"Backward-Forward-Looking" Prospect Theory Demand and Stock Returns

by*

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Keywords: Prospect theory; Decision-making process; Capital gains overhang; Asset pricing; Behavioral finance

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1.Introduction

How investors make decisions is of fundamental importance to asset pricing. While traditional financial theory states that investors make rational decisions based on available information, behavioral finance argues that investors often exhibit cognitive biases (preferences) that further influence their decisions. Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), which is the fundamental theory of behavioral finance, suggests that investors exhibit four preferences: reference-dependence, loss aversion, diminishing sensitivity, and overweighting of small probabilities. Previous research study the impact of prospect theory preferences on investors' decisions and asset prices (Barberis et al., 2001; Grinblatt & Han, 2005; Barberis & Huang, 2008). However, the existing research on prospect theory mostly focuses on certain preferences and lacks a unified framework for describing the decision-making process when investors exhibit four preferences simultaneously[2].

In this paper, we present a decision-making framework based on the four preferences of prospect theory. This framework describes how stockholders try to address a recurring problem: whether to sell stocks immediately or to maintain holding them continuously. Intuitively, investors tend to make the choice that presents a higher value between immediate-selling and continuous-holding. To make their decision, investors begin by forming return distributions for both immediate-selling and continuous-holding, and then evaluate these return distributions. Prospect theory preferences play an important role throughout the decision-making process. Reference-dependence leads investors to form return distributions based on the capital gains overhang (unrealized past

[2] Barberis et al. (2021) present a model of asset prices in which investors evaluate risk according to prospect theory. Their equilibrium model studies the impact of each prospect theory preference on portfolio returns. In contrast, we propose an alternative pricing implication by considering the four preferences as a unified decision-making process, and we consider the demand generated by this decision as a firm characteristic for individual stock.

gains or losses). Investors exhibit loss aversion, diminishing sensitivity, and overweighting of small probabilities when evaluating return distributions.

In the first stage, investors form return distributions for both immediate-selling and continuous-holding. Investors, with the “reference-dependent” preference, derive the utility of a stock from gains and losses relative to the initial purchase price (Kahneman & Tversky, 1979). Different from rational "forward-looking" investors who only consider future return distribution, reference-dependent investors, who also “look backward”, formulate return distributions based on the capital gains overhang. Intuitively, if an investor purchased a stock in the previous month and incurred a 10% loss, the investor’s current decision-making process would involve not only considering the future performance of the stock but also assessing the potential to "recoup" the 10% loss.

The return distribution for immediate-selling is certain, which is the capital gains overhang. On the other hand, the return distribution for continuous-holding is the cumulative return calculated based on the initial purchase price and the possible future selling price, accounting for both the capital gains overhang and uncertain future price changes. For example, a stockholder has an unrealized loss of -10%. The investor predicts that in the future, the stock price will increase by 20% with a probability of 0.2 and decrease by 5% with a probability of 0.8, forming a future return distribution: $(20\%, 0.2; -5\%, 0.8)$. As a consequence, the return distribution for immediate-selling remains at -10%, and it becomes $(8\%, 0.2; -14.5\%, 0.8)$[3] for continuous-holding. Given the uncertainty of future return distributions, in line with the approach of Barberis et al. (2016) and Cosemans and Frehen (2021), we suggest that investors mentally represent each stock by the distribution of its past returns and infer the set of future return states from past states. We assume that investors use the past 60-months[4] return distribution as a proxy for the future return distribution in our empirical analysis.

In the second stage, investors evaluate the return distributions for immediate-selling and continuous-holding. Investors also exhibit prospect theory preferences, including loss aversion, diminishing sensitivity, and overweighting of small probabilities. Investors use the cumulative prospect theory value (Tversky & Kahneman, 1992), instead of the expected utility theory, to evaluate the return distributions. Specifically, investors experience a greater negative value from losses than a positive value from equivalent gains. Investors are risk-averse for gains and risk-seeking for losses, and they tend to overestimate the probability of extreme events occurring.

In the third stage, investors simply compare the value of capital gains overhang of immediate-selling and the value of cumulative return of continuous-holding, and then make the choice with a

[3] $8\% = (1 - 10\%) \times (1 + 20\%) - 1$. $-14.5\% = (1 - 10\%) \times (1 - 5\%) - 1$.

[4] With China's widely-used stock market analysis software, the default monthly candlestick chart typically covers approximately 60 months.

higher value. Investors finally decide to whether to sell stocks immediately or to maintain holding them continuously.

Figure 1 illustrates why "backward-forward-looking" investors, who consider capital gains overhang, make different decisions compared to "forward-looking" investors, who only focus on future return distributions. The graph plots the S-shaped value function from prospect theory, reflecting loss aversion and diminishing sensitivity. Assuming that investors focus on individual stocks separately and do not consider asset portfolios due to narrow framing (Barberis et al., 2016).

Suppose that there is a future return distribution for a stock with upward return R_u and downward return R_L, and the value for this return distribution is positive. In this case, "forward-looking" investors (Figure 1a) who solely consider the future return distribution would hold the stock. However, "backward-forward-looking" investors (Figure 1b) take into account both the capital gains overhang and the future return distribution. Assuming that the capital gains overhang is represented by point A, then the cumulative return distribution for continuous-holding can be illustrated as: A_u for the upward situation and A_L for the downward situation. A_u is in the profit region with a diminishing marginal value, leading to a small incremental value for A. On the other hand, A_L falls in the loss region, incurring a significantly negative value for investors with loss aversion. As a result, the value of selling the stock at point A surpasses that of continuous-holding. Thus, "backward-forward-looking" investors sell the stock despite the positive value of the future return distribution. Conversely, in some situations, investors may still choose to maintain stockholding continuously even if the future return distribution has a negative value.

