A Behavioral Factor Model for China A-share Market

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Abstract

The China A-share market is dominated by retail investors. Based on the uniqueness of the China stock market, we propose a behavioral factor model, including market factor, trading factor and disposition effect factor. The trading factor is designed to exploit mispricing from behavioral biases behind the excessive trading volume. The disposition effect factor combines investors' underreaction and investor disposition effect to capture mispricing from firm fundamentals. Our behavioral three-factor model outperforms other prominent factor models in stock returns prediction and digesting significant anomalies in China A-share market.

Keywords: Behavioral factor, asset pricing, overconfidence, disposition effect, mispricing
JEL classification: G4, G10, G12

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1. Introduction

Factor models have been popular topics in empirical asset pricing studies since the pioneer of Fama & French (1993) three-factor model. Due to their parsimony and empirical performance, these factor models have generally gained their popularity in both academia and industry. Asset expected returns comove with factor returns' covariance, which indicates that factor exposure is beneficial to future returns. Academically, researchers interpret the covariance structure between asset returns and systematic factor premiums as rational asset pricing models. Hou et al. (2015) q-factor model and Fama & French (2015) five-factor model are becoming benchmarks for factor model performance comparisons and trading strategies. On the contrary, the behavioral interpretation of this comovement comes from the expected return variation associated with stock characteristics. It is the firm characteristics and not the factor premia that explain the cross-sectional variation in stock returns (Daniel & Titman, 1997). Orthogonal to the rational view of the covariance structure, the behavioral interpretation suggests plausible explanations of inefficiencies in the way markets incorporate information into prices (Lakonishok et al., 1994) and finds evidence of characteristics from the Japan stock market (Daniel et al., 2001). Different from both standard interpretations, Kozak et al. (2018) argue that there is no clear distinction between rational asset pricing and behavioral asset pricing as long as the near-arbitrage opportunities can be secured. In an economy with both arbitrageurs and belief-distorted investors, the friction in asset demand driven by belief-distorted investors is neutralized by the arbitrageurs and thus does not affect the factor covariances. Only when the arbitrageurs trade extremely, will asset returns be affected. However, the risk of greater exposure to common risk factors prevents them from aggressive trading. As a result, the SDF in this economy can be approximated as a function of a low-dimensional factor model, even though all deviations of expected returns are caused by belief biases. Therefore, the fact of the covariance relationship between expected returns and factor premia is consistent with behavioral as well as rational explanations. Behavioral factor models are a good fusion of both rational models and behavioral interpretations. Asset returns comove with the covariance of factor returns, which are motivated by behavioral theories. In this paper, we propose to utilize a behavioral three-factor model to explain the cross-section of stock returns and digest significant anomalies in the China A-share stock market.

Previous literature on behavioral factor models has mainly focused on the US. stock market. To examine mispricing and cross-sectional asset returns, Hirshleifer & Jiang (2010) construct an external financing factor to identify commonalities in stock mispricing. They find that the loadings of general firms on the mispricing factor serve as proxies for systematic underpricing, thus positively predicting future returns" for clarity and conciseness. Stambaugh & Yuan (2017) develop two mispricing factors by averaging characteristics known from previous research to predict the cross-section of returns. They construct their two factors using the eleven well-documented anomalies studied by Stambaugh et al. (2012). In a more recent study, Daniel et al. (2020) extend the CAPM model with a post-earning announcements drift factor (PEAD hereafter) and a financing factor to capture short and long-horizon anomalies. However, De Long et al. (1990) point out that investors in less developed stock markets are more likely to be affected by their behavioral biases. The China A-share market, the second largest capital market, is a more desirable laboratory for behavioral finance research than any mature markets. Due to less transparent controls, lack of investment instruments and less clear accountability, the China stock market is still at an immature stage. China's stock market is featured by enormous retail investors, unsophisticated speculative investors as well as a lot of noisy information unrelated to firm fundamentals. At the end of 2018, individual investors held about 86% of the market value of the entire China stock market. Compared with sophisticated institutional investors, the large proportion of retail investors makes the China A-share market full of transactions affected by behavioral biases. Due to the market surge in the first half of 2015, the new account number was 1.1 million during that period, which is more than the sum of numbers in the following three years. In the first half of 2015, individual investors rushed into the market, exhibiting a market-wide herding phenomenon and overconfidence bias. Another feature of retail investors is that they trade too much (Odean, 1999). In 2019, 68% of stock accounts' holding periods were less than three months and the market turnover ratio was 158%. The dominance and prevalence of retail trading in China bring retail investors to the forefront of the China A-share market. As a 30-year history market, the China A-share market is crossing the river by testing the stability of the stepping-stones. The circuit Policy was implemented at the beginning of 2016 but it was terminated after a 7-day trial because the market plunged about 15%. The introduction of short-selling mechanism in 2010, the adjustment of Stamp Duty tax and many other policies were applied by the China Securities Regulatory Commission (CSRC) to increase the effectiveness of the stock market. The immature development and prevalence of retail investors make the behavioral approach more appealing to study the Chian A-share market.

The most recently prominent work on behavioral factor model in the US. market is Daniel et al. (2020). They propose a behavioral factor model, which extends CAPM with a

PEAD factor and a financing factor to capture short-term and long-term mispricing accordingly. Due to limited attention, investors may underreact to high-frequency earnings-related information, leading to short-term systematic mispricing. However, some mispricing is driven by persistent investor misperceptions, which may need a longer time to correct, captured by stock insurance and repurchase instead of changes in investment levels. Their behavioral factor model outperforms other prominent rational factor models in the US. stock market. However, their model does not behave well in the China A-share market for several reasons, which we will show the empirical results later in the body part. First, listed companies in the A-share market rarely repurchase stocks, which may limit the stock universe to a small group and lead to a biased financing factor. Second, the PEAD factor is constructed by the cumulative abnormal returns around the most recent earnings announcement date. However, companies with highly volatile revenue, especially for the GEM Board, are required to publish a revenue forecasting or brief revenue report before the official quarterly or annual financial reports. Consequently, the PEAD will be observed before the official earning release date. Third, their model is designed for the US. stock market which may neglect the unique characteristics of the A-share stock market.

To better accommodate the characteristics of the A-share market, we construct a behavioral factor model (BF3 hereafter) that augments CAPM with two behavioral factors, while our model takes into account the uniqueness of the A-share market, excessive trading, and investor behavioral biases to construct A-share behavioral factors. Our model is motivated by the China stock market's characteristics and the retail investors' bounded rationality. Empirical results demonstrate that our model outperforms established factor models in explaining cross-sectional asset returns. This paper makes two main contributions. First, our conceptual contribution is not devising the crowded factor zoo. Instead, we offer a behavioral consideration to factor models in explaining asset returns. When pursuing a new factor model, marginal attention has been paid to investors' cognitive biases. One of the reasons is that modern finance theories leave no space for investors' behavioral biases. Even if some of the investors are irrational, modern finance theories indicate that their price deviation impact is offset by rational investors' arbitrage. However, people share similar cognitive errors, such as overconfident investors overestimating the probability of beating the market and investors' preference to make facile investment decisions instead of researching comprehensively. When common cognitive biases are formed among investors, these patterns will also affect stock returns. In addition to Daniel et al. (2020), our paper provides more evidence of the success of behavioral theories motivated factors in capturing cross-sectional asset returns. Second, our empirical works add credits for the factor model and anomaly studies of the China stock market. We propose a new behavioral factor model, which provides greater explanatory power for the China A-share market. Our BF3 model outperforms the other four prominent factor models and is more suitable for practical implementation in the industry. The success of our BF3 model underscores the importance of model localization when applying outstanding factor models in non-US. markets.

2. Behavioral factor motivations

Our first factor is motivated by the rationale behind excessive trading. According to the annual report of the Shanghai Stock Exchange in 2016, individual investors trade about 85% of stocks in the A-share market, whereas institutional investors contribute only around 15%.

Behind the high trading volumes are tens of millions of retail investors in China. In addition to normal trading volume such as portfolio rebalancing and liquidity needs, abnormal trading volume is most likely attributed to behavioral issues. Liu et al. (2022) and Liao et al. (2022) have highlighted the behavioral tendencies of Chinese retail investors, noting that overconfidence, gambling preferences, and extrapolative expectations contribute significantly to excessive trading volume. Jones et al. (2023) have similarly observed strong overconfidence and gambling preferences among smaller retail investors. We utilize abnormal trading volume (hereafter ATV), orthogonal to normal trading volume, to proxy the behavioral rationales behind excessive trading volume. With a market model, all the transactions made by rational investors are explained by the volume market factor. Controlling for market transactions, abnormal transactions stem from irrational investors and generate their ATV. Thus, ATV from irrational investors creates an additional demand for stocks, leading to deviations from fundamental value and generating mispricing. An alternative explanation for the relationship between stock returns and ATV is investor attention. Using ATV as a proxy, Barber & Odean (2008) and Chen et al. (2022) find a negative relationship between investor attention and future stock returns. Peng and Xiong (2006) suggest that investors' tendency to allocate more attention to market and sector-wide information, rather than firm-level information, influences asset price dynamics, posing challenges for standard rational expectations models. In this paper, the trading factor is designed to capture mispricing stemming from the behavioral biases behind abnormal excessive trading and is expected to digest the anomalies in trading frictions.

