paper explicitly shows the stock characteristics that contribute most to the risk perceptions. In addition, we use LLM models to explore how investors express their perceived risks.

Lastly, our paper is related to the investment literature. Previous literature has demonstrated the performance of prominent factors is not static (Daniel and Moskowitz (2016), Barroso and Santa-Clara (2015), Chui, Titman, and Wei (2010), Asness, Moskowittz and Pedersen (2013), Fama and French (2021), Smith and Timmermann (2022)). Some studies conduct analysis from holding-based analysis on how investment industries conduct stock selection and conduct investment strategies (Daniel et al. (1997), Jiang, Yao, and Yu (2007), Agarwal, Jiang and Wen (2022)). The investment industry is known to specify several investment styles, such as small caps, growth, value, or momentum stocks. Our paper is related to them as we directly examine the outcome of risk perception in equity investments. We start with the representative investment styles. However, we can further extend our research to more specific training or fund-level analyses.

The paper proceeds as follows. We have a short motivation model in Section 2. Data description is in Section 3. Section 4 reports the empirical results and Section 5 is our LLM-based textual analyses. We conclude our paper in Section 6.

2.2 Motivating Model

Pflueger et al. (2020) demonstrate that perceived risk is related to stock expected returns by linking stock return to a firm's cost of capital in their q-theory based production model. Their model implies that:

$$E_t\left[R_{i,t+1}\right] = r_{ft} + \gamma s_i V_t(\varepsilon_{t+1}) \tag{1}$$

where r_{ft} is the risk-free rate in month t, γ is the risk aversion that is assumed to be constant, s_i is the firm production volatility of firm i. $V_t(\varepsilon_{t+1})$ is the perceived risk, which is the conditional variance of aggregate consumption growth. The variance of aggregate consumption growth is assumed to be normal distributed with 0 mean and not serially correlated. Alternatively, Eq. (1) can be rewritten as:

$$E_t\left[R_{i,t+1}\right] = r_{ft} + \gamma s_i V_t(\varepsilon_{t+1}) = a_{t,i} + \beta_{i,t}^{PR} V_t(\varepsilon_{t+1}) = a_{t,i} - \beta_{i,t}^{PR} PVS_t, \tag{2}$$

where $PVS_t = -\gamma \delta_s V_t(\varepsilon_{t+1})$, δ_s is a scaler that stands for the difference in production volatility between high risky firm and low risky firm. $\beta_{i,t}^{PR}$ is stock i's exposure to perceived risk in month t. Eq. (2) implies that PVS_t should have a negative price. We move on to the empirical part to examine how PVS_t is priced in the cross-section of stock returns.

2.3 Data

We first replicate PVS to monthly frequency as the average book-to-market ratio of low volatility stocks minus the average book-to-market ratio of high volatility stocks following the empirical specification of Pflueger et al. (2020). CRSP provides the stock return related data. The financial statements accounting numbers are from Compustat Quarterly database. To avoid look-ahead bias, we merge the financial statements information with a 4-month lag to the stock return information. We include the 36 firm characteristics as in Kelly et al (2019): market beta (beta), assets-to-market (a2me), total assets (assets), sales-to assets (ato), book-to-market (bm), cash-to-short-term investment (c), capital turnover (cto), capital intensity (d2a), ratio of change in property, plants and equipment to the change in total assets (dpi2a), earnings-to-price (e2p), fixed costs-to-sales (fc2y), cash flow-to-book (freecf), idiosyncratic volatility with respect to the FF3 model (idiovol), investment (invest), leverage (lev), market capitalization (mktcap), turnover (turn), net operating assets (noa), operating accruals (oa), operating leverage (ol), price-to-cost margin (pcm), profit margin (pm), gross profitability (prof), Tobin's Q (q), price relative to its 52-week high (w52h), return on net operating assets (rna), return on assets (roa), return on equity (roe), momentum (mom), intermediate momentum (intmom), short-term reversal (strev), long-term reversal (ltrev), sales-to-price (s2p), the ratio of sales and general administrative costs to sales (sga2s), bid-ask spread (bidask), and unexplained volume (suv). The sample period spans from January 1970 to December 2020 and our sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges.

To maintain a cross-section that is as large as possible, we standardize each characteristic so that every characteristic has a mean of 0 and a standard deviation of 1 distribution each month. If a stock has missing values for any of the 36 characteristics, we fill the missing characteristic with 0 so that the overall distribution of each characteristic does not get affected. Prior to standardizing, we winsorize all characteristics at the 1st and 99th percentiles. This helps mitigate the influence of extreme outliers.

We first refer to different risk factors as our starting point for exploring different investment styles. As we seek more details on the style-investing related asset allocations, we strictly replicate the risk factors as described in Fama and French (1993) and Fama and French (2015). Our own versions of risk factors have similar magnitudes, t-statistics with the ones on Ken French's website. The correlations between ours and the website's are at least 0.97.

2.4 Empirical Results

2.4.1 PVS and factor performance

We start with our examination by first testing the relation between the time-varying risk perception measure PVS and the market return and other representative factor returns. By running OLS regression of factor returns on lagged PVS, we can have a clear view of whether PVS is related to aggregate wealth or future investment opportunities. Table 1 presents both in-sample and out-of-sample results for the predictive power of PVS on future factor performance. In the 1-month horizon, Panel A suggests that PVS has negative and significant predictive power for the future size factor, and the out-of-sample R^2 (0.672%) is also economically large at 0.67%. Campbell and Thompson (2008) suggest that OOS R^2needs to be at least greater than 0.5% to be economically significant. We also find that it is statistically significant measured by Clark and West (2007) statistic at 0.31. We find in-sample evidence that PVS has some predictive power for the future market return, although it is only marginally significant at the 10% level. Since PVS is negatively linked to the magnitude of risk perceptions, the above negative coefficients for the market and size factors indicate that when market risk perception is high, the future 1-month size and market factor returns tend to be higher. Profitability and momentum have positive coefficients in the OLS regression with lagged PVS, and they are also marginally significant. The positive coefficients on lagged PVS suggest that when financial market risk perception rises, the profitability and momentum factor return decrease. The out-of-sample tests remain significant for the momentum factor, but not for profitability factor. The value and investment factor returns are not predicted by PVS in the OLS analysis.

[Insert Table 1 here]

In Panel B, we extend the forecasting horizon to the future 12 months. We find that the results shown in Panel A continue to hold. In the longer horizon, the out-of-sample significance becomes stronger for market, size, profitability, and momentum factors. Their out-of-sample R^2s all become statistically and economically significant at the 99% confidential level with the 12-month horizon.[8] The predictive results echo the Merton (1973) ICAPM model, providing evidence that risk perception has an effect on the future investment opportunity set.

[8] Pfleuguer et al. (2020) fail to document a significant coefficient between PVS and the market factor in the 12-month horizon. We suspect that the reason is due to some minor differences between our and their constructions of PVS in terms of the sample period and regression frequency. In their study, the PVS was constructed at the quarterly frequency and the accounting information was set to lag only three months to the stock prices. These minor construction differences might be the reasons for the inconsistency.

Consequently, we construct a mimicking factor to track the risk premium associated with its dynamics.

2.4.2 Mimicking PVS with individual stocks

We construct our mimicking factor for PVS in this section to examine the risk premium associated with its dynamics. As we mention in our previous subsection, one of the focuses of this paper is to evaluate how equity investors incorporate risk perception in their investment decisions. The magnitude of PVS is actually the outcome of how people perceive different risks in the market and react to their subjective perception through their investment choices. The intuition is simple as indicated by Pflueger et. al (2020): if investors expect the current market to be risky, they prefer safer assets and push the price for them to be higher. In this spirit, we would observe the outcome (i.e., PVS) and seek to back out which firms are most sensitive to the dynamics of risk perception. Moreover, we examine if and how risk perception is priced in the cross-section and whether there are any observable characteristics that might be useful information for investors to assess its holdings regarding market risk perception.

Fortunately, we are able to reach the above goals by applying the instrumented principal analysis (IPCA) method by Kelly et. al (2019) to first estimate each stock's exposure to PVS, and simultaneously track the characteristics that contribute the most to such exposures. Our empirical approach is as follows:

$$\begin{aligned} r_{i,t} &= \beta_{i,t-1}^{pvs} PVS_t + \beta_{i,t-1}^{mkt} mkt_t + \epsilon_{i,t} \\ &= z_{i,t-1} \Gamma_{\beta^{pvs}} PVS_t + z_{i,t-1} \Gamma_{\beta^{mkt}} mkt_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $r_{i,t}$ is the excess return for stock i in month t. PVS_t is specified in the model in order to estimate each individual stock's exposure to it, while controlling for the market excess return mkt_t. $\beta_{i,t-1}^{pvs}$ is the dynamic risk exposures to PVS. $z_{i,t-1}$ is the 36 characteristics for stock i in month $t-1$, and $\Gamma_{\beta^{pvs}}$ maps the 36 characteristics to the exposures to the PVS exposure $\beta_{i,t-1}^{pvs}$.

Similarly, $\beta_{i,t-1}^{mkt}$ stands for the stock's exposure to the market excess return and $\Gamma_{\beta^{mkt}}$ maps the 36 characteristics to $\beta_{i,t-1}^{mkt}$. With this IPCA approach, we can obtain each stock's exposure to PVS in every month while controlling for the market return. Unlike the traditional construction of factor exposure that might slowly incorporate useful information, $\beta_{i,t-1}^{pvs}$ receives the latest information and is not subject to potential staleness problems. Moreover, as the exposures are strictly linked to stock characteristics, we can also observe which are the important characteristics that contribute to a firm's exposure to PVS.

2.4.3 Univariate sorting

We conduct parametric and nonparametric tests to assess the predictive power of the $\beta_{i,t-1}^{pvs}$ over future stock returns. We first sort stocks into deciles according to their $\beta_{i,t-1}^{pvs}$ along with some characteristics that are informative to understand what kind of stocks might be sensitive to market risk perception. For each month, stocks are divided into deciles based on their PVS betas $\beta_{i,t-1}^{pvs}$, where decile 1 contains stocks with the lowest PVS beta and decile 10 contains the highest one. Panel A of Table 2 shows that firms that are the least sensitive to market risk perception (therefore a highest PVS beta) are on average the ones with largest size, smallest market beta, lowest volatility, highest past 11-month return, and are likely to be growth stocks. In addition, such stocks have a very large positive monthly return in the past month (14.43%). On the other hand, the stocks that are most sensitive to risk perception are smallest in size, likely to be value stocks, have highest volatility and worst past performance.