Considering the substantial presence of retail investors in A-share market, we modify this PEAD factor from Daniel et al. (2020) by incorporating investors’ disposition effect, the tendency of investors to ride losses and realize gains, into factor construction. Frazzini (2006) argues that the returns predictability of PEAD is caused by investors' disposition effect. When stocks experience good news, realizing gains will generate pressure on price increases, hampering information transmission. On the other hand, stock price downward pressure will be alleviated by deferring loss, which renders transactions at an inflated price. The presence of disposition investors prevents information, such as quarterly or annual earnings announcements, from being incorporated into the stock price, thereby generating a post-announcement price drift. While bad news travels slowly across assets trading at large capital losses and generates negative return predictability, good news travels slowly across assets trading at large capital gains, which generates positive post-event return predictability. The magnitude of post-event drift is greater when news and capital gains share the same sign, and it is directly correlated with the level of unrealized gains (or losses) held by investors at the time of the event. Following Frazzini (2006), we employ the interaction between capital gains overhang—measured by the difference between the current price and the purchase cost—and abnormal returns around the most recent earnings announcement date to construct the modified PEAD factor, referred to disposition effect factor hereafter. Due to the investor composition in the A-share market, our disposition effect factor is better suited to capture the behavioral biases underlying stock price movements than the original PEAD factor in Daniel et al. (2020). Since we utilize information on firms' fundamentals to construct the disposition effect factor, we anticipate that this factor will capture mispricing arising from companies' fundamentals.

Our BF3 model augments CAPM with the trading factor and the disposition effect factor to capture both rational risk compensation and common mispricing stemming from investors' cognitive biases and excessive tradings. This approach is consistent with popular factor models, such as Daniel et al. (2020) and Stambaugh & Yuan (2017). Based on the variables used in factor construction, our behavioral factors are expected to capture both trading friction mispricing and fundamental mispricing in the cross-section of stock returns.

3. Empirical methodologies

To relatively examine the empirical properties of our BF3, we compare our model's performance with that of traditional models and recently proposed models, including Fama & French (2015) five-factor model (FF5), Hou et al. (2015) q-factor model (HXZ4), Stambaugh & Yuan (2017) mispricing factor model (SY4) and Daniel et al. (2020) behavioral factor model (DHS3)[1]. Following Barillas & Shanken (2017), we conduct factor spanning tests to assess how well other factors in these competing models price our trading factor and disposition effect factor, and vice versa. Our findings reveal that all competitive models fail to fully explain our two behavioral factors. In contrast, our BF3 model is able to price most of the traded factors, except for the profitability factors (RMW), finance factor and PEAD factor from DHS3.

We then attempt to accommodate the anomalies with various models. A better explanation of stock returns is not the only criteria for an empirical parsimony model. Furthermore, superiority can be demonstrated by effectively explaining anomalies. Therefore, the bottom

[1] We exclude the Chinese version size and value factor model (Liu et al., 2019) for performance comparison because of different stock universe. To accommodate the "Shell Values", they delect the smallest 30% market cap stock to construct the size and value factors for the A-share market. In contrast, owing to arbitrage and short-sale constraints, we hypothesize that behavioral factors are better suited to explain returns of stocks with high arbitrage frictions, such as those with smaller market capitalization. As a result, we include all stocks in both factor construction and the comparison of factor models.

line for a superior model is that the anomalies should shrink when we apply that model to accommodate the anomalies. We examine 154 anomalies from Jensen et al. (2023) and find 47 CAPM-adjusted significant anomalies, 14 trading frictions, and 33 fundamentals based on anomaly classification by Hou, et al. (2023)[2]. We find that our BF3 can shrink the significant anomaly number from 47 to 18 and decrease average absolute pricing errors to 0.42%, both of which are the lowest among all models. The incremental performance can be attributed to our behavioral factors. Trading-related anomalies load more significantly on the trading factor, while fundamental anomalies comove more with the disposition effect factor. To future assess the performance of our behavioral model, we check whether our model is able to predict stock returns in the cross-section. We follow Daniel et al. (2020) to perform Fama & Macbeth (1973) cross-section regressions to estimate firms' loadings on these factors using daily stock returns over a short horizon. We find tha the disposition effect factor significantly and positively

[2] Different from Hou et al. (2023), we categorize four momentum anomalies as fundamental anomalies for the sake of convenience. Typically, momentum and reversal are associated with trading friction. However, Grinblatt & Han (2005) propose a theory in which momentum is driven by the disposition effect. Their model posits that disposition effect investors exhibit demand distortions inversely related to the unrealized profit they have experienced on a stock. Disposition effect investors prefer to sell stocks with high unrealized profit, thereby decreasing their demand. Conversely, their demand increases when stocks are deeply out of the money because disposition effect investors tend to hold stocks with unrealized losses. This demand function distorts the equilibrium price from what is predicted by standard utility theory. The price distortion depends on the degree of unrealized gain or loss experienced by the disposition effect investors. As positive news hits the market, the price goes up, but the advance is offset by the selling pressure from the disposition effect investors. Likewise, if disposition effect investors hold a stock for which bad news is revealed, they tend to retain their shares rather than selling, thus mitigating downward pressure on the stock price. If any rational investors trading against the disposition effect investors do not fully correct their demands for stocks based on disposition bias, the stock price will underreact to public information. This leads to a discrepancy between the fundamental value of the stock, determined solely by fully rational investors, and the market price of the stock, influenced by the interaction between disposition effect investors and rational investors. In equilibrium, past winners tend to be undervalued and past losers tend to be overvalued, which is described as momentum. In this paper, our disposition effect factor is designed to capture mispricing from companies' fundamentals as well as momentum.

predict next month's stock returns, with or without other predictors. Finally, limits to arbitrage, which may hinder arbitrageurs from exploiting mispricing, is one of the cornerstones of behavioral theories. We expect that behavioral factors are particularly effective in explaining returns of stocks facing high arbitrage frictions, such as those in the short-leg portfolios and stocks with smaller market value, fewer institutional holdings and higher illiquidity. For industry practical purposes, implementing a long-only strategy is more feasible due to short-selling constraints in the China A-share market. Hence, we expect that the long leg of our behavioral factors will yield greater profit compared to the short legs.

The rest of this paper is organized as follows. Section four outlines the detailed construction methodologies of the trading factor and disposition effect factor. Section five shows the empirical results of behavioral factors and other competitive factors. Sections six and seven present the predictability of behavioral factors and their ability to accommodate anomalies. Section eight examines the performance of behavioral factors under different market friction scenarios. The concluding section summarizes the paper and discusses its implications for academia and industry.

4. Factor constructions

4.1 Trading factor

China A-share market is dominated by retail investors, which induces excessive trading volumes. Liu et al. (2022) summarize behavioral motivations for excessive trading and find gambling preference and perceived information advantage are the primary drivers. We do not distinguish between these behavioral biases behind excessive trading volume in this paper. Instead, we employ ATV, which is orthogonal to market trading volume, to capture all behavioral biases induced by excessive trading. With a market model, all the transactions made by rational investors are explained by the volume market factor. Controlling for market transactions, abnormal transactions stemming from irrational investors generate their ATV, which cannot be captured by the market trading volume. Building on this intuition, we can construct a trading factor by taking a long position of stocks with the lowest ATV and a short position of the opposite. The trading factor is designed to capture mispricing caused by excessive trading, which remains unexplained by the market trading volume.

The trading factor is constructed as follows. ATV for each stock can be extracted from a market model as follows:

$$V_{i,t} = A_i + B_i V_{m,t} + \varepsilon_{i,t}$$

Where $V_{i,t} = natural\ log\ of\ trading\ volume\ for\ stock\ i\ at\ month\ t$

$$V_{m,t} = natural\ log\ of total\ market\ trading\ volume\ at\ month\ t$$

$$\varepsilon_{it} = abnormal\ trading\ volume for\ stock\ i\ at\ month\ t$$

Using monthly data in the past five years[3], we run time-series regression for each stock and obtain the regression residuals as the ATV for each month. At the beginning of each month t,

[3] It is a common practice to use five-year time horizon to construct financial variables. Examples can be found from Barberis et al. (2016), Barberis et al. (2021), Grinblatt & Han (2005). We also construct the alternative

stocks are split into five groups: small (S) containing the smallest 20% and big (B) group representing the largest 20%, based on quintiles of stock's market cap t-1. Independently stocks are divided into five groups, over (O) consisting of the highest 20% and under (U) containing the lowest 20%, based on the quintiles of the prior month's ATV. Taking intersection yields four size-ATV portfolios, named SO, SU, BO and BU. Monthly value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced at the beginning of month t+1. The trading factor is the value-weighted difference between yields of over portfolios and returns on under portfolios: TRADING = ((SU+BU) - (SO+BO))/2.

4.2 Disposition effect factor

The original PEAD factor in the DHS3 model is designed to capture investors' underreaction to firms' fundamental information. However, Grinblatt and Han (2005) and Frazzini (2006) document that investors' underreaction is induced by disposition effect, which then generates asset return drifts. Considering the massive retail investors in the A-share market, we modify the original PEAD factor to capture mispricing from both underreaction to fundamentals and investors' disposition effect. We follow Frazzini (2006) to construct our modified PEAD factor, named the disposition effect factor (DE hereafter). The conjecture is that post-earnings announcement drift is magnified when news content and unrealized profit have the same sign. The drift is larger when good news comes to stocks at capital gain or bad news hit stocks at capital loss. If a stock is trading at capital gain when bad news arrives, the tendency

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trading factors with three-year and one-year horizon and the empirical properties of these alternatives remain robust. Table A1 in the Appendix A provides more detailed information.

to realize gain from disposition effect investors helps the market to incorporate the information, and thus the stock price should quickly drop to the new fundamental value. On the other hand, if a stock is experiencing capital loss, disposition effect investors are reluctant to realize loss when bad news are coming, then decelerating price discovery and generating drift. Similarly, this argument can be made for positive news stocks.