[Insert Table 2 here]

Panel B presents a closer look at both the equal-weighted and value-weighted average portfolio $\beta_{i,t-1}^{pvs}$ at the formation month and the following month, as well as the next month's excess return $r_{i,t}$. Pre-ranking beta refers to the PVS beta $\beta_{i,t-1}^{pvs}$ in the portfolio formation month and post-ranking beta is the ones in the following month, which is the same month with the excess stock return $r_{i,t}$. Columns (1)-(2) and also Columns (4)-(5) show that each decile's average PVS beta $\beta_{i,t-1}^{pvs}$ shrinks to zero substantially in the following months, reflecting the swiftly and dynamically changes of firm's exposure to PVS. The value-weighted portfolios have even more drastic changes for negative β^{pvs}. Moreover, in Columns (3) and (6), we observe that the average stock return in the next 1 month monotonically decreases from Decile 1 to Decile 10, consistent with the implication of the ICAPM model. Stocks belonging to the bottom decile of $\beta_{i,t-1}^{pvs}$ have an EW return of 2.753% per month and a VW return of 1.381%. Stocks in the top decile has an EW return of 0.138% and a VW return of 0.405%. The higher magnitude of EW returns than that of VW returns in Decile 1 indicates that more small firms are grouped to Decile 1. This is consistent with our observation in Panel A that small firms on average have a low exposure to PVS, and therefore are more sensitive to risk perception. The difference in EW returns between Decile 10 and Decile 1 is -2.614% per month with a Newey-West adjusted *t*-statistic of -7.41. For the difference in VW returns, it continues to be significant both economically and statistically, with a monthly return difference of -0.986% (*t*-stat = -3.22).

Apart from the average raw excess returns, Columns (3) and (6) also show the magnitude and statistical significance of the risk-adjusted returns (alphas) from (i) Fama-French three-factor model (FF-3), (ii) Fama-French five-factor model (FF-3 factors plus investment and profitability factor), and Fama-French six-factor model (FF-5 factors plus momentum factor). The alphas per month between the top and bottom deciles continue to be both statistically and economically significant.

2.4.4 Average stock characteristics: *Γ* matrix

One of the features of the IPCA approach is that it dynamically maps a firm's characteristics to its exposure or beta of a factor. As is shown in Eq. (3), the $\Gamma_{\beta^{pvs}}$ matrix indicates each characteristic and its contribution to the sensitivity of PVS beta $\beta_{i,t-1}^{pvs}$.

In Figure 1, we show the $\Gamma_{\beta^{pvs}}$ estimates for each characteristic. The magnitude of the $\Gamma_{\beta^{pvs}}$ matrix describes how each characteristic maps into a firm's PVS beta on the PVS dynamics. Inspection of this mapping offers insight into the nature of the estimated IPCA PVS exposures for each stock. Figure 1 shows that the firm exposure to PVS is primarily determined by size, total assets, past 1-month return, constant, sales to assets, and unexplained trading volume. The constant characteristic means that all the firms share a common baseline exposure to PVS. The $\Gamma_{\beta^{pvs}}$ matrix helps to visualize what observable characteristics are closely related to a firm's exposure to PVS. Generally speaking, firms that have a large size-to-asset ratio, higher past return, and higher sales might have a larger exposure to PVS, and therefore less sensitive to market risk perception. The mapping between firm characteristics and firm sensitivity to market risk perception improves our understanding of the perceived risk.

[Insert Figure 1 here]

2.4.5 Mimicking factor of PVS

Following Kelly et al. (2019) and also Fama and French (2020), cross-sectionally regressing stock returns on each individual's PVS exposure ($\beta_{i,t-1}^{pvs}$) actually facilities us to estimate the mimicking factor of PVS in every month:

$$r_{i,t} = \gamma_t + fPVS_t \beta_{i,t-1}^{pvs} + \epsilon_{i,t}, \tag{4}$$

where $\beta_{i,t-1}^{pvs}$ is stock i's exposure to PVS in month $t-1$ and $fPVS_t$ is the cross-sectional (CS) mimicking factor of PVS at month t. We standardize each stock's $\beta_{i,t-1}^{pvs}$ before we run the cross-sectional regression to estimate $fPVS_t$ in each month. Therefore, we can obtain the tradable mimicking factor $fPVS_t$ when running the cross-sectional regression of individual stock's return $r_{i,t}$ on each stock's standardized PVS beta ($\beta_{i,t-1}^{pvs}$) at every month.

The intuition is very similar to the Fama and MacBeth (1973) regression, except for the standardization procedure. Fama and French (2020) comprehensively assess the cross-sectional factors and Kelly et al. (2019) also implies a similar methodology. We bring and apply this idea estimate a mimicking factor here. Table 3 tabulates the average the risk premium of the mimicking factor $fPVS$.

[Insert Table 3 here]

Panel A of Table 3 reports that the time-series average return of the mimicking factor $fPVS$ is -0.709% per month with a Newey-West t-statistic of -6.96. The result is from a univariate regression and is consistent with the univariate sorting results. Column (2) controls for standardized characteristics (size, book-to-market value, past 11-month return, profitability and 1-month return) as cross-sectional factors. We find that the significant coefficient on β^{pvs} continues to hold with the magnitude slightly reduced to -0.622% (t-stat = -5.49). In Columns (3) and (4), we control for the industry effect. We assign each stock to one of the Fama-French 12 industries and repeat our regressions as in the first two columns. The significant coefficients continues to hold.

Panel B of Table 3 examines the negative relation between β^{pvs} and future stock returns in a longer horizons (h = 2, 3,…,12). The multivariate regression results show that controlling for other characteristics as cross-sectional factors, the risk premium of $fPVS$ in longer horizons continues to be persistent and robust, but the magnitudes reduce significantly by 39% to 68%.

Figure 2 plots both the dynamics of PVS and the mimicking factor $fPVS$ on the same graph. For the months where PVS has drastic changes, we observe that *fPVS* can well capture those dynamics. Table 4 reports the correlations between $fPVS$ and PVS as well as other risk factors. The mimicking factor $fPVS$ is moderately correlated with PVS with a correlation of 0.24, and is significantly and negatively correlated with market and size factors (-0.338 and -0.427) and positively correlated with profitability and momentum factors (0.380 and 0.452).

[Insert Figure 2 here]

[Insert Table 4 here]

The analyses in previous subsections are so far based on the full-sample estimation, including the $\Gamma_{\beta^{pvs}}$ matrix estimation and the dynamic β^{pvs}. Next, we estimate out-of-sample betas as a robustness check to see if the out-of-sample version of the mimicking factor continues to be significant. In this way, we also explore if there exists any evolution of the $\Gamma_{\beta^{pvs}}$ matrix in the past history. For out-of-sample estimation, we use the first 60 months as our initial training sample for the factor construction. Later, we gradually expand the training sample to the most recent month in order to incorporate the most updated information. Figure 3 plots the out-of-sample $\Gamma_{\beta^{pvs}}$ weights in the time series. We observe some fluctuations regarding which are the relatively significant characteristics that contribute most to a firm's exposure to risk perception during some periods of the past 50 years. However, in general, we notice that the tendencies are getting stabilized as we approach the 2000s.

[Insert Figure 3 here]

Table 5 replicates the results in the first 2 columns of Panel A in Table 3, but with the out-of-sample β^{pvs} instead. The magnitude of the average out-of-sample *fPVS* diminishes a little compared with the full-sample estimates. Nevertheless, the out-of-sample mimicking factor continues to be economically and statistically significant in the time-series.

[Insert Table 5 here]

Overall, these portfolio-level and firm-level analyses indicate that the premium related to the exposure to the financial market risk perception is statistically and economically significant in the in-sample and out-the-sample tests.

2.4.6 Robustness check

We next test whether alternative measures of the dynamic PVS beta predict future stock returns. In Eq. (3), we show that the firm-level PVS beta is estimated, while simultaneously controlling for the market return. In this section, we use two alternative models to estimate PVS betas:

$$\text{Model 1: } r_{i,t} = \alpha + \beta_{i,t-1}^{pvs} PVS_t + \epsilon_{i,t}; \tag{5}$$

$$\text{Model 2: } r_{i,t} = \alpha + \beta_{i,t-1}^{pvs} PVS_t + \beta_{i,t-1}^{k_1} K_1 + \beta_{i,t-1}^{k_2} K_2 + \epsilon_{i,t}, \tag{6}$$

where K_1 and K_2 are the latent factors that can be obtained through IPCA estimation. Table 6 presents both univariate sorting results on $\beta_{i,t-1}^{pvs}$ and Fama-MacBeth regression results on the two alternative specifications.

[Insert Table 6 here]

Panel A of Table 6 suggests that under the univariate sort, the differences in both EW and VW returns between the top and bottom deciles of estimated $\beta_{i,t-1}^{pvs}$ based on both models are statistically and economically significant. The EW monthly return spread for Model 1 is -2.507% with a *t*-statistic of -6.66, and the VW return spread is -0.866% with a *t*-statistic of -2.75. For Model 2, we continue to find significant long-short portfolio return spreads of -2.074% (*t*-stat =-6.22) for EW and of -1.593% (*t*-stat = -4.62) for VW. Panel B confirms the results in Panel A with the individual stock-level Fama-MacBeth regression. The mimicking factor *fPVS* with both alternative model specifications continue to be statistically and economically significant in the times-series.

In Table 7, we examine the premiums of the exposure to risk perception in different Fama-French 12 industries. We find that across different industries, the magnitude of premiums vary, ranging from -0.399% (Energy) to -1.572% (Telecom). Among them, only the premium in the energy industry is not significant. The rest of the industries all have significant premiums for risk perception dynamics.

[Insert Table 7 here]

2.4.7 Factor investing and market risk perception

From the observations in the previous section that the premiums of PVS vary across different industries, we attribute the differences to the association between different investment styles and market risk perceptions. Table 1 also document the predictive power of PVS on several risk factors, including the market, size profitability, and momentum factors. Having obtained the tradable mimicking factor and as each individual stock's exposure to $\beta_{i,t-1}^{PVS}$, we can better evaluate how each investment styles incorporate the risk perceptions with a framework of holding-based analysis. We start with the prominent risk factors as our first set of tests on style investing. The aforementioned Fama-French six factors are what we focus on in this subsection.

Each risk factor is constructed with the corresponding strategy described in Fama and French (1993, 2015) by assigning weights for different individual stocks. We try to follow the practice of the stock selection of fund managers. For instance, the size factor, SMB, is constructed using the six VW portfolios formed on size and book-to-market, and is the average return on the three small portfolios minus the average return on the three big portfolios. Therefore, each month, we can have stock weights in the SMB strategy and apply the weights to construct the factor. For the market factor each month, the weights are simply the value-weighted average of β_{t-1}^{PVS}.

$$\beta_{t-1}^{factor} = \sum w \times \beta_{t-1}^{PVS} \tag{7}$$

We call this factor beta as the CS beta as it is constructed with the weights of all stocks in the cross-section.

Alternatively, the traditional method to obtain a portfolio or a factor's beta in regard to another factor return can be obtained by running the OLS regressions:

$$f_t = a + b \times fPVS_t + c \times f_1 + \epsilon_{\mathrm{t}} \tag{8}$$

where $fPVS_t$ is the mimicking factor of PVS in month t and f_1 is the constant that comes together with the cross-sectional OLS regression. Unlike the holding-based CS portfolio beta which we can have in each month, the time-series (TS) regression beta b (TS b) can only output one average beta that describes the overall relationship between the two factors.

Table 8 first shows the average factor performance during our sample period as well as the TS b on *fPVS* for each factor. Panel A reports the average factor premiums. We find that all six factors in the FF-6 factor model have positive premiums and all are statistically significant at the 1% level except the size factor and the value factor. Panel B shows that market, profitability, and momentum factors have a positive and significant beta coefficient on *fPVS* at the 10% level or better. The size, value, and investment factors have a negative TS beta on the mimicking factor of PVS. The value and size factors do have a statistically significant TS b. Notice that we also show the *fPVS* adjusted factor returns (i.e., α in Panel B). Our goal here is not to focus on the explanatory power of *fPVS* on other factor premiums, but is to examine the pairwise relationship, i.e., each factor strategy's exposure to market risk perception.

[Insert Table 8 here]

Observing the exposure of each factor to PVS paves the way to identify what is the magnitude of the realized return of a factor or investment style regarding risk perception by multiplying the β_{t-1}^{factor} with $fPVS_t$. As we have the more dynamic and timely CS factor betas as described in Eq. (7), we plot the six-month moving average factor returns and the realized return regarding the CS PVS exposure in Figure 4.

[Insert Figure 4 here]

Figure 4 Panel (a) shows the dynamics of market factor with its realized return regarding PVS. It is obvious that the realized return ($\beta_{t-1}^{factor} \times fPVS_t$) and the market factor seem to be negatively correlated with each other. For size, investment, profitability, and momentum factors tabulated in Panels (b), (d) and (e) and (f), their risk premiums all have similar dynamics with the realized returns by exposing to PVS and are correspondingly positively related. Particularly for the momentum factor, the realized return due to exposure to market risk perception accurately caught up some prominent momentum crash points during the dotcom bubble and the global financial crisis (GFC). These figures support the idea that style investors incorporate risk perceptions when making investment decisions, as risk perception might be correlate with large loss. It is interesting to see in Panel (c) that the value factor premium and the PVS-associated realized return are sometimes positively and sometimes negatively correlated. In the next section, we will break our sample period into subperiods and conduct detailed analyses.

To sum up, we find evidence showing how different risk factors incorporate risk perception when making investment decisions. Moreover, we evaluate how the realized returns of factor exposure to PVS comoves with each factor premium. Our analyses in this section provide some empirical evidence of how style investors might incorporate risk perception when making their investment decisions.

2.4.8 Subperiod analysis: Factor premiums, business cycle, and market sentiment

Previous literature has documented that the performance of risk factors is not always stable across different periods. For instance, Fama and French (2020) argue that the value premium seems to have disappeared. The disastrous momentum cash also occurs around periods with dramatic market downward trends (Daniel et al. (2016)). Smith and Timmerman (2022) also identify “breaks” for each risk factor as their performance differs. Moreover, the state variable’s risk premia might also be time-varying (Barroso et al. (2021)). Instead of accurately identifying the breaks of factor performance, we are curious about if risk perception plays a role in each factor’s state switch. We therefore conduct subperiod analysis regarding β_{t-1}^{factor} and their realized return due to the exposure when factor premiums are different.

Table 9 presents each factor's PVS beta and PVS realized return during high versus low factor premium periods, boom-bust business cycle, and high versus low market sentiment periods. Panel A shows the PVS beta for each factor and Panel B displays the PVS realized return for each factor. In Columns (1) to (3), we explore each factor's PVS exposure as its realized return in months of different factor premium levels. Momentum beta poses a similarly positive magnitude among different momentum premium periods (Panel A), while the realized return driven by PVS (Panel B) is significantly more negative during the low momentum return months than during the high return months. The investment factor has negative PVS beta during both period with similar magnitude, but the realized return is significantly larger in high investment premium periods than in the low premium periods. Specifically, all the realized returns attributed to the PVS exposure are higher in the high-risk premium months except for the market return, roughly consistent with the distribution of risk premiums. Interestingly, the realized returns attributed to the PVS exposure are positive in both periods, but it is significantly higher during the high than the low value premium months. Given the insignificant difference in beta PVS, it is more likely that it is the $fPVS_t$.that contributes to the difference in realized returns. When the value premium is high, $fPVS_t$ might also be higher. Similar to the value factor, the momentum and investment factors also have similar performance.

[Insert Table 9 here]

The remaining market, size, and profitability realized factor returns attributed to the PVS exposure during different factor premium months seems to be associated with their PVS exposures. The average β_{t-1}^{factor} of the latter two factors are significantly higher during high-risk premium periods, and the realized returns of PVS are also significantly higher during the high-risk premium months. However, the market factor PVS realized return is significantly lower during the high market premium months.

Market risk perception itself comoves with macroeconomy condition and is consistent with the risk-centric theory. We therefore partition our sample periods into NBER business cycles as in Columns (3) to (6). During our sample period, there are 519 boom months and 93 recession months. The mimicking factor premium of $fPVS$ is actually more negative during recession months than during the boom months, although statistically insignificant. Factor realized returns attributed to the PVS exposure for value, size, and profitability factors are higher in recession months, which is consistent with the risk-centric theory that investors may require higher risk compensation during a recession. The size, profitability, and momentum factors continue to have different PVS exposures during different phases of business cycle, suggesting that these strategies might incorporate or project different exposure to risk perception in different market conditions. The value factor still has no distinguishable PVS beta during different subperiods. However, the difference in PVS betas might offset with the dynamics of $fPVS$, resulting in a non-significant differences in realized returns. The momentum factor is a special case as its realized returns attributed to the PVS exposure are negative. The behavior of momentum resembles $fPVS$ in some sense.

Finally, we partition our sample period into high versus low sentiment months according to the Baker and Wugler (2006) equity investor sentiment index in Columns (7) to (9). Risk perception can be included as a component of market sentiment, while market sentiment contains elements other than prospects about risk, such as optimism or pessimism. Nevertheless, risk perception is considered to be correlated with equity market sentiment.

Sentiment seems to separate the value factor's exposure to PVS. In high sentiment months, the average value PVS beta β_{t-1}^{value} is positive, while it is negative during low sentiment months. The difference is also statistically significant. We present the sentiment subperiod analysis in Column (7), (8) and (9). We find some differences in terms of $fPVS$, with the ones in low sentiment periods being more negative, although it is not significantly different from 0. Although the realized returns attributed to the PVS exposure during high sentiment periods and low sentiment periods are not statistically different from each other, we find the value strategy possibly incorporates risk perception. In addition to the value factor, the market, investment and profitability factors all have larger exposure to PVS during high sentiment months, among them investment always have negative beta to PVS. Therefore, the larger investment PVS beta means the factor are less exposed to PVS in high sentiment months. While investment and profitability have larger exposure to PVS during high sentiment months, we do not find significant difference in realized returns attributed to the PVS exposure during different market sentiment periods.

The above subperiod analyses are informative in helping us understand how each factor strategy alters its considerations of risk perceptions in varying market conditions.

2.4.9 Nonlinear time-varying of *fPVS*

We explore to simply illustrate the time-series fluctuations of the mimicking factor *fPVS*. We investigate how the *fPVS* varies over time by plotting the CS mimicking factor together with analyst perceived risk, which is defined as the average analyst forecast deviation on future earnings. Figure 5 shows that during the spikes or giant rises of market participants (analysts) perceived risk, the magnitude of *fPVS* changes drastically, indicating its premium is state-dependent and switches during different market risk perception states. The dynamics are consistent with previous literature such as Smith and Timmerman (2022) who identify "breaks" for each risk factor and the time-varying state variable's risk premia (Barroso et al. (2021)).

[Insert Figure 5 here]

2.5 Interpretable Risk Perception with Text Data

With the LLM models and generative AI tools, we can further visualize how investors express their perceived risk or subjective risk. In this section, we try to extend our scope to text data and further add interpretability to the perceived risk of investors on the overall financial market. The text data are from StockTwits, which is a popular social networking platform for investors to share their opinions about stocks. Users on this platform can post short messages (up to 140 characters) and can tag the stock ticker symbol to indicate the stock they are discussing. To make sure the text messages in our sample are about the overall financial markets, we narrow our analysis to the texts that are specifically tagged with at least one of the following ticker symbols: SPY, QQQ, DIA and VIX.[9] The text data span from January 2010 to July 2020.