To calculate our disposition effect factor, we need measurements of unrealized capital gain and earnings surprise. The key point in computing unrealized capital gain is to measure the reference price, the purchasing price of stocks. Grinblatt and Han (2005) propose a turnover-based metric to proxy the market's cost basis in stock and assume it is the purchase price:

$$R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n}$$

Where V_t is week $t's$ turnover ratio for the stock. The term in the parentheses multiplying P_{t-n} is a weight, and all the weights sum to one. The interpretation of the cost basis is as follows. R_t is a probability-weighted price, where the probability estimates that a share was previously purchased at week $t-n$ and has not been traded since then. If a stock had high turnover at week t but the turnover has been very low since then. Therefore, it is likely that investors have held the stocks since week t. We can assign more weight to closing pricing at week t to estimate the purchase prices. Weighted averaging of all possible purchase prices provides the estimated cost basis for the stocks. We use five years to calculate the purchase price because distant prices have minimal influence on the cost basis[4]. With this purchase price, we can calculate the unrealized gain or loss g_t at week t as follows:

$$g_t = \frac{P_t - R_t}{P_t}$$

To calculate the monthly premium of the disposition effect factor, we only use the last week's unrealized gain/loss in every month. Following the methodology of Chan et al. (1996), Frazzini (2006), and Daniel et al. (2020), we compute the earnings surprise as the 4-day cumulative abnormal return around the most recent quarterly earnings announcement date, spanning from 2 days before to 1 day after the announcement. This approach accounts for the likelihood of insider information leakage or delayed market response, especially for illiquid stocks. Earnings surprises can be calculated as follows:

$$CAR_i = \sum_{d=-2}^{d=1} \left(R_{i,d} - R_{m,d}\right)$$

Where $R_{i,d}$ is stock $i's$ return on day d and $R_{m,d}$ is the market return on day d relative to the earnings announcement date. Accounting for the release of the revenue brief or revenue forecasting ahead of the quarterly report, we include these pre-released documents in calculating the earnings surprise. We construct the disposition effect through monthly independent triple sorts on earnings surprise, unrealized gain and firm size. At the beginning of each month, we first divide all firms into three size groups (small(S), middle(M), big(B)) based on the 20% and 80% breakpoints of market cap at the end of month $t-1$. Likewise, all stocks are

[4] We follow Grinblatt and Han (2005) to use five-year time horizon. But our disposition effect factor remains robust with one-year and three-year time horizons. Table A in Appendix A reports the results of these robustness checks.

independently sorted into three portfolios (low(L), middle(M), high(H)) by 20% and 80% breakpoints of the unrealized gain. Finally, we use the median of last month's cumulative abnormal returns around the most recent earnings announcement date to classify all stocks into above(A) and below(B) groups.[5] As underreaction to fundamentals is more pronounced when the unrealized gain and earnings surprise align, our disposition effect factor takes long positions on stocks with the largest unrealized gains and good news and short positions on stocks with the largest unrealized losses and bad news. The monthly disposition effect factor return is the average return of DE = ((LBS+LBB) - (HAS+HAB))/2

Augmented from the CAPM model, our BF3 adds a trading factor and disposition effect factor to form a three-factor model, which is designed to capture market risks and mispricing from both excessive trading volume and firm fundamentals. In comparison to prominent factor models, our BF3 considers the unique characteristics of the Chinese stock market and the irrational behaviours of retail investors, aiming to develop a more robust factor model suitable for the A-share market.

[5] There are two main reason we don't use the quantiles of cumulative abnormal return for portfolio sorting. First, we need to ensure sufficient number of stocks in each portfolio. Second. the median of CAR happens to be around zero, which indicates that all stocks are divided into a bad news portfolio and a good news portfolio. The disposition effect factor remain robust when we use the alternative tripl-sort method of unrelaized gain/loss and cumulative abnormal returns quantiles and market cap median. Appendix A reports the detailed results.

5. Empirical properties

5.1 Data

For the comparison factor models, we obtain the competitive factor model data from the Factorwar website, which specializes in factor model research of the China stock market[6]. In terms of anomalies, we utilize the Global Factor Data constructed by Jensen et al. (2023). To construct our behavioral factors, all data are from the China Stock Market & Accounting Research (CSMAR) database. Individual stock information, such as stock prices and trading volumes are obtained directly from the database. The construction of factors and anomalies includes all A-share stocks listed on the A-share market, except for ST companies and those with zero or negative book values. While the selection criteria are primarily based on those outlined by Liu et al. (2019), modifications have been made due to data availability. The sample spans the period from January 2000 to December 2022. We believe that the A-share market becomes more stable after almost 10 years of development. Regulations for fair trade and financial disclosure were initiated in China in 1993, but the implementation of those governing public companies' financial reporting was gradual until 1999. During this period, companies had varying standards, limiting the comparability of accounting data across firms. By 1998, the accounting system and regulations were more thoroughly designed and implemented, leading to increased transparency and competitiveness in accounting statements. Detailed guidelines

[6] The Factorwar website provides monthly factor premiums, and the extreme portfolio returns in both short and long-legs. Please click here for more information.

for corporate operating revenue disclosure were issued in December 1998 and implemented in January 1999. Securities laws were passed in December 1998 and implemented in July 1999.

5.2 Factors summary

From Table 1, our trading factor yields an average monthly return of 0.98% and a Sharpe ratio of 0.33, both of which are the highest among all competing factors. The t-value of 5.6 suggests that the trading factor premium is significantly different from zero. The disposition effect factor generates a significant monthly return of 0.69% (t-value = 2.76), which is slightly lower than the returns of various versions of the size factor. Among all the competitive factors, only size factor variants and the profitability factor in HXZ4 generate significant returns. This observation aligns with our argument that the application of established US. market factors to the A-share market requires modifications. According to the literature[7], the A-share market is characterized by irrational investors. However, the behavioral and mispricing factors (FIN_DHS3, PEAD_DHS3, MGMT_SY4 and PERF_SY4) derived from the two competitive models fail to generate significant monthly returns. In terms of the model maximum Sharpe ratio, the BF3 (0.11) is second to that of HXZ4 (0.18). Table 2 reports pairwise correlation coefficients between all factors. A moderate correlation (-0.34) is found between our trading factor and disposition effect factor. Although the two behavioral factors aim to capture different sources of mispricing, the moderate correlation may be attributed to the inclusion of turnover

7 Feng & Seasholes (2005) find that sophistication and trading experience cannot eliminate the reluctance to realize losses but only result in a 37% likelihood of realizing gains. Frino et al. (2015) use individual account data from Oct 2010 to Aug 2012 to find that Chinese investors are more likely to suffer from disposition effect. However, the conclusions drawn by Demirer & Kutan (2006) and Chiang et al. (2007) contradict the findings above.

ratio in the construction of the disposition effect factor. Therefore, we conduct several robustness checks to verify the validity of our two behavioral factors in the main results. Details of these robustness tests are provided in Appendix A. Regarding the other factors, our trading factor exhibits minimal interactions, with a maximum RMW_FF5 coefficient of -0.11. In terms of the disposition effect factor, it is strongly correlated with the PEAD_DHS3 (0.52), indicating that they share some information on post-event drifts. Additionally, two profitability factors (RMW_FF5 and RMW_HXZ4) are also highly correlated with the disposition effect factor, with coefficients of 0.39 and 0.50. The RMW_FF5 and RMW_HXZ4 factors are sorted by operating profit and ROE, which are variables from the earnings announcements. Although the profitability factor and the disposition effect factor have different rationales, their proxies are similar, resulting in high correlations.

【Table 1 area】

【Table 2 area】

5.3 Factor spanning tests

For the factor spanning test suggested by Barillas & Shanken (2017), we perform time series regressions of factors' monthly return on other previously used factors and examine the regression intercepts. If a factor can be explained by a set of other factors, we can expect the regression intercepts to be indifferent from zero. Panel A of Table 3 reports the results of regressions of our behavioral factor returns on other factors in the competition models. The significant intercepts from all regressions indicate that our two behavioral factors are able to yield abnormal returns after controlling for other factors in the competitive models. In Panel B, we utilize our BF3 to regress on other factors. Except for profitability factors and two behavioral factors in DHS3, our BF3 fully captures the factor premiums in the competitive models. The insignificant t-values of three versions of size factor show the redundancy of including another size factor in our behavioral model. Another observation from the spanning test is the significant alphas of the FIN_DHS3 and PEAD_DHS3 factors. The two behavioral models can't fully explain each other, indicating different information carried by the two models. Overall, our BF3 captures 8 out of 12 factors premiums, but not vice versa. The premiums of the factors from the alternative models are not fully captured by our BF3, suggesting that our trading factor and disposition effect factor contain important incremental information about average returns relative to existing factors. This motivates further testing of their ability to explain well-known return anomalies in the next section.

【Table 3 area】

6. Digesting anomalies with behavioral factors

In this section, we first identify which anomalies are capable of generating abnormal returns relative to the CAPM model. To avoid redundancy, we only assess our behavioral factors' overall performance in accommodating these significant anomalies. Then, we move to detailed results to shed light on the superior performance of the behavioral factors.