We input the messages posted by users that are associated with the stock market into the state-of-the-art LLM model Gemini 2.0 Flash to check whether a posted message implies an increased level of risk perception. The prompt is:

"*As a StockTwits user and experienced finance researcher with deep market knowledge, analyze the following tweet for indications of increased risk perception within the market. Focus on keywords, sentiment, and any discussion of volatility, uncertainty, or negative catalysts. Return 1 if the tweet strongly suggests increased risk perception, and 0 otherwise. Only return the number. If the evidence is inconclusive, return 0. The tweet is:…*"

As such, we count the number of increased risk perception each month and compute the percentage number of the ratio of risk perception posts over the total market posts (i.e., the LLM-based risk perception ratio). We also use the Gemini 2.0 Flash model to extract the expressions which represent the increased level of risk perceptions and make the subjective feelings of investors more "interpretable". Unlike the traditional "bag-of-words" approach

[9] SPY is the one of the most liquid ETF that tracks the S&P 500 index and is the most active symbol that messages are tagged on among the StockTwits users. Opinions on SPY broadly represent those on the market from the perspective of equity investors. QQQ is also another very popular and liquid ETF, and it tracks the Nasdaq-100 index. QQQ primarily reflects the large-cap technology companies and is also actively tagged by investors. DIA is the Dow Jones Industrial Average ETF. VIX stands for the CBOE volatility index.

which defines a word dictionary beforehand, we try to reverse the word dictionary from LLM model.

Figure 6 illustrates the monthly LLM-based risk perception ratio along with the monthly *PVS* through a time series plot. We find that the trend for *PVS* and the LLM-based risk perception ratio is positively correlated. The LLM-based risk perception ratio also positively predict *PVS* in a univariate regression. Figure 7 shows the word clouds for risk perception expressions as identified by the LLM model and Table 10 tabulates the high-frequency bigram and trigram phrases of expressing increased level of perceived risks.

[Insert Figure 6 and 7 here]

[Insert Table 10 here]

We find that when the subjective risk of investors rises, they more often talk about the market and volatility (words like “market”, “vix”, “volaitlity”). They also directly express their pessimistic views on the market (“bear”, “bearish”, “bear market”, “short”, “low”, “dead cat bounce”, “bear must retake”). Specific scenarios or concurrent events happening around the world also raise people concerns (“trade war”). Interestingly, investors may directly call out others to act on the pessimistic market (such as “short”, “sell”, “go”).

In this section, we use the LLM to identify how investors express their subjective risk or perceived risk on the financial markets through their postings on social media data. The texts provide another dimension on interpreting the perceived risks from market participants.

2.6 Conclusion

Our paper focuses on how to interpret the unobservable subjective risks of market participants on the financial markets. We focus on how market participants project their risk perception about the financial market in the equity investment process. We first identify that the price of volatile stocks (PVS) is priced in the cross-section of stocks. Moreover, it is also related to several risk factors, such as size, profitability, and momentum. As we emphasize, our article is not to construct a mimicking factor that seeks to improve a factor pricing model. Instead, we try to add interpretable details on the dynamics of PVS to better understand how equity investors are subject to the fluctuations of their risk perception.

With IPCA, we are able to map stock characteristics onto each stock's exposure to PVS. The dynamic loadings came with IPCA also allow us to test the time-varying risk premiums associated with PVS. The average magnitude of the mimicking factor *fPVS* yields an annualized return of 5%. Out-of-sample estimation and alternative model specifications continue to generate robust and significant results for the *fPVS* risk premium. The *fPVS* is on average negative in the time series. Given that PVS negatively reflects market risk perception, the results are consistent with the theoretical framework that if the risk perception is high, investors are willing to pay a premium for low risky stocks. Stocks with high asset-to-me ratios, low past return, and low sales are likely to be more sensitive to market risk perception.

PVS negatively forecasts future market returns, indicating its usefulness as a variable that captures future consumption and changes in investment opportunities. We also find PVS contains predictive power for several risk factors, such as the size, profitability, and momentum factors. To measure how equity investors assess or project their risk perception onto their investment decisions, we explicitly evaluate those risk factors to represent popular investment styles. We investigate the exposure of each factor to PVS from a holding-based perspective. Our analyses show that except the value factor, all other prominent factors in the FF-6 factor model seem to incorporate risk perception in their portfolio holdings. The factor betas and realized returns attributed to the exposure to PVS also have their time-varying performance during different market conditions.

With LLM and direct texts from investors, we observe how market participants express their subjective perceptions in the social media. We try to understand more how investors incorporate or project their risk perception in the equity investment world.

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Table 1: PVS and factor performance: Predictive analysis

This table is the predictive analysis of lag PVS on future 1 month and future 12-month overlapping factor return. Both the in-sample univariate regression coefficient and out-of-sample (OOS) R^2 are presented in the table. Panel A displays the 1-month predictive results and Panel B presents the 12-month results. The standard errors are adjusted for autocorrelation using Newy-West with four lags. CW-stat is the Clark and West (2007) statistic to assess the significance of OOS R^2.

Panel A: 1-month analysis

	(1) mktrf	(2) smb	(3) hml	(4) cma	(5) rmw	(6) umd
Lag_PVS	-0.0106*	-0.010***	0.003	0.002	0.004*	0.019*
	(-1.66)	(-3.15)	(0.55)	(0.60)	(1.76)	(1.96)
Constant	0.004**	-0.000	0.003**	0.003***	0.003***	0.009***
	(2.14)	(-0.01)	(1.97)	(3.32)	(3.25)	(4.81)
N	612	612	612	612	612	612
R-sq	0.007	0.014	0.001	0.001	0.003	0.025
OOS R^2	-0.064	0.672**	-0.302	-0.115	0.132	1.988**
CW stat	0.31	1.89	-1.11	-0.34	0.84	1.77

Panel B: 12-month analysis

	(1) mktrf	(2) smb	(3) hml	(4) cma	(5) rmw	(6) umd
Lag_PVS	-0.067***	-0.080***	0.019	-0.006	0.046***	0.103***
	(-3.54)	(-6.55)	(1.15)	(-0.58)	(4.11)	(5.92)
Constant	0.063***	0.007	0.036***	0.034***	0.043***	0.096***
	(8.62)	(1.44)	(5.78)	(8.53)	(9.97)	(14.31)
N	600	600	600	600	600	600
R-sq	0.021	0.067	0.002	0.001	0.027	0.055
OOS R^2	0.891***	9.040***	-0.486	-0.748	1.018***	1.221***
CW stats	3.22	7.02	-2.30	-2.29	2.56	2.57

Table 2. Univariate sorting

We sort stocks into deciles according to their dynamic exposure to PVS β^{pvs} at each month. In Panel A, we show the average pre-ranking stock characteristics of each decile, including size (ME), book-to-market ratio (BE/ME), market beta (beta), stock volatility (Vol), past 12-month cumulative return (ret(-12,-2)) and past month return (ret(-1,0)). Stock volatility is the last 2 month daily stock return standard deviation. Panel B displays the equal-weighted and value weighted β^{pvs} of each decile. Pre-rank refers to the β^{pvs} of each decile when we do decile sorting, and Post-rank refers to the β^{pvs} that is the next month of the formation of decile betas. Both the equal-weighted and value-weighted average excess returns (xret) of each portfolio in the month following each decile formation period are calculated. We also compute the average long-short portfolio return and the Fama-French three-factor, five-factor, and six-factor model (with momentum factor) adjusted alphas.

Panel A: Univariate sorting firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
β^{pvs}	ME	BE/ME	beta	Vol (%)	Ret(-12,-2)	Ret(-1,0) (%)
1	108.134	1.079	1.162	5.839	-0.120	-14.332
2	228.143	1.020	1.035	4.296	0.005	-6.227
3	377.791	0.964	0.991	3.715	0.063	-2.946
4	555.283	0.912	0.960	3.336	0.100	-0.797
5	810.484	0.867	0.937	3.050	0.130	0.924
6	1,149.904	0.825	0.920	2.838	0.151	2.420
7	1,675.818	0.786	0.912	2.677	0.173	3.852
8	2,435.711	0.751	0.906	2.557	0.192	5.461
9	3,908.537	0.714	0.915	2.508	0.217	7.649
10	5,920.553	0.702	0.969	2.945	0.288	14.430

Panel B: Average beta and returns

	Equal-Weighted			Value-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
β^{pvs}	Pre-rank	Post-rank	xret (%)	Pre-rank	Post-rank	xret (%)
1	-1.989	-1.146	2.753	-1.786	-0.405	1.381
2	-1.005	-0.641	1.142	-0.982	-0.083	1.052
3	-0.574	-0.376	0.889	-0.562	0.091	1.132
4	-0.264	-0.176	0.778	-0.255	0.225	0.995
5	-0.008	-0.011	0.668	0.000	0.342	0.898
6	0.222	0.140	0.611	0.230	0.453	0.827
7	0.446	0.288	0.530	0.453	0.581	0.830
8	0.682	0.437	0.479	0.690	0.702	0.692
9	0.964	0.602	0.349	0.975	0.850	0.553
10	1.530	0.867	0.138	1.543	1.204	0.405
(10-1)			-2.614			-0.976
			(-7.41)			(-3.22)
FF-3 alpha			-2.211			-0.410
			(-7.21)			(-1.72)
FF-5 alpha			-2.429			-0.498
			(-6.41)			(-1.76)
FF-6 alpha			-2.982			-1.003
			(-7.95)			(-3.74)

Table 3: Cross-sectional mimicking factor $fPVS$: Fama-MacBeth regressions

We run Fama-MacBeth regression to get the mimicking factor's risk premium following the spirit of Fama and French (2020). We also control for other characteristics as other cross-sectional factors that may influence stock return. In order to tease out potential industry influences, we also control for industry fixed effect in some of the empirical specifications. The time-series autocorrelation is adjusted using Newey-West with four lags and t-statistics are in parentheses. In Panel A, the dependent variable is the next month's excess stock return. In Panel B, the dependent variable is stock's next 2 to 12 month's excess return.

Panel A: 1-month horizon

	Without industry fixed effect		With industry fixed effect	
	(1)	(2)	(3)	(4)
β^{pvs}	-0.709***	-0.622***	-0.812***	-0.626***
	(-6.96)	(-5.49)	(-8.38)	(-6.44)
ME		0.107***		0.105***
		(3.56)		(3.57)
BE/ME		0.154***		0.185***
		(2.70)		(3.94)
Ret(-12,-2)		0.401***		0.343***
		(5.76)		(5.55)
Profitability		0.0237		0.0498*
		(0.70)		(1.79)
Ret(-1,0)		-0.354***		-0.443***
		(-4.57)		(-6.67)
N	2,491,570	2,482,059	2,491,570	2,482,059
R-sq	0.014	0.036	0.039	0.055

Panel B: Longer horizon (2 to 12 month)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
h=	2	3	4	5	6	7	8	9	10	11	12
β^{pvs}	-0.378***	-0.315***	-0.249**	-0.275***	-0.251***	-0.201**	-0.264***	-0.300***	-0.283***	-0.300***	-0.284***
	(-3.50)	(-3.04)	(-2.47)	(-2.68)	(-2.60)	(-2.13)	(-2.72)	(-3.07)	(-2.88)	(-2.95)	(-2.77)
ME	0.0424	0.0238	0.00291	0.0120	0.00191	-0.00745	0.00433	0.0128	0.00910	0.0138	0.0148
	(1.52)	(0.87)	(0.11)	(0.44)	(0.07)	(-0.27)	(0.16)	(0.47)	(0.34)	(0.51)	(0.54)
BE/ME	0.195***	0.207***	0.219***	0.196***	0.215***	0.225***	0.176***	0.164***	0.161***	0.149***	0.141***
	(3.52)	(3.88)	(4.21)	(3.78)	(4.13)	(4.31)	(3.48)	(3.23)	(3.11)	(2.88)	(2.75)
Ret(-12,-2)	0.274***	0.158***	0.117*	0.0899	0.0342	-0.00978	-0.0222	-0.0381	-0.0629	-0.106**	-0.160***
	(4.42)	(2.60)	(1.93)	(1.57)	(0.59)	(-0.16)	(-0.40)	(-0.71)	(-1.23)	(-2.20)	(-3.32)
Profitability	0.0507	0.0625*	0.0711**	0.0731**	0.0799**	0.090***	0.0739**	0.0699**	0.0615*	0.0534	0.0615*
	(1.53)	(1.91)	(2.17)	(2.22)	(2.40)	(2.62)	(2.13)	(2.01)	(1.78)	(1.52)	(1.75)
Ret(-1,0)	0.139**	0.278***	0.157**	0.201***	0.206***	0.215***	0.194***	0.244***	0.199***	0.239***	0.334***
	(2.01)	(4.28)	(2.58)	(3.05)	(3.17)	(3.49)	(3.15)	(3.79)	(3.04)	(3.40)	(4.51)
N	2,457,654	2,433,467	2,410,473	2,387,836	2,365,529	2,343,677	2,322,048	2,300,535	2,279,195	2,258,060	2,237,097
R-sq	0.030	0.029	0.028	0.027	0.026	0.025	0.025	0.024	0.024	0.023	0.023

Table 4. Correlation matrix of mimicking factor of PVS and factor premiums
We show the correlation matrix of mimicking factor of PVS (*fPVS*) with PVS, and other risk factor performance.

	fPVS
fPVS	1.000
PVS	0.240
mktrf	-0.338
smb	-0.427
hml	0.016
cma	0.088
rmw	0.380
umd	0.452

Table 5: Out-of-sample estimation of $\boldsymbol{\beta_{oos}^{pvs}}$: Fama-MacBeth regressions

The estimation of β_{oos}^{pvs} is based on an out-of-sample where the initial estimation window is the first 60 months of the whole sample period and then gradually expand to the most-updated available window. We run Fama-MacBeth regression to get the mimicking factor's risk premium. Meanwhile, we also control for other characteristics that may act as cross-sectional factors and influence stock return. The time-series autocorrelation is adjusted using Newey-West with four lags and *t*-statistic are parentheses.

	(1)	(2)
β_{oos}^{pvs}	-0.565***	-0.359***
	(-5.49)	(-2.95)
ME		0.00543
		(0.18)
BE/ME		0.161***
		(2.65)
Ret(-12,-2)		0.259***
		(3.41)
Profitability		0.0964***
		(2.79)
Ret(-1,0)		-0.434***
		(-4.95)
N	2,354,377	2,345,517
R-sq	0.012	0.032

Table 6. Robustness test: Mimicking factor with alternative specifications

We estimate the dynamic loadings on PVS with two alternative models: Model 1: $Ret_{i,t} = \alpha + \beta_{i,t-1}^{pvs} PVS_t + \epsilon_{i,t}$; Model 2: $Ret_{i,t} = \alpha + \beta_{i,t-1}^{pvs} PVS_t + \beta_{i,t-1}^{k_1} K_1 + \beta_{i,t-1}^{k_2} K_2 + \epsilon_{i,t}$, K_1 and K_2 are the latent factors that can be obtained through IPCA estimation. We try to do both univariate sorting and Fama-MacBeth regressions to show the robustness of PVS to be cross-sectionally priced. The time-series autocorrelation is adjusted using Newey-West with four lags and t-statistics are in parentheses.

Panel A: Univariate sort

	Equal-Weighted		Value-Weighted	
	(1)	(2)	(3)	(4)
β^{pvs}	Model 1	Model 2	Model 1	Model 2
1	2.648	1.368	1.244	0.853
2	1.186	1.243	0.958	0.779
3	0.842	1.170	0.971	0.693
4	0.760	1.128	0.962	0.664
5	0.693	1.105	0.903	0.632
6	0.611	0.998	0.856	0.482
7	0.563	0.920	0.808	0.396
8	0.487	0.711	0.703	0.441
9	0.407	0.399	0.605	0.252
10	0.141	-0.705	0.378	-0.739
(10-1)	-2.507	-2.074	-0.866	-1.593
	(-6.66)	(-6.22)	(-2.75)	(-4.62)

Panel B: Fama-MacBeth regression

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 1	Model 2
β^{pvs}	-0. 667***	-0.625***	-0.490***	-0.356***
	(-6.07)	(-5.90)	(-4.09)	(-2.87)
ME			0.0740**	-0.105***
			(2.57)	(-3.59)
BE/ME			0.178***	0.213***
			(3.13)	(4.12)
Ret(-12,-2)			0.354***	0.107
			(5.47)	(1.54)
Profitability			0.0206	0.0417
			(0.61)	(1.21)
Ret(-1,0)			-0.450***	-0.644***
			(-5.94)	(-7.06)
N	2,491,570	2,491,570	2,482,059	2,482,059
R-sq	0.016	0.018	0.037	0.043

Table 7. Risk perception premium of stocks in different industries

We construct quintile portfolios based on β^{pvs} for each industry. Stocks are classified into 12 industries according to Fama-French 12 industry SIC code. For each month, we calculate the long-short portfolio (quintile 5-quintile 1) return for every industry. The standard errors are Newey-West adjusted with 4 lags. The returns are in percentage.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
β^{pvs}	Non-durable	Durable	Manufacturing	Energy	Chemistry	Business Equipment	Telecom	Shops	Health	Utilities	Money
1	1.753	1.282	1.555	0.834	1.849	1.321	2.180	1.286	1.978	0.907	1.368
2	1.028	1.109	1.158	0.816	1.369	1.193	0.707	1.131	1.234	0.912	1.249
3	1.110	0.934	0.951	0.686	0.947	0.798	0.693	0.983	0.980	0.645	0.918
4	0.916	0.587	0.767	0.801	0.760	0.840	0.720	0.843	0.906	0.531	0.688
5	0.520	0.431	0.337	0.436	0.461	0.602	0.607	0.560	0.432	0.325	0.393
(5-1)	-1.233	-0.851	-1.217	-0.399	-1.388	-0.719	-1.572	-0.726	-1.547	-0.582	-0.975
	(-4.29)	(-3.12)	(-5.37)	(-1.11)	(-4.45)	(-2.49)	(-3.33)	(-2.52)	(-4.57)	(-3.14)	(-4.89)

Table 8. Factor exposure to PVS

We show how different investment styles as represented by popular factors might be exposed to or reflect the risk perception dynamics. Panel A reports the average premiums (α) of different factors during our sample period. The *t*-statistics are based on Newey-West adjusted standard errors. Panel B reports the OLS coefficients of regressing factor returns on *fPVS*. The coefficient on *fPVS* is called time-series beta of PVS in our specification.

Panel A: Average factor premium						
	(1)	(2)	(3)	(4)	(5)	(6)
	mkt	smb	hml	cma	rmw	umd
α	0.962	0.247	0.143	0.291	0.279	0.517
	(5.10)	(1.68)	(1.16)	(3.14)	(2.76)	(2.99)
Panel B: Factor *fPVS* adjusted risk premium						
α	0.773	0.211	-0.185	0.291	0.454	1.041
	(8.43)	(1.21)	(-1.92)	(2.62)	(4.20)	(6.63)
$b_{pvs}^{\mathrm{factor}}$	0.696	-0.0925	-0.198	-0.152	0.133	0.714
	(11.51)	(-1.01)	(-1.54)	(-1.89)	(1.78)	(7.05)
N	612	612	612	612	612	612

Table 9. Factor PVS exposure and realized return in periods of high/low factor premiums

We partition our sample period into high and low factor premium sub-periods due to each factor's performance. With the time-varying CS factor beta of PVS, we can further explore the time-varying of each factor's exposure to PVS in Panel B. Moreover, in Panel B, we can further get the realized return of each factor's exposure to PVS by multiply each factor's PVS beta with fPVS, and see the difference in each sub-period. The t-statistics are in the parentheses and calculated based on Newey-West adjusted standard errors.