We focus on the significant anomalies, which are defined as abnormal returns adjusted by the CAPM model, in the database compiled by Jensen et al. (2023). They argue about the replication crisis in factor research and construct a global factor dataset covering 93 countries.[8] As for the China A-share market, there are 157 anomalies in their database, which we apply to regress against the CAPM model. We find only 47 significant anomalies at a 5% significance level, which are listed in Table 4 and Table 5. Our behavioral factors are designed to account for trading frictions and fundamental anomalies. Therefore, we further categorize these 47 anomalies into 14 trading-related and 33 fundamental anomalies based on the classification of Hou et al. (2023). For the sake of parsimony, our examination in the following section only focuses on the 47 significant anomalies. We present the short names and related literature of these anomalies in Table 4 and their CAPM-adjusted abnormal returns in Table 5.

【Table 4 area】

【Table 5 area】

To evaluate the performance of our behavioral factors in accommodating various anomaly returns, we first focus on the mispricing portions from the high minus low portfolios for each anomaly. Using the zero investment portfolios in the LHS and the various factor models in the RHS, we can run a time-series regression to estimate the mispricing parts (alphas) for all significant anomalies. If a model is effective, the regression alphas of the hedged portfolios should be statistically indistinguishable from zero. We compare the performance of our BF3 with other competing models. Given the effectiveness of behavioral models in explaining

[8] Please visit their website for detailed information https://www.jkpfactors.com/

anomalies, we can analyse the behavioral factor loadings to uncover the sources of the superior performance of behavioral models.

Table 5 summarizes the comparative performance of competing factor models in explaining the set of 47 significant anomalies. Panel A compares all the models' alphas in explaining 14 significant trading-related anomalies. Combining the market factor with our two behavioral factors, our BF3 fully captures all 14 anomalies. All other competitive models don't behave well in digesting trading-related anomalies. Excluding our BF3 model, the best performance comes from FF5 and SY4 models reducing the number of significant anomalies to 8. The inferior performance can be attributed to the factor construction proxies. All factors[9] in the competitive models are calculated from the fundamental variables, without taking into account trade frictions. Panel B suggests that the two behavioral factor models, DHS3 and our BF3, provide incremental ability in explaining fundamental anomalies, by reducing the number of significant alphas number from 33 to 16 and 18 respectively. Compared to other models, behavioral factor models might be superior in capturing abnormal returns arising from fundamental information in a retail investor-dominated A-share market. Panel C summarizes all models' performance on the 47 significant anomalies. Our BF3 yields only 18 significant alphas at a 5% significance level, while the numbers of other models hover around 30 at minimum. The smallest average absolute alphas and absolute t-values, 0.42% and 1.80 respectively, also confirm our BF3's best performance in reducing mispricing among the significant anomalies. Although the F-tests suggest that the average of the squared t-values for the estimated alphas

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[9] Although price momentum is one of the five variables to construct the PERF factor in SY4, the average weight may reduce the impact from momentum.

(t^2) under DHS3 does not significantly differ from the average t^2 of the BF3's alphas, the average t^2 of FF5, CARH4, SY4 and HXZ4 alphas are significantly larger than that of BF3 alphas. In summary, our BF3 model with a market factor and two behavioral factors surpasses prominent models in explaining the 47 CAPM-robust anomalies.

In this section, we try to delve deeper into finding out why our BF3 is able to digest the significant anomalies better. Table 6 reports alphas and factor loadings from time-series regressions of each hedged anomaly portfolio returns on our BF3. We examine the factor loadings to gain insight into the superior performance in absorbing anomalies. In Panel A, as we anticipated, 11 out of 14 trading-related anomalies significantly load on the trading factor. In contrast, we find that 22 out of 33 fundamental anomalies comove with the disposition effect factor in Panel B. Overall, consistent with our hypothesis, an ATV proxied factor has more comovement with trading-related mispricing, while fundamental variables are more capable of explaining mispricing stemming from companies' periodic reports.

【Table 6 area】

7. Portfolio returns predictability

Our trading factor is proxied by ATV and designed to capture the common mispricing caused by investor excessive trading. Another interpretation of ATV is investor attention. Barber & Odean (2008) and Chen et al. (2022) use ATV to proxy investor attention and find a significant positive relationship between investor inattention and portfolio returns in the next month.[10] Therefore, we expect the loadings of trading factor to positively predict the cross-section of future stock returns. Our disposition effect factor is constructed from a zero-investment portfolio, consisting of longing good news stocks with the largest paper gain and shorting the opposite, in order to exploit the mispricing behind underreaction to firm fundamentals. We also expect the loadings on this factor to be an underpricing proxy and to positively predict future stock returns. To account for the constantly changing nature of stock mispricing (over or under), we follow Daniel et al. (2020) to estimate firms' loadings on both behavioral factors and factors in the competitive models using daily excess returns over a 1-month horizon instead of using the previous 60 months for estimation for Fama & Macbeth (1973) regression. The monthly returns of each stock are in the LHS of the regression, while we use different factor combinations in the RHS.

【Table 7 area】

Table 7 reports the regression results, including BF3 (Model 1), Model 2 to Model 13 where our behavioral size factor[11] and the factors in the competitor models are added one at a time to BF3, and model 14, which consists of all factors. We find that β_{DE} loadings are able to positively and significantly predict the following month's stock returns, with or without other factor controls. The disposition effect factor loading remains significantly positive when we add other predictors. Therefore, the other prominent factors in the competitive models

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[10] The original finding from Barber & Odean (2008) and Chen et al. (2022) is a negative relationship between investor attention and next month's portfolio return.

[11] We form 4 tiny portfolios and 4 mega portfolios when we construct trading and disposition effect factors. The behavioral size factor is calculated by SIZE_BF = ((SU+SO+HAS+LBS-BU-BO-HAB-LBB))/4.

cannot provide any incremental explanatory power for stock returns. Also, the disposition effect factor loadings are dominating (the largest coefficients) in explaining stock returns in all 14 models. Finally, the highest disposition effect factor loading of 0.21 (t-value 2.6) in Model 14 indicates that the disposition effect factor outperforms all the other control factors to provide significantly positive predictability for stock returns.

However, the positive predictability of the $\beta_{trading}$ is only significant in 7 regressions out of 14 regressions. More specifically, the trading factor outperforms other control variables in Models 2 to 5, 7, 12 and 13. Although we cannot confirm the trading factor's predictive power across all models, its performance is superior to most control factors. According to Model 2 to 13, there are only two control factors, SMB_FF5 in Model 3 and MGMT_SY4 in Model 13 respectively, that significantly predict future returns. Nevertheless, our trading factor also demonstrates the predicting power in both models. Another finding from Table 6 is the redundancy in including a size factor in our BF3. Model 2, consisting of our BF3 and a size factor (SMB_BF3), shows that the coefficient on the size factor becomes marginally significant when we control for the disposition effect factor and trading factor.

Overall, our findings suggest that the loadings of disposition effect factor positively and significantly forecast future stock returns. This predictive power is robust to controlling for many well-known return predictors in the literature. The evidence validates our hypothesis that the disposition effect factor captures return comovement arising from common mispricing. Although the predictability of trading factor can be found only in 7 models, its performance is superior to most other control factors.

8. Robustness of BF3

Limits to arbitrage is one of the cornerstones of behavioral finance theories (Barberis & Thaler, 2002). In this part, we examine the performance of our behavioral factors in the presence of different situations that impose limits to arbitrage. First, we focus on short-selling constraints, which can induce price asymmetry. Compared with developed financial markets, short-selling constraints are more prevalent in the A-share market. Although the short-selling mechanism was introduced since 2010, the reality is that borrowing shares to short is unrealistic. For practical purposes, a long-only trading strategy is more appropriate for fund managers to implement in the A-share market. Therefore, we expect the long-leg portfolios of our behavioral factors to be more profitable than the short-leg portfolios. Second, due to short-sale constraints, mispricing of overpriced stocks in the short-leg portfolios is more difficult to correct. If our behavioral factors capture mispricing, they are expected to explain the returns of the short-leg portfolios better than the returns of the long-leg portfolios. We expect that the short-leg portfolios of the significant anomalies should load more on the behavioral factors than the long-leg portfolios do. Finally, market frictions will affect arbitrageurs' ability to exploit mispricing, thereby affecting the covariance structure of behavioral factors and portfolio returns. For stocks with high market frictions, including high illiquidity, low institutional ownership, and small firms, we should observe a high sensitivity of expected returns to the behavioral factor coefficients.

【Table 8 area】

Table 8 reports the return asymmetry within the hedged portfolios. In Panel A, we can observe a significantly positive return of the long-leg portfolios, which indicates that the long-leg contributes positively to the factor returns. Surprisingly, all the short-leg portfolios of the control factors, which consist of overvalued stocks, also generate significantly positive returns with a significance level of 10% in Panel B. The failure of these control factors in predicting future stock returns and digesting anomalies may be due to the misbehaviour of the short-leg portfolios in identifying overpriced stocks. Although our two behavioral factors also have positive returns in the short legs, both are insignificant and much lower in magnitude (first two rows in panel B). The last column in Panel C presents the return asymmetry ratio calculated by the return difference between long and short portfolios over the short portfolio returns. The behavioral factors, including the trading factor and the disposition effect factor from BF3, as well as the FIN and PEAD factors from DHS3, have higher ratios (21.61, 2.08, 3.11 and 3.40 respectively) than other traditional factors with ratios lower than 1. Since the long-leg portfolio returns are approximately the same (column 1 of Panel A), this observation suggests that the accuracy of identifying overpriced stocks using behavioral proxies is higher than the traditional firm fundamental proxies. Especially in the A-share market, behavioral factors seem to provide incremental information for asset pricing.