Panel A: Each factor beta to PVS during different sub-period

	Factor premium: High vs. Low			Business cycle			Market sentiment: High vs. Low		
	Low	High	Diff	Boom	Recession	Diff	Low	High	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market	0.756***	0.776***	0.0206*	0.771***	0.736***	-0.0353	0.730***	0.802***	0.0717***
	(47.03)	(52.92)	(1.71)	(62.83)	(31.37)	(-1.34)	(44.34)	(61.78)	(3.58)
Size	-0.593***	-0.550***	0.0422***	-0.579***	-0.527***	0.0525*	-0.564***	-0.579***	-0.0145
	(-36.43)	(-29.06)	(2.83)	(-40.48)	(-18.73)	(1.67)	(-31.34)	(-31.77)	(-0.59)
Value	-0.0253	-0.0234	0.00193	-0.0227	-0.0339	-0.0113	-0.0570***	0.00826	0.0653***
	(-1.51)	(-1.18)	(0.11)	(-1.59)	(-0.82)	(-0.27)	(-3.29)	(0.42)	(2.61)
Investment	-0.210***	-0.197***	0.0130	-0.213***	-0.148***	0.0654	-0.225***	-0.182***	0.0430**
	(-18.28)	(-10.84)	(0.75)	(-21.27)	(-3.25)	(1.42)	(-16.58)	(-10.54)	(2.00)
Profitability	0.0656***	0.105***	0.0397***	0.0952***	0.0309	-0.0643**	0.0627***	0.108***	0.0455**
	(4.16)	(7.01)	(3.21)	(7.69)	(1.04)	(-2.06)	(4.39)	(6.11)	(2.21)
Momentum	0.247***	0.251***	0.00383	0.309***	0.238***	0.0714**	0.265***	0.232***	0.0337
	(13.87)	(13.97)	(0.23)	(9.78)	(16.12)	(2.15)	(17.07)	(10.89)	(1.30)
N	306	306		519	93		306	306	

Panel B: Each factor PVS realized return during different sub-period

	Factor premium: High vs. Low			Business cycle			Market sentiment: High vs. Low		
	Low	High	Diff	Boom	Recession	Diff	Low	High	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market	-0.274***	-0.747***	-0.474***	-0.452***	-0.838***	-0.386	-0.575***	-0.445***	0.130
	(-2.68)	(-5.67)	(-2.99)	(-6.13)	(-2.89)	(-1.31)	(-4.95)	(-4.33)	(0.87)
Size	-0.0968*	0.709***	0.806***	0.268***	0.520***	0.253	0.382***	0.230***	-0.152
	(-1.82)	(8.47)	(8.44)	(5.73)	(2.74)	(1.31)	(4.87)	(3.72)	(-1.58)

Value	0.0415	0.167***	0.125***	0.0844***	0.214**	0.129	0.102***	0.106***	0.00336
	(1.57)	(4.15)	(2.89)	(3.63)	(2.38)	(1.46)	(3.19)	(2.96)	(0.07)
Investment	0.0901***	0.244***	0.154***	0.161***	0.201**	0.0404	0.193***	0.142***	-0.0513
	(2.97)	(6.13)	(3.14)	(6.58)	(2.56)	(0.52)	(4.97)	(4.85)	(-1.08)
Profitability	-0.117***	0.0650***	0.182***	-0.0374*	0.0382	0.0756	-0.0230	-0.0289	-0.00591
	(-3.77)	(2.62)	(4.98)	(-1.96)	(0.81)	(1.43)	(-0.93)	(-1.05)	(-0.16)
Momentum	-0.476***	-0.0224	0.454***	-0.217***	-0.428***	-0.210	-0.273***	-0.226***	0.0465
	(-5.46)	(-0.62)	(4.62)	(-5.77)	(-2.72)	(-1.28)	(-4.54)	(-4.42)	(0.59)
N	306	306		519	93		306	306	

Table 10. Expressions of increased risk perception: high-frequency bigrams and trigrams
This table presents the top 10 frequently bigrams and trigrams in expressing an increased level of perceived risk on the financial market from StockTwits users. We use Gemini 2.0 Flash model to identify if a message posted by a user expressed an increased level of risk perception and also extract the related expressions. The sample period of the textual analysis January 2010 to July 2020.

Bigram	Count	Trigram	Count
bear market	3,309	dead cat bounce	705
trade war	2,164	sell qqq hedge	557
short term	2,106	short broken target	513
stock market	1,768	bad present quality	456
uvxy tvix	1,761	present quality setup	456
gon na	1,481	fear greed index	440
vix	1,454	bear need retake	338
pull back	1,392	sell sell sell	337
vxx uvxy	1,378	bear must retake	326
tvix uvxy	1,306	bad technical rating	323

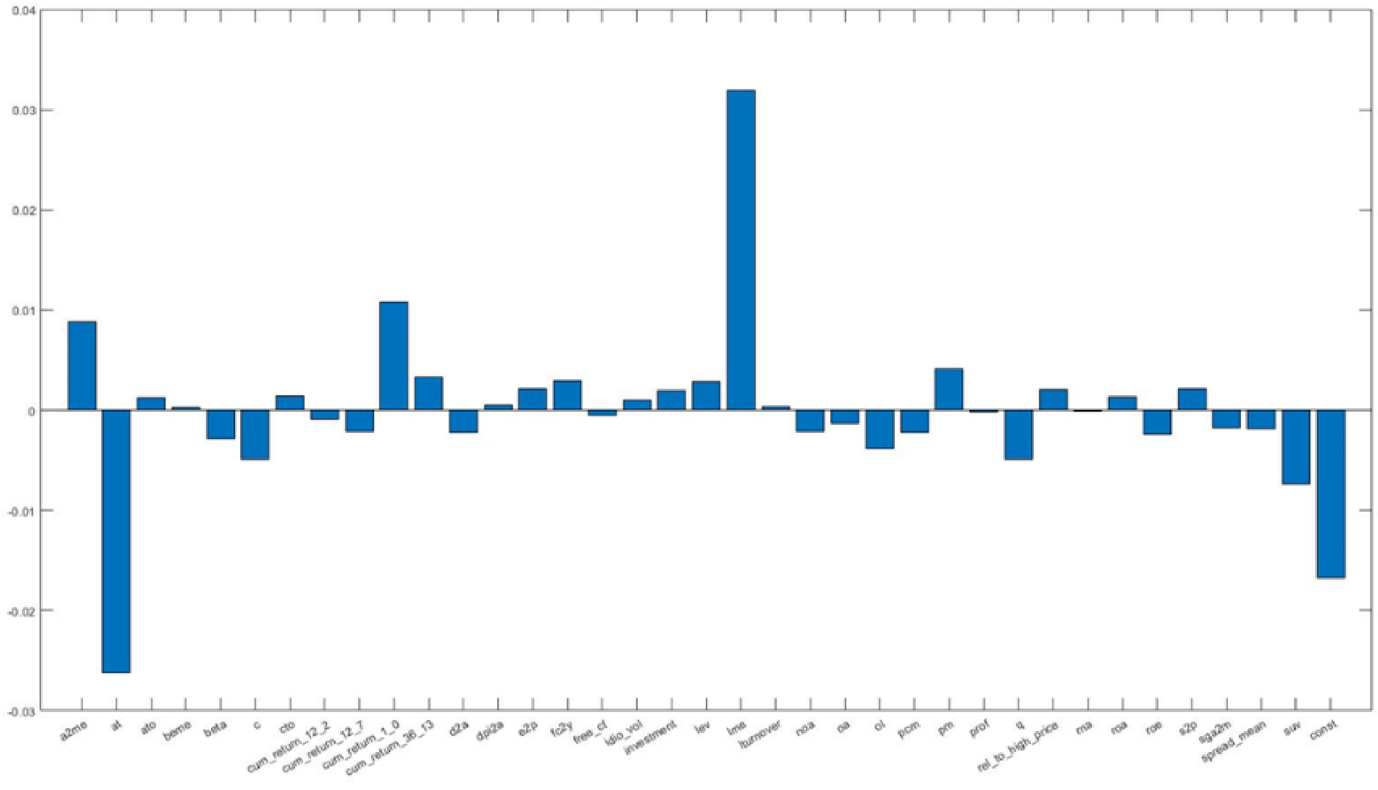


Figure 1. Gamma coefficient estimates ($\Gamma_{\beta^{pvs}}$)

The figure shows how each characteristic contributes to each stock's exposure to PVS

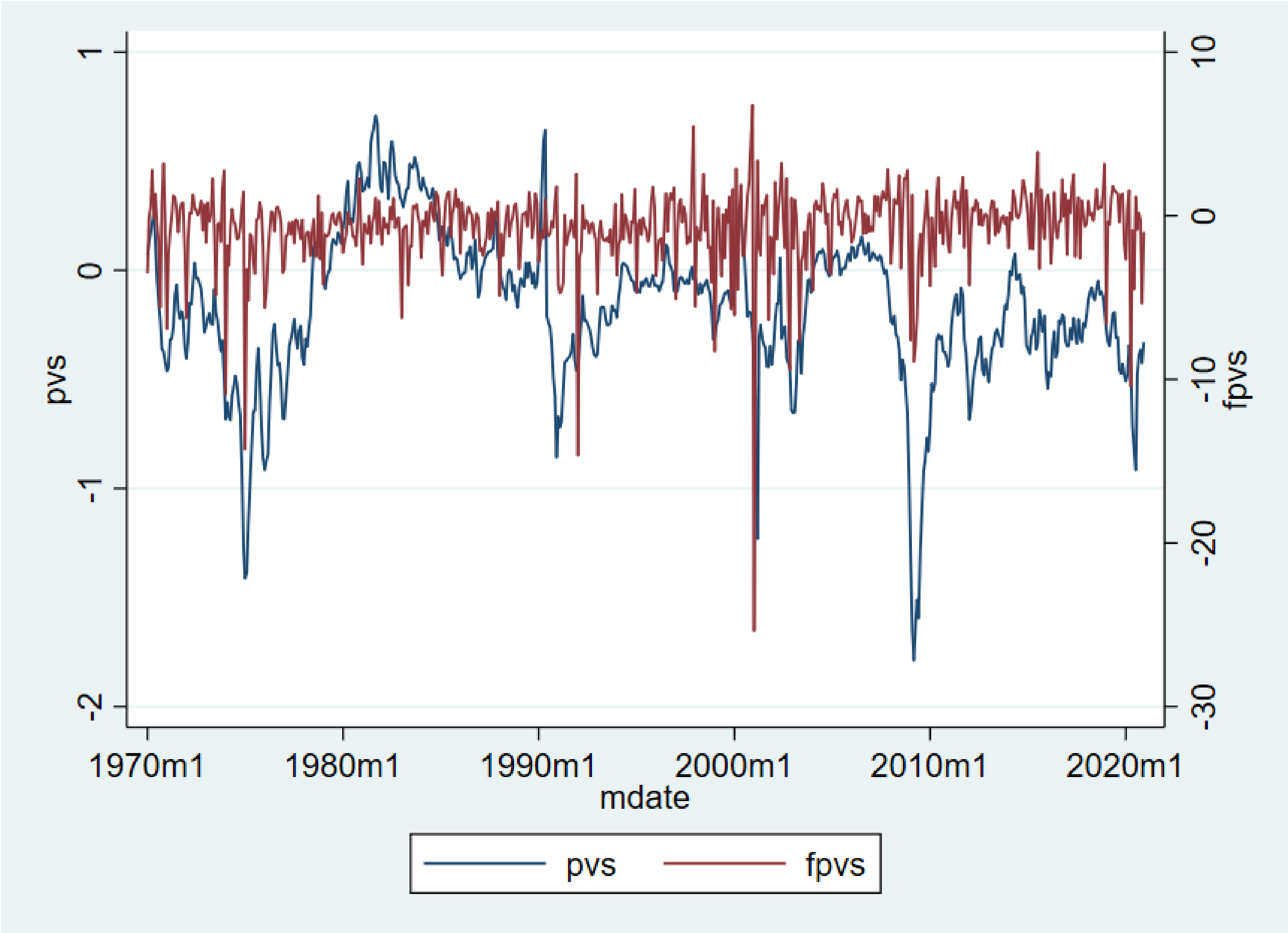


Figure 2. The time-series performance of monthly PVS and the mimicking factor (*fPVS*)