Table 9 confirms our hypothesis that our behavioral factors load more on the short-leg portfolios than long-leg portfolios. We conduct time-series regressions of the long- and short-leg portfolio returns of 47 significant anomalies on our BF3 model respectively. Panel A shows the results of regressions of the long-leg and short-leg from trading-related anomalies against BF3. As the trading factor is designed to capture trading-related anomalies, we focus on the coefficients of the trading factor in the last two columns. Compared with 6 significant coefficients in the long-leg portfolios, the number is 10 in the short-leg portfolios. In terms of magnitude shown in the bottom line of Panel A, the average coefficient is 0.32 across all 14 short-leg portfolios, which is more than double of the average coefficient of 0.13 observed in the long-leg portfolios. In Panel B, more attention is paid to disposition effect factor coefficients in the first two columns. We can find 21 significant coefficients in the short-leg portfolios, higher than the 14 significant coefficients observed in the counterparts. As shown in the bottom row of Panel B, the average coefficient magnitude is 0.2 in short-leg portfolios, which is also higher than the average of 0.15 observed in the long-leg portfolios. All the results above confirm that the trading factor primarily captures trading-related mispricing and the disposition effect factor captures mispricing embedded in fundamentals. Both behavioral factors explain the returns of the short-leg portfolios better. Overall, the findings support the idea that our behavioral factors capture commonality in mispricing.

【Table 9 area】

In Table 10, we report the results of market friction portfolios' sensitivity to our behavioral factors. By using illiquidity (Amihud, 2002), institutional ownership and market cap as proxies for market friction, we find that stocks with higher market friction exhibit greater sensitivity to our behavioral factors' loadings. At the beginning of each month, we rank firms into 10 portfolios based on various proxies of market friction at the end of month $t-1$. We calculate the value-weighted returns for each portfolio for the current month and all portfolios will be rebalanced in the following month. To obtain the factor loading, we run time-series regressions of the returns for each portfolio sorted by each market friction proxy against the BF3 model. All three panels indicate a monotonically decreasing pattern in the loadings from the highest market friction portfolio to the lowest one. For example, in Panel A, $\beta_{trading}$ and β_{DE} increase from 0.03 and 0.13 (in magnitude), respectively, for the portfolio with the largest market capitalization, to 0.21 and 0.45 (in magnitude) for the portfolio with the smallest market capitalization. The same patterns can also be observed in the panels for illiquidity and institutional ownership. Therefore, the results confirm our hypothesis that the relation between the behavioral factors' loadings and expected returns should be stronger for stocks with higher market frictions.

【Table 10 area】

9. Conclusion

Behavioral asset pricing theories (Barberis & Shleifer, 2003; Daniel et al., 2001) imply that there is common mispricing across firms, which induces systematic comovement in stock returns. Based on the excessive trading volume and prevalence of massive retail investors in the Chian A-share market, we construct a trading factor proxied by the ATV and a disposition effect factor which modifies the original PEAD_DHS3 factor by including the investors' disposition effect. The rationale behind the trading factor is that investors' behavioral biases induce excessive trading (Liu et al., 2022; Liao et al., 2022). The motivations for the disposition effect factor stem from the literature suggesting that investors' underreaction to firm fundamentals is caused by their cognitive biases. Therefore, following Frazzini (2006), we combine the cumulative abnormal returns, the PEAD_DHS3 proxy, with the unrealized gain/loss to construct our disposition effect factor. Based on the proxies, we expect the trading factor and disposition effect factor to capture the mispricing associated with trading frictions and firm fundamentals respectively. We supplement the market factor of the CAPM with these two behavioral factors intended to capture commonality in mispricing associated with psychological biases. Empirical results show that our BF3 significantly outperforms the existing factor models in terms of explanatory power. Not only can it explain the factors in other models, including FF5, HXZ4, SY4, and DHS3, but it also digests 47 CAPM-adjusted anomalies better than other competitive models. Consistent with our expectations, the trading-related anomalies primarily comove significantly with the trading factor, while the fundamental anomalies load more on the disposition effect factor. Using Fama & MacBeth (1973) cross-sectional regressions, we confirm that the disposition effect coefficients positively and significantly forecast the next month's stock returns, even after controlling for most of the other predominate factors examined. Although the predictability of trading factor can only be observed in some cases, its performance is superior to other competing factors. Finally, we find that the trading and disposition effect factors are particularly useful for predicting the returns of stocks with high arbitrage frictions, such as stocks in short-leg portfolio, and stocks with greater trading frictions. In short, we propose a new behavioral factor model for the Chinese stock market, which outperforms the other outstanding factor models.

This paper contributes to a large literature on factor pricing models and anomalies. The pioneers in the field of behavioral factors research are Hirshleifer & Jiang (2010), Daniel et al. (2020) and Stambaugh and Yuan (2017). However, our BF3 model outperforms these models almost by all criteria in China A-share market. Daniel et al. (2020) is the most similar to our work. The superior performance of our model underscores the importance of model localisation in application. This research conveys a message that investors' cognitive biases carry information about asset mispricing, and it emerges as a beneficial approach to use behavioral-motivated factors to detect asset mispricing, comovement and return predictability.

Appendix A Robustness check for behavioral factors

We use a five-year time horizon to calculate the cost basis for the construction of disposition effect factor and to obtain ATV for each stock of the trading factor. For robustness checks, we use one-year and three-year time horizons to construct alternative disposition effect and trading factors. Meanwhile, we follow the method of Barber & Odean (2008) to proxy abnormal trading volume using a ratio of trading volume at the end of each month to the average over the previous 1 year for each stock. Table A reports the empirical results of these alternative factors with various construction methods. In Panel A, the statistics of one-year and three-year trading factors are nearly identical to our original trading factor in the first line. For instance, the Sharpe Ratios for TRADING, TRADING_36M AND TRADING_12M are 0.33, 0.33 and 0.34 respectively. Although the mean (0.70) and Sharpe Ratio (2.89) of TRADING_BO, which represents the Barber & Odean (2008) method, are lower than those of our original trading factor, it remains significant with a t-value of 4.08. Panel B reports the statistics of alternative disposition effect factors. These alternatives remain robust to various construction time horizons and breakpoints. The t-values for our original disposition effect factor and three alternatives are 2.76, 2.72, 2.65 and 2.17 respectively. In summary, our two behavioral factors are robust with different proxies and time horizons.

【Table A area】

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Table 1 Summary statistics of factors and models

	Mean(%)	T-value	SD(%)	SR	N	Max SR
MKT	0.62	1.41	7.37	0.08	281	
TRADING	0.98	5.60***	2.94	0.33	281	0.11
DE	0.69	2.76***	4.19	0.17	281	
SMB_FF5	0.70	2.58***	4.57	0.15	281	
HML_FF5	0.15	0.76	3.29	0.05	281	0.09
RMW_FF5	0.04	0.25	2.99	0.01	281	
CMA_FF5	0.06	0.43	2.31	0.03	281	
FIN_DHS3	0.31	1.78*	2.79	0.11	253	0.04
PEAD_DHS3	0.18	1.40	2.11	0.09	253	
SMB_HXZ4	0.80	2.80***	4.37	0.18	236	
RMW_HXZ4	0.58	2.56***	3.46	0.17	236	0.18
CMA_HXZ4	0.07	0.50	2.05	0.03	236	
MGMT_SY4	0.17	0.68	3.87	0.04	253	
PERF_SY4	0.21	1.25	2.69	0.08	253	0.09
SMB_SY4	0.69	1.97**	5.57	0.12	253	

Panel A reports the summary statistics of the monthly factor premium. In addition to mean values, standard deviation, observation numbers, and t-test statistics, we also report the Sharpe Ratio for each factor and Max Sharpe Ratio for each model. The last column reports the factor models' maximum Sharpe Ratio calculated by $\sqrt{\mu_f' V_f^{-1} \mu_f}$ in which μ_f the vector of mean factor returns for a given factor model, and V_f is the variance-covariance matrix of factor premiums. MKT is the market factor. TRADING and DE are two behavioral factors in our BF3. SMB_FF5, HML_FF5, RMW_FF5 and CMA_FF5 are from Fama & French (2015) five-factor model. FIN_DHS3 and PEAD_DHS3 belong to Daniel et al. (2020) behavioral factor model. SMB_HXZ4, RMW_HXZ4 and CMA_HXZ4 are factors in Hou et al. (2015) q-factor model. PERF_SY4 and MGMT_SY4 and SMB_SY4 are from Stambaugh & Yuan (2017) mispricing factor model. The MKT factor data is from the CSMAR database. We calculate the TRADING and DE factor premiums. All the factors of the competitive models are from the Factorwar website. ***, ** and * represent 1%, 5% and 10% significance levels respectively.

Table 2 Correlation matrix

	TRADING	DE	MKT	SMB FF5	HML FF5	RMW FF5	CMA FF5	FIN DHS3	PEAD DHS3	SMB HXZ4	RMW HXZ4	CMA HXZ4	MGMT SY4	PERF SY4	SMB SY
TRADING	1.00														
DE	-0.34	1.00													
MKT	-0.07	-0.17	1.00												
SMB_FF5	0.05	-0.28	0.11	1.00											
HML_FF5	-0.08	0.08	-0.09	-0.36	1.00										
RMW_FF5	-0.11	0.39	-0.28	-0.69	0.09	1.00									
CMA_FF5	0.07	-0.22	0.13	0.34	0.30	-0.58	1.00								
FIN_DHS3	0.06	0.14	-0.18	-0.40	0.55	0.25	0.13	1.00							
PEAD_DHS3	-0.03	0.52	-0.28	-0.35	0.20	0.42	-0.28	0.09	1.00						
SMB_HXZ4	0.08	-0.28	0.09	0.96	-0.54	-0.70	0.32	-0.39	-0.32	1.00					
RMW_HXZ4	-0.10	0.50	-0.26	-0.68	0.25	0.83	-0.56	0.26	0.48	-0.55	1.00				
CMA_HXZ4	0.09	-0.11	-0.04	-0.02	0.55	-0.28	0.72	0.37	0.02	-0.06	-0.15	1.00			
MGMT_SY4	0.07	0.01	-0.20	-0.48	0.70	0.18	0.22	0.57	0.15	-0.53	0.14	0.50	1.00		
PERF_SY4	-0.07	0.27	-0.11	0.03	-0.19	0.28	-0.35	-0.13	0.21	0.14	0.40	-0.35	-0.57	1.00	
SMB_SY4	0.08	-0.38	0.11	0.97	-0.49	-0.77	0.42	-0.37	-0.39	0.95	-0.69	0.00	-0.46	0.00	1.00

This table reports the correlations between all the factors, including our behavioral factors and the factors in the competitive models.

Table 3 Factor spanning test

Panel A Competitive factors to explain behavioral factors

	CAPM	FF3	FF5	SY4	HXZ4	DHS3
DE	0.63	0.37	0.71	0.61	1.12	1.02
	(2.69)	(1.52)	(3.03)	(2.57)	(4.52)	(4.89)
TRADING	1.01	0.94	0.99	0.95	1.07	1.02
	(6.95)	(6.06)	(6.56)	(5.62)	(5.68)	(5.79)

Panel B Behavioral factors to explain competitive factors

SMB	HML	RMW	CMA	FIN	PEAD	SMB	RMW	CMA	MGMT	PERF	SMB
FF5	FF5	FF5	FF5	DHS3	DHS3	HXZ4	HXZ4	HXZ4	SY4	SY4	SY4
0.22	0.29	0.39	-0.16	0.37	0.37	0.34	1.03	0.01	0.20	0.35	0.18
(1.42)	(1.27)	(2.81)	(-1.18)	(2.21)	(2.70)	(1.76)	(6.01)	(0.10)	(0.64)	(1.41)	(0.79)

Panel A reports the intercepts from the time series regression of two behavioral factors against the competitive factor models. Two behavioral factor monthly premiums are used as dependent variables and competitive factor models are the independent variables. We report regression intercepts in percentage values. If a factor is subsumed by a set of other factors, we expect the regression intercept to be statistically indistinguishable from zero. Newey-West corrected t-statistics (six lags) are reported in the parentheses. In panel B, we change the positions of independent variables and dependent variables and run the same regressions again.

Table 4 List of significant anomalies

Panel A Trading-related			
ba	The high-low bid-ask spread, Corwin & Schultz (2012)	rmax5	Highest 5 days of return, Bali, Brown, Murray and Tang (2017)
ivol_ff3	Idiosyncratic volatility from the Fama-French 3-factor model Ang et al. (2006)	beta	Market Beta Fama and MacBeth (1973)
ivol_capm	Idiosyncratic volatility from the CAPM (21 days) Ali, Hwang & Trombley (2003)	dolvol	Dollar trading volume, Brennan Chordia and Subrahmanyam (1998)
ivol_hxz4	Idiosyncratic volatility from the q factor model	rd	R&D-to-market, Chan Lakonishok and Sougiannis (2001)
zt	Number of zero trades (1 month), Liu (2006)	prc	Price per share, Miller and Scholes (1982)
rmax1	Maximum daily return, Bali et al. (2011)	me	Market Equity, Banz (1981)
betabab	Frazzini-Pedersen market beta, Frazzini & Pedersen (2014)	rskew	Total skewness, Bali Engle and Murray (2016)
Panel B Fundamental			
ret60_12	Long-term reversal, De Bondt and Thaler (1985)	ret1_0	Price momentum t-1, Jegadeesh (1990)
ret3_1	Price momentum t-3 to t-1, Jegadeesh and Titman (1993)	ret12_7	Price momentum t-12 to t-7
cowc	Change in current operating working capital, Richardson et al. (2005)	seas2_5	Years 2-5 lagged returns, nonannual, Heston and Sadka (2008)
accni	Percent operating accruals, Hafzalla Lundholm and Van Winkle (2011)	noagr	Change in net operating assets, Hirshleifer et al. (2004)
accat	Operating accruals, Sloan (1996)	tang	Asset tangibility, Hahn and Lee (2009)
col	Change in current operating liabilities, Richardson et al. (2005)	niqbe	Change in quarterly return on equity, Abarbanell and Bushee (1998)
saleqgr	Sales growth (1 quarter), Lakonishok Shleifer and Vishny (1994)	niqsu	Standardized earnings surprise, Foster Olsen and Shevlin (1984)
saleqsu	Standardized Revenue surprise, Foster Olsen and Shevlin (1984)	seas1_1	Year 1-lagged return, annual, Heston and Sadka (2008)
qmj	Quality minus Junk, Asness, Frazzini and Pedersen (2019)	niqat	Change in quarterly return on assets, Abarbanell and Bushee (1998)
salebev	Assets turnover, Soliman (2008)	eqnpo	Equity net payout, Daniel and Titman (2006)
copatl	Cash-based operating profits-to lagged book assets, Bali et al. (2016)	sale	Sales-to-market, Barbee Mukherji and Raines (1996)
copat	Cash-based operating profits-to book assets, Bali et al. (2016)	fcf	Free cash flow-to-price, Lakonishok Shleifer and Vishny (1994)
gp	Gross profits-to-assets, Novy-Marx (2013)	be	Book-to-market equity, Rosenberg Reid and Lanstein (1985)
seas11_15	Years 11-15 lagged returns, non-annual, Heston and Sadka (2008)	netis	Net total issuance, Bradshaw Richardson and Sloan (2006)

Table 4 List of significant anomalies (Continued)

ni	Earnings-to-price, Basu (1983)	ocf	Operating cash flow-to-market Desa, Rajgopal and Venkatachalam (2004)
ebitda	Ebitda-to-market enterprise value, Loughran and Wellman (2011)	ival	Intrinsic value-to-market, Frankel and Lee (1998)
div	Dividend yield, Litzenberger and Ramaswamy (1979)		

This table lists the 47 CAPM-adjusted significant anomalies in this paper. The original anomalies' data we use is from Jensen et al. (2023). There are 157 anomalies in their database, but we only find 47 significant CAPM-adjusted anomalies at 5% significance level from 2000 to 2022. According to Hou et al. (2023), we reclassify the 47 significant anomalies into two categories, 14 in trading-related and 33 in fundamentals. For each anomaly variable, we list its symbol, brief description, and source in the academic literature.

Table 5 Model performance in digesting significant anomalies

	CAPM	FF3	FF5	SY4	HXZ4	DHS3	BF3
Panel A Trading-related							
ba	-0.72***	-0.8***	-0.78***	-0.82***	-1.09***	-0.73***	-0.25
ivol_ff3	0.93***	1.02***	0.97***	0.88***	1.22***	0.79***	0.29
ivol_capm	0.86***	0.88***	0.86***	0.8***	1.12***	0.81***	0.16
ivol_hxz4	0.96***	1.16***	1.06***	0.87***	1.26***	0.75***	0.39
zt	0.79***	1.2***	1.02***	1.04***	1.12***	0.54**	0.32
rmax1	0.64***	0.63***	0.58***	0.57**	0.85***	0.63***	-0.04
betabab	0.74***	0.96***	0.73***	0.66**	0.69***	0.25	0.59
rmax5	0.61***	0.6**	0.59***	0.57**	0.91***	0.62**	-0.19
beta	0.6**	0.66**	0.44	0.32	0.28	0.18	0.47
dolvol	0.91***	0.14	0.22	-0.04	0.28**	0.95***	0.29
rd	1.08**	0.92	0.83	0.73	1.17**	0.9***	1.1
prc	0.59**	0.02	0.5**	0.11	1***	0.36	0.18
me	0.78**	-0.12	-0.03	-0.2	0.19	0.98***	0.17
rskew	0.36**	0.13	0.24	0.2	0.22	0.46***	0.13
No. Significant	14	9	8	8	11	11	0
Panel B Fundamental							
ret60_12	0.86***	0.22	0.4	0.06	0.72***	0.58**	0.66
ret3_1	-0.5**	-0.43	-0.62**	-0.4	-0.77***	-0.63***	-0.17
ret12_7	0.75***	0.99***	0.69***	0.86***	0.15	0.76***	0.86***
ret1_0	0.61***	0.46**	0.5**	0.55**	0.88***	0.89***	0.04
cowc	0.24**	0.29***	0.38***	0.39***	0.54***	0.23**	0.2
accni	0.32**	0.23	0.39***	0.20	0.52***	0.14	0.22
accat	0.22**	0.25***	0.34***	0.26***	0.42***	0.09	0.19
col	-0.3***	-0.51***	-0.39***	-0.58***	-0.32***	-0.38***	-0.42***

Table 5 Model performance in digesting significant anomalies (Continued)