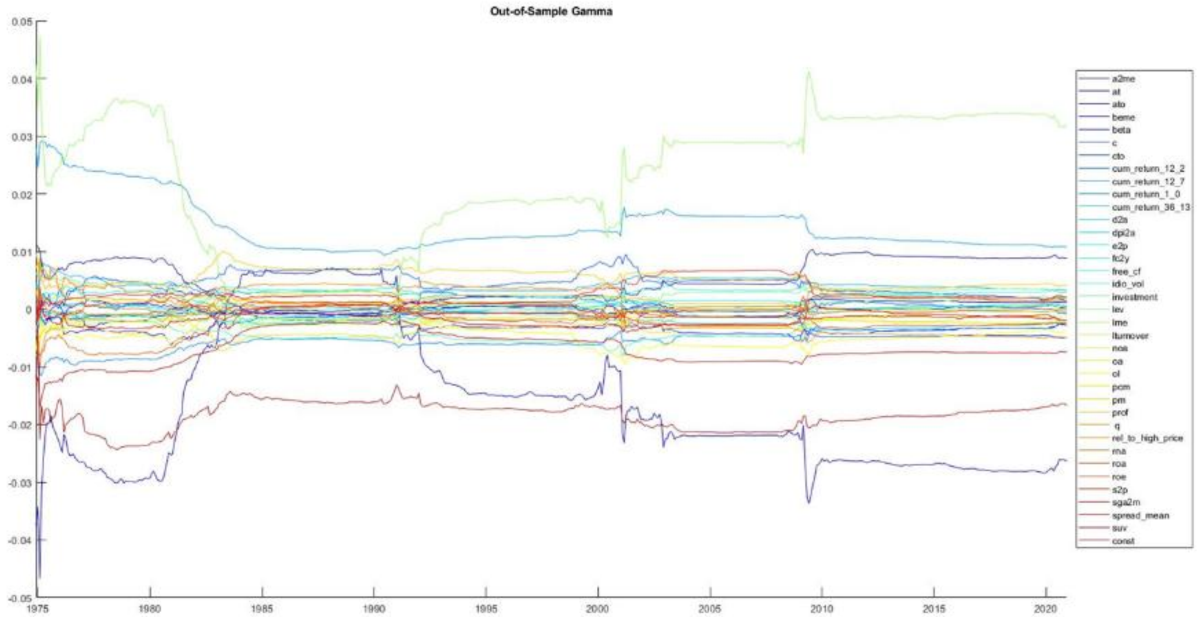
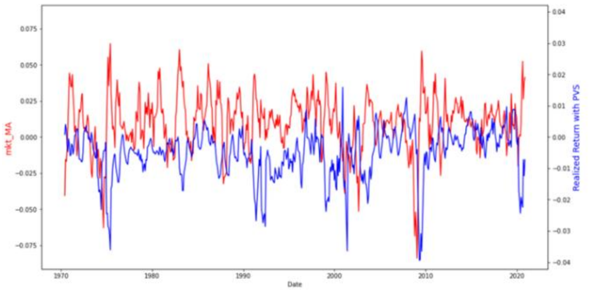
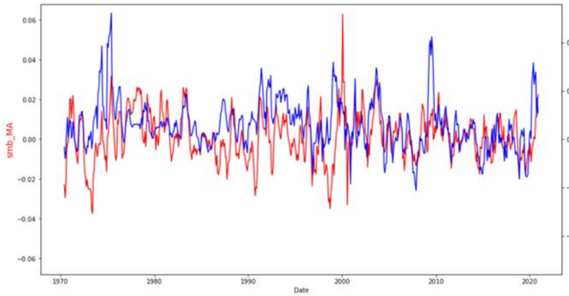


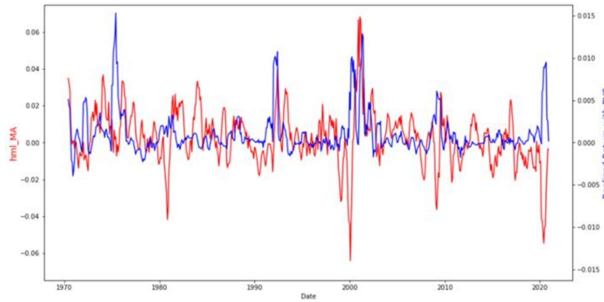
Figure 3. Gamma matrix ($\Gamma_{\beta^{pvs}}$) with out-of-sample estimation



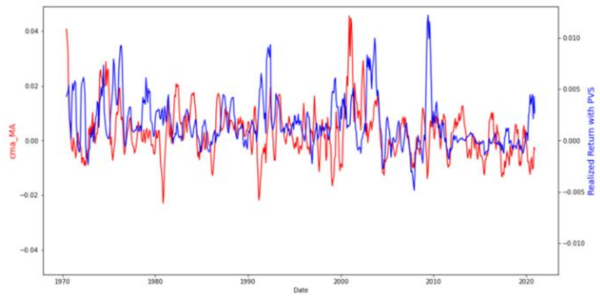
Panel(a) Market



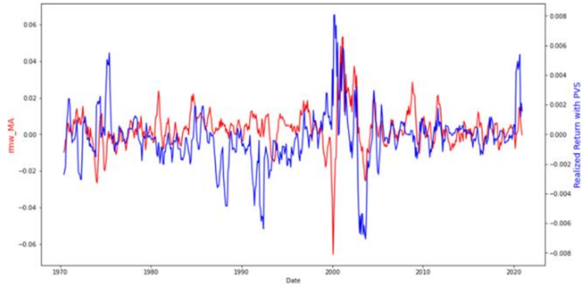
Panel(b) Size



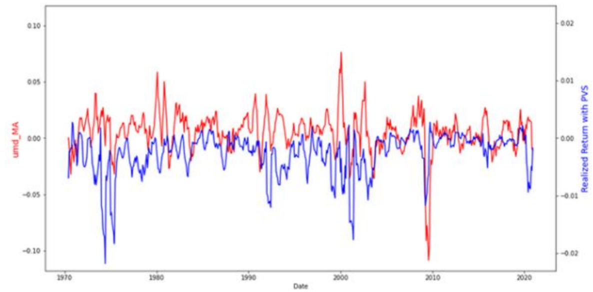
Panel(c) Value



Panel(d) Investment



Panel(e) Profitability



Panel(f) Momentum

Figure 4. Factor realized return ($\beta_{t-1}^{factor} \times fPVS_t$) and factor performance: 6-month moving average