Panel B Fundamental	CAPM	FF3	FF5	SY4	HXZ4	DHS3	BF3
saleqgr	-0.53***	-0.72***	-0.56***	-0.71***	-0.2	-0.51***	-0.77***
seas2_5	0.98***	0.43	0.55**	0.1	0.81***	0.54**	0.93**
noagr	0.26**	0.16	0.3**	0.18	0.47***	0.22	0.15
tang	0.46***	0.61***	0.4***	0.46***	0.28	0.36***	0.58***
niqbe	0.57***	0.72***	0.59***	0.67***	0.21	0.51***	0.7***
niqsu	0.52***	0.65***	0.58***	0.49***	0.19	0.44***	0.64***
seas1_1	0.81***	0.93***	0.78***	0.78***	0.46	0.66***	0.86***
niqat	0.43***	0.56***	0.45***	0.55***	0.12	0.39***	0.59***
saleqsu	0.41***	0.47***	0.45***	0.48***	0.21	0.41***	0.86***
qmj	0.44**	0.84***	0.49***	0.59***	0.27	0.29	0.51***
salebev	0.33**	0.44***	0.23	0.40**	0.07	0.43**	0.57***
copatl	0.42**	0.89***	0.58***	0.76***	0.41**	0.2	0.36
copat	0.39**	0.8***	0.55***	0.66***	0.41**	0.17	0.63***
gp	0.45**	0.9***	0.4**	0.68***	0.12	0.45	0.56***
seas11_15	0.87**	1***	1.32***	1.07***	0.94**	0.82**	0.68**
ni	0.61**	0.88***	0.71***	0.76***	0.92***	0.31	0.62**
ebitda	0.63**	0.84***	0.72***	0.72***	1.02***	0.28	0.59
eqnpo	0.38**	0.47***	0.36**	0.33**	0.51***	0.07	0.49**
sale	0.49**	0.28	0.44**	0.31	0.88***	0.28	0.2
fcf	0.29**	0.42***	0.3**	0.27**	0.26	0.12	0.35**
be	0.61**	0.28	0.61***	0.31	1.29***	0.34	0.33
netis	0.26**	0.24**	0.31***	0.22	0.35***	0.18	0.26
ocf	0.43**	0.51***	0.55***	0.43**	0.92***	0.13	0.35
ival	0.54**	0.77***	0.63***	0.64**	0.89***	0.20	0.47
div	0.54**	0.46	0.52**	0.37	0.96***	0.10	0.36
No. Significant	33	25	31	27	21	16	18

Table 5 Model performance in digesting significant anomalies (Continued)

Panel C Overall	CAPM	FF3	FF5	SY4	HXZ4	DHS3	BF3
No. Significant	47	34	40	32	32	27	18
Average $\lvert\alpha\rvert$	0.58	0.59	0.55	0.51	0.61	0.45	0.42
Average $\lvert t\rvert$	2.63	3.06	2.91	2.51	2.82	2.07	1.80
F-value	0.24	2.38	1.47	1.51	1.89	0.86	
p-value	0.00	0.00	0.01	0.01	0.00	0.19	

This table compares all the models' performance in explaining CAPM-adjusted significant anomalies. Panel A reports the mispricing alphas from the time-series regressions of trading-related anomaly monthly returns against different factors models. at the bottom of Panel A, No. significant represents the number of significant alphas at a 5% significance level from the time-series regressions. Panel B reports the same information for fundamental anomalies. Panel C presents the overall performance of all factor models. We summarize the number of significant alphas at a 5% level, the average absolute alphas and t-values, the F-statistics and p-values that test whether the average t^2 of alphas under a given model is significantly larger than the average t^2 of the competitive model alphas. ***, ** and * represent 1%, 5% and 10% significance levels respectively.

Table 6 BF3 model regressions of significant anomalies

Panel A Trading-related

	ba	ivol_ff3	ivol_capm	ivol_hxz4	zt	rmax1	betabab	rmax5	beta	dolvol	rd	prc	me	rskew
α	-0.25	0.29	0.16	0.39	0.32	-0.04	0.59	-0.19	0.47	0.29	1.10	0.18	0.17	0.13
β_{MKT}	0.12***	-0.08	-0.11**	-0.06	-0.15***	-0.14***	-0.24***	-0.18***	-0.24***	-0.04	0.27	0.05	0.04	0.02
β_{DE}	0.09	-0.04	-0.07	-0.04	0.04	-0.06	0.20**	-0.15	0.25***	-0.10	-0.03	-0.44***	-0.1	-0.10
β_{OVER}	-0.49***	0.66***	0.69***	0.61***	0.63***	0.65***	0.40***	0.72***	0.34***	0.27***	0.00	0.12	0.18**	0.09

Panel B Fundamental

	r60_12	r3_1	r12_7	r1_0	cowc	accni	accat	col	saleqgr	seas2_5	noagr	tang	niqbe	niqsu
α	0.66	-0.17	0.86***	0.04	0.20	0.22	0.19	-0.42***	-0.77***	0.93**	0.15	0.58***	0.70***	0.64***
β_{MKT}	0.11**	0.04	0.01	-0.08	-0.02	-0.02	-0.05**	0.02	0.02	0.07	0	-0.06***	0.04	0.02
β_{DE}	-0.13	0.38***	0.28***	-0.43***	-0.04	-0.09**	-0.07**	-0.08**	-0.13***	-0.14	-0.03	0.19***	0.18***	0.15***
β_{OVER}	0.03	-0.03	0.08	0.19	0.06	0.08	0.04	0.03	0.10	-0.08	0.09	0.02	0.02	0.00

	seas1_1	niqat	saleqsu	qmj	salebev	copatl	copat	gp	seas11_15	ni	ebitda	eqnpo	sale	fcf
α	0.86***	0.59***	0.51***	0.57***	0.36	0.63***	0.56***	0.68**	1.03***	0.62**	0.59	0.49**	0.20	0.35**
β_{MKT}	0.05	0.03	-0.02	-0.15***	-0.01	-0.08**	-0.08***	-0.09**	0.01	-0.05	-0.03	-0.01	-0.01	-0.1***
β_{DE}	0.17***	0.17***	0.09	0.25***	0.09	0.17***	0.16***	0.25***	0.11	-0.17**	-0.13	0.00	-0.3***	0.05
β_{OVER}	0.08	0.00	-0.03	0.12	-0.01	0.03	0.06	-0.02	-0.07	0.08	0.17	0.01	0.18	0.03

	bm	netis	ocf	ival	div
α	0.33	0.26	0.35	0.47	0.36
β_{MKT}	0.00	-0.09***	-0.09**	-0.06	-0.03
β_{DE}	-0.49***	-0.01	-0.22***	-0.18**	-0.37***
β_{OVER}	0.06	0.03	0.11	0.15	0.06

This table reports alphas and factor loadings for the BF3 model. β represents the respective factor loadings in regressions. The dependent variable is high minus low anomaly decile value-weighted monthly excess return. The independent variables are the MKT, DE and TRADING factors. For each anomaly, we can run time-series regressions to yield factor loadings and alphas. ***, ** and * represents 1%, 5% and 10% significance levels respectively.

Table 7 Firm-level Fama-MacBeth regressions on behavioral factor loadings

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MKT	0.15	0.10	0.08	0.12	0.19	-0.01	0.20	0.17	0.23	0.19	0.21	0.17	0.15	0.15
	(0.85)	(0.58)	(0.46)	(0.78)	(1.41)	(-0.03)	(1.34)	(1.11)	(1.47)	(1.21)	(1.31)	(1.20)	(1.01)	(1.14)
DE	0.26	0.21	0.27	0.25	0.26	0.19	0.15	0.25	0.26	0.22	0.21	0.25	0.19	0.21
	(2.69)	(2.62)	(3.20)	(2.92)	(3.05)	(2.21)	(2.61)	(2.66)	(2.58)	(2.39)	(2.38)	(2.70)	(2.67)	(2.68)
TRADING	0.09	0.13	0.11	0.16	0.15	0.05	0.13	0.00	0.00	0.10	0.00	0.11	0.13	0.00
	(1.36)	(1.96)	(1.75)	(2.26)	(2.14)	(0.50)	(2.00)	(1.49)	(1.29)	(1.31)	(1.26)	(1.69)	(1.88)	(1.47)
SMB_BF3		0.18												0.11
		(1.62)												(0.87)
SMB_FF5			0.18											0.16
			(2.42)											(1.66)
HML_FF5				-0.08										-0.01
				(-1.48)										(-0.26)
RMW_FF5					-0.07									-0.11
					(-1.34)									(-1.29)
CMA_FF5						0.13								0.07
						(1.58)								(1.30)
PEAD_DHS3							-0.02							-0.10
							(-0.63)							(-2.57)
FIN_DHS3								-0.01						0.05
								(-0.27)						(0.86)
SMB_HXZ4									0.14					0.06
									(1.67)					(0.70)
RMW_HXZ4										-0.06				-0.12
										(-1.07)				(-1.76)
CMA_HXZ4											0.02			-0.02
											(0.40)			(-0.45)

Table 7 Firm-level Fama-MacBeth regressions on behavioral factor loadings (Continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MGMT_SY4												-0.10		-0.10
												(-1.70)		(-1.13)
PERF_SY4													0.12	0.03
													(1.37)	(0.28)
No.	564,978	564,867	564,867	564,867	564,867	564,867	540,200	540,200	564,867	518,821	518,821	540,200	540,200	564,682
Adj R-squared	0.04	0.06	0.06	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06

This table reports the firm-level Fama-MacBeth regression results for BF3 (Model 1), and controlling for factors from the competitive models (Model 2-14). The dependent variables are the value-weighted monthly excess returns of all individual firms. The independent variables are the loadings on different factors. The loadings on each factor are estimated by monthly rolling regressions of daily stock returns in the previous month with a minimum of 15 daily returns required. The estimated factor loadings are used in the second step of the Fama-MacBeth test as independent variables on a cross-sectional regression. Alphas are reported in percentage. T statistics are reported in parentheses and adjusted with the Newey-West method (6 lags). ***, ** and * represents 1%, 5% and 10% significance levels respectively. Adj R square are average values from each time point cross-sectional regression. No. is the observation number in each regression.

Table 8 Summary Statistics of long-leg and short -leg portfolios

	Panel A Long-leg			Panel B Short-leg			Panel C
	Mean(%)	T-value	Long-SR	Mean(%)	T-value	Short-SR	Asymmetry Ratio
TRADING	1.03	2.42	0.14	0.05	0.10	0.01	21.61
DE	1.00	2.10	0.13	0.32	0.78	0.05	2.08
SMB_FF5	1.32	2.36	0.14	0.80	1.82	0.11	0.65
HML_FF5	1.18	2.44	0.15	0.90	1.80	0.11	0.30
RMW_FF5	1.11	2.49	0.15	0.93	1.69	0.10	0.19
CMA_FF5	1.00	1.95	0.12	1.11	2.27	0.14	-0.10
FIN_DHS3	1.13	2.20	0.14	0.27	1.81	0.11	3.11
PEAD_DHS3	1.15	2.17	0.14	0.26	1.68	0.11	3.40
SMB_HXZ4	1.71	2.64	0.17	0.92	1.72	0.11	0.87
RMW_HXZ4	1.60	3.02	0.20	1.02	1.59	0.10	0.56
CMA_HXZ4	1.33	2.24	0.15	1.26	2.13	0.14	0.05
MGMT_SY4	1.26	2.53	0.16	1.10	1.93	0.12	0.15
PERF_SY4	1.45	2.82	0.18	1.24	2.33	0.15	0.17
SMB_SY4	1.38	2.23	0.14	0.69	1.44	0.01	1.00

This table reports the long-leg and short-leg portfolio statistics for each factor in this paper. Panel A presents the time series average, t statistics and Sharpe ratio for long-leg portfolios. Panel B reports these statistics for the short-leg portfolios. The last column in Panel C reports the asymmetry ratio calculated by the difference between long-leg portfolio return and short-leg portfolio return over short-leg portfolio returns.

Table 9 Behavioral factor loadings of the long- and short-leg portfolios

	Long-leg β_{DE}	Short-leg β_{DE}	Long-leg $\beta_{trading}$	Short-leg $\beta_{trading}$
Panel A Trading-related				
ba	0.14	0.14**	0.42***	0.11
ivol_ff3	0.08	0.14	0.17**	0.53***
ivol_capm	0.15***	0.15	0.19**	0.53***
ivol_hxz4	0.09**	0.17	0.15***	0.51***
zt	0.05	0.27**	0.12**	0.57***
rmax1	0.15***	0.12	0.18	0.48***
betabab	0.01	0.35***	0.09	0.37**
rmax5	0.19***	0.09	0.21**	0.54***
beta	0.01	0.33***	0.06	0.31***
dolvol	0.38***	0.04	0.00	0.14***
rd	0.02	0.02	0.09	0.08
prc	0.31***	0.13	0.02	0.13
me	0.41***	0.09	0.05	0.06
rskew	0.23***	0.05	0.09	0.14**
Average	0.16	0.15	0.13	0.32
Panel B Fundamental				
cowc	0.18**	0.19**	0.12	0.2
accni	0.22**	0.17**	0.08	0.18
accat	0.16	0.16	0.09	0.16
col	0.24***	0.12	0.12	0.14
saleqgr	0.29***	0.13	0.12	0.21
seas2_5	0.28**	0.09	0.18	0.07
ret60_12	0.32***	0.09	0.11	0.11
noagr	0.18**	0.15	0.09	0.18

Table 9 Behavioral factor loadings of the long- and short-leg portfolios (Continued)

		Long-leg	Short-leg	Long-leg	Short-leg
		β_{DE}	β_{DE}	$\beta_{trading}$	$\beta_{trading}$
Panel B	Fundamental				
	tang	0.07	0.26***	0.12	0.14
	ret3_1	0.06	0.36***	0.19	0.17
	niqbe	0.04	0.25***	0.13	0.16
	niqsu	0.1	0.25***	0.13	0.14**
	seas1_1	0.06	0.24***	0.05	0.13
	niqat	0.05	0.26***	0.13	0.15
	ret12_7	0.01	0.32***	0.06	0.16**
	saleqsu	0.15	0.23**	0.14	0.11
	qmj	0.07	0.28***	0.03	0.19**
	salebev	0.14	0.18***	0.11	0.09**
	copatl	0.02	0.33***	0.09	0.19
	copat	0.03	0.32***	0.08	0.19
	gp	0.01	0.31***	0.11	0.12
	seas11_15an	0.05	0.17	0.1	0.04
	ret1_0	0.41***	0.12	0.12	0.27***
	ni	0.14**	0.2**	0.03	0.21
	ebitda	0.08	0.18**	0.01	0.25
	eqnpo	0.08	0.2***	0.07	0.13
	sale	0.25***	0.04	0.04	0.26
	fcf	0.15	0.27***	0.05	0.1
	be	0.31***	0.07	0.06	0.17
	netis	0.17	0.2**	0.16	0.21
	ocf	0.2***	0.16**	0.03	0.22
	ival	0.13**	0.18	0.03	0.27

Table 9 Behavioral factor loadings of the long- and short-leg portfolios (Continued)

		Long-leg β_{DE}	Short-leg β_{DE}	Long-leg $\beta_{trading}$	Short-leg $\beta_{trading}$
Panel B	Fundamental				
	div	0.21**	0.00	0.1	0.23
	Average	0.15	0.20	0.09	0.17

This table reports time-series regressions of the long- and short-leg portfolio returns on the BF model. Panel A compares two behavioral factor betas of the long- and short-leg portfolios for trading-related anomalies, and panel B shows two behavioral factor betas for fundamental anomalies. At the bottom of each panel, we summarize the average trading and disposition effect betas. The first two columns compare the disposition effect factor betas for long-leg and short-leg portfolios, while the last two columns present the comparison for trading factor. T statistics are reported in parentheses and adjusted with the Newey-West method (6 lags). ***, ** and * represents 1%, 5% and 10% significance levels respectively.

Table 10 Market frictions and behavioral factor sensitivity

	Highest	2	3	4	5	6	7	8	9	Lowest
Panel A Market Cap										
β_{DE}	0.03	0.10	0.14	0.17	0.18	0.19	0.20	0.21	0.21	0.21
$\beta_{trading}$	-0.13	-0.22	-0.27	-0.30	-0.33	-0.35	-0.36	-0.39	-0.41	-0.45
Panel B Illiquidity										
β_{DE}	0.21	0.21	0.20	0.20	0.19	0.18	0.17	0.15	0.11	0.05
$\beta_{trading}$	-0.40	-0.40	-0.38	-0.36	-0.35	-0.33	-0.31	-0.28	-0.24	-0.15
Panel C Institutional Holding										
β_{DE}	0.13	0.14	0.15	0.15	0.16	0.17	0.18	0.18	0.19	0.20
$\beta_{trading}$	-0.27	-0.28	-0.29	-0.30	-0.31	-0.32	-0.33	-0.35	-0.37	-0.39

This table reports the market friction portfolios' sensitivity to our behavioral factors. Market frictions are proxied by market cap, illiquidity and institutional holding. At the beginning of each month, we rank firms into 10 portfolios based on various proxies of market friction at the end of month t-1. We calculate the value-weighted returns for each portfolio for the current month and all portfolios will be rebalanced in the following month. To obtain the factor sensitivity, we run time-series regressions of the returns for each portfolio sorted by each market friction proxy against the BF3 model.

Table A Comparison between Alternative Behavioral Factor Constructions

	Mean(%)	T-value	SD(%)	SR	N
Panel A Alternative trading factors					
TRADING	0.98	5.60***	2.94	0.33	281
TRADING_36M	0.91	5.38***	2.83	0.33	281
TRADING_12M	0.92	5.66***	2.73	0.34	281
TRADING_BO	0.70	4.08***	2.89	0.24	281
Panel B Alternative disposition effect factors					
DE	0.69	2.76***	4.19	0.17	281
DE_36M	0.68	2.72***	4.20	0.16	281
DE_12M	0.69	2.65***	4.33	0.16	281
DE_552	0.64	2.17**	4.95	0.13	281

This table reports the robustness checks for our two behavioral factor constructions. TRADING and DE are the original factors used in this paper. In Panel A, TRADING_36M and TRADING_12M represent the alternatives of the original TRADING factor when we calculate abnormal trading volume by 36 months and 12 months horizons instead of 60 months. TRADING_BO follows Barber & Odean (2008) method to proxy abnormal trading volume using a ratio of trading volume at the end of each month to the average over the previous 1 year for each stock. Following Frazzini (2006), DE_36M and DE_12M report the alternative time horizons to calculate the cost basis for each stock. DE_552 represents an alternative triple-sort method to construct the disposition effect factor, in which we use last month's quantiles of cumulative abnormal returns late month’s quantiles of unrealized gain/loss and last month’s market cap median to split stocks.