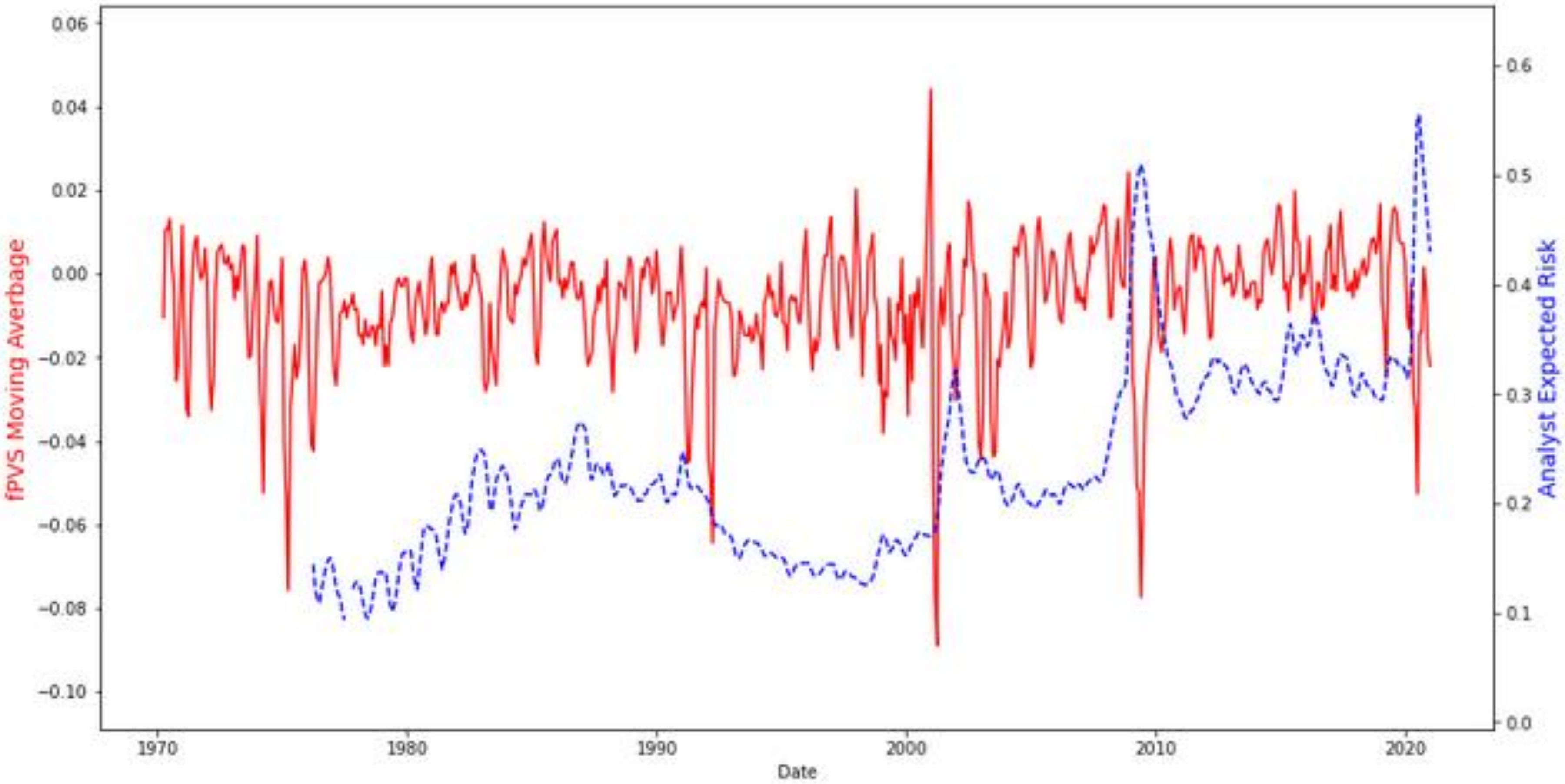


Figure 5. Mimicking factor of PVS *fPVS* and analyst expected risk
In the figure, the solid line depicts the 6-month moving averages of the fPVS and the dashed line shows the 6-month moving averages of the monthly analyst expected risk. Analyst expected risk is defined as analyst forecast dispersion on future 1-year firm's EPS across all the firms within a month.

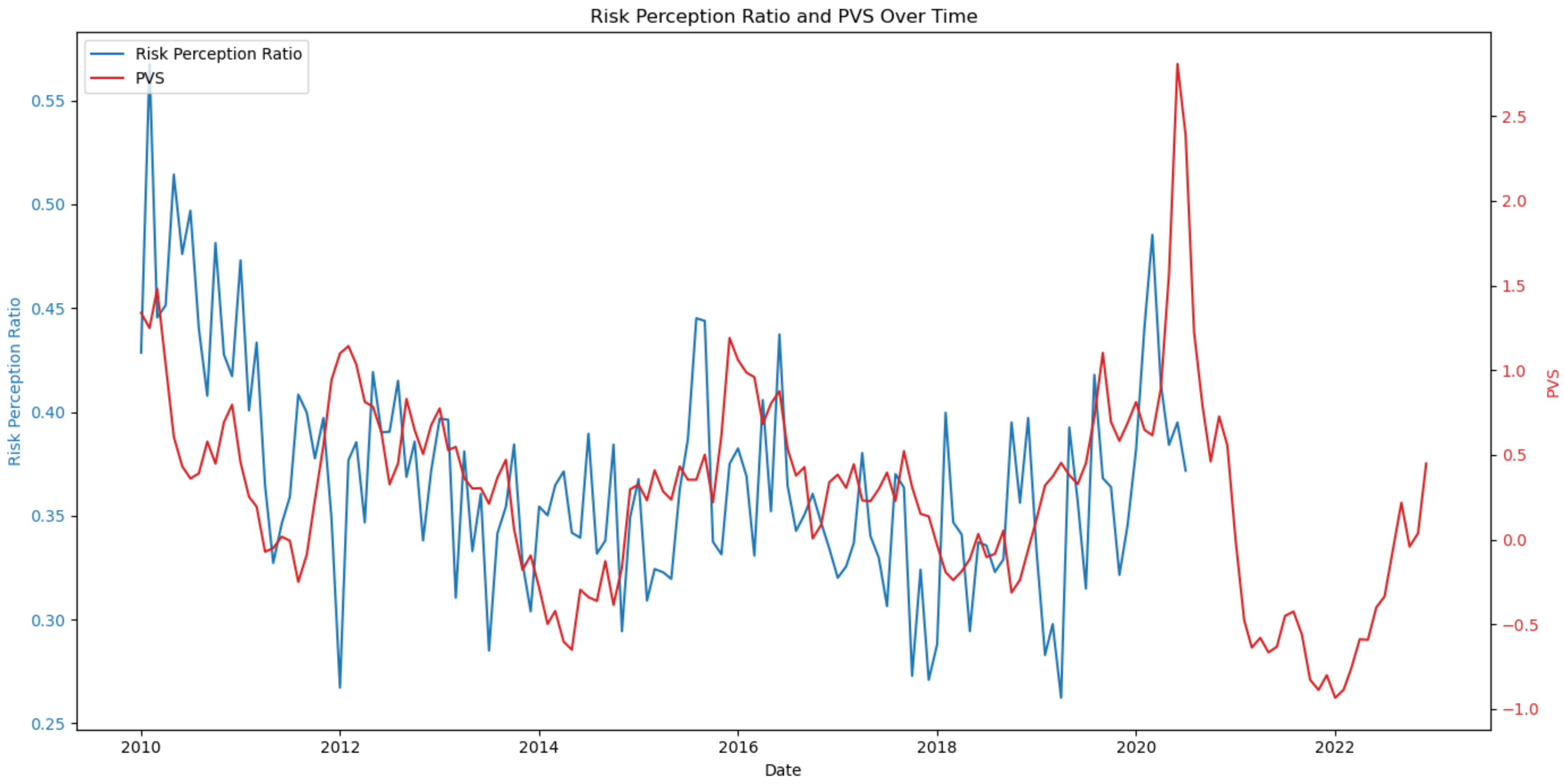


Figure 6. LLM-based risk perception ratio and PVS

We plot the LLM-based risk perception ratio and PVS together to compare their dynamics. The LLM-based risk perception ratio is calculated using the Gemini 2.0 Flash Model to analyze StockTwits user messages.

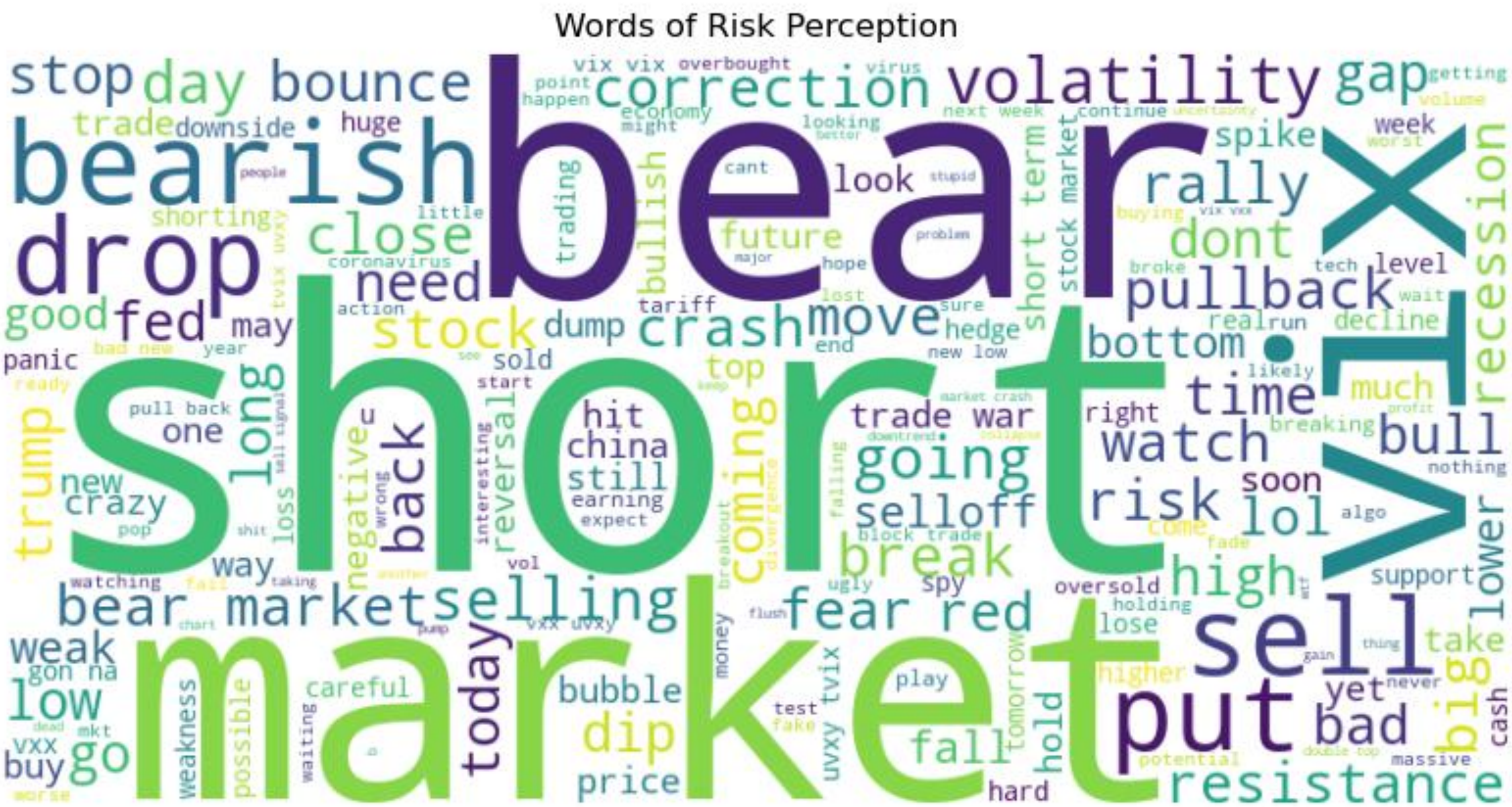


Figure 7. Word cloud for risk perception

This figure is the word cloud in expressing an increased level of perceived risk on the financial market from StockTwits users. We use Gemini 2.0 Flash model to identify if a message posted by a user expressed an increased level of risk perception and also extract the related expressions. The sample period of the textual analysis January 2010 to July 2020.