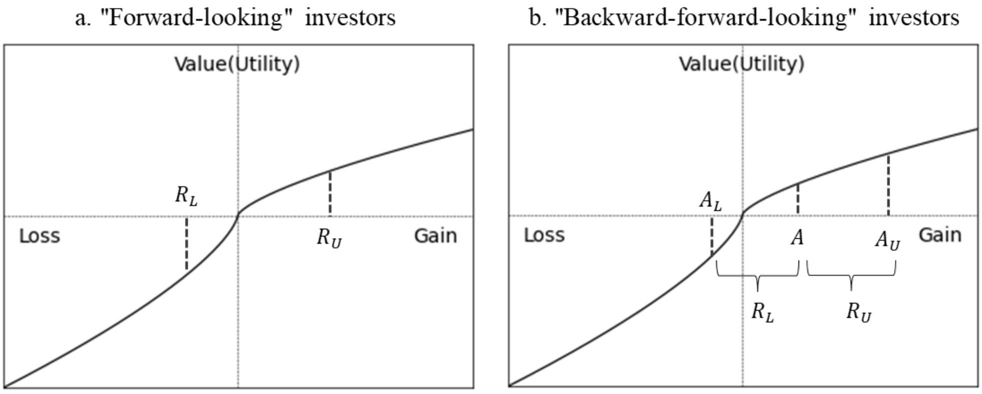

Figure 1. "Forward-looking" and "backward-forward-looking" investors' decisions

The decision-making framework presents a pricing implication. Investors' choices are based on prospect theory preferences and may not necessarily reflect the stock's fundamental value. As a result, investors' decisions lead to abnormal pressure on stock prices. When the immediate-selling value surpasses the continuous-holding value, investors choose to sell the stock. This generates excessive selling pressure, leading to underpricing of the stock, consequently yielding higher future returns. Conversely, when the continuous-holding value exceeds the immediate-selling value, investors decide to maintain stockholding continuously, leading the stock to be overpriced and earn lower future returns. Through our analysis, we introduce the prospect theory demand variable PTD, defined as the difference between the value of continuous-holding and that of immediate-selling. PTD captures the excess demand from investors with prospect theory preferences and is expected to negatively predict the stock's subsequent return.

Our empirical results show that stocks with high (low) PTD have low (high) subsequent returns. Our dataset includes all A-share stocks in the Chinese stock market spanning from January 2000 to January 2023. A univariate portfolio analysis indicates that the return difference between stocks in the lowest and highest PTD deciles is statistically significant and economically large. A zero-cost strategy that buys low-PTD stocks and shorts high-PTD stocks generates a monthly alpha of approximately 1%. The alphas remain statistically significant after controlling for other variables through double-sorted portfolio analysis. The coefficients on PTD in the Fama-MacBeth regressions are all negative and statistically significantly, and an increase of one standard deviation in PTD predicts a decrease in next month's stock return of 0.24% when accounting for all the control variables.

In further analysis, we demonstrate that the predictive power of PTD on subsequent returns indeed originates from the investors' entire decision-making process under prospect theory preferences, which involves forming the return distributions for immediate-selling and continuous-holding based on the capital gains overhang, evaluating these return distributions using the cumulative prospect theory value, and making the value comparison between two choices. We discuss and rule out a variety of alternative explanations. First, we examine the situation in which investors form return distributions without considering the capital gains overhang. We control for the related variables TK (Barberis et al., 2016), CGO (Grinblatt & Han, 2005) and $VNSP$ (An, 2015) in the Fama-MacBeth regression. Such variables fail to explain the predictive ability of PTD for future returns, indicating that investors indeed take unrealized gains or losses into account when forming return distributions.

Subsequently, we examine the case in which investors evaluate return distributions without using the cumulative prospect theory value. When investors use the expected utility function to evaluate return distributions, the CH-3 alphas of corresponding long-short portfolios are not statistically or economically significant. Additionally, when investors consider only partial preferences within the cumulative prospect theory value, the predictive power of PTD becomes weak. These findings indicate that investors indeed evaluate return distributions based on the cumulative prospect theory value. Moreover, we analyze the situation in which investors do not make the value comparison between immediate-selling and continuous-holding. Predictive power is absent if investors consider only the value of immediate-selling or only the value of continuous-holding, demonstrating that investors indeed make the value comparison.

We suppose that PTD primarily characterizes individual investors' behavior because they are more likely to exhibit prospect theory preferences. We find that the predictive power of PTD is strong for stocks with low institutional ownership. Additionally, we suggest that the predictive power of PTD declines in stocks with strong speculative characteristics. Speculative investors tend to seek speculative opportunities through frequent short-term trading rather than long-term stock holdings. In such cases, their decision-making process deviates from the PTD framework that involves value comparison between immediate-selling and continuous-holding.

We repeat our analysis in the U.S. stock market. PTD continues to exhibit significant predictive power on subsequent returns. The results from the Fama-MacBeth regression indicate that an increase of one standard deviation in PTD leads to a decrease in next month's stock return of 0.17%. We also demonstrate that the predictive power depends on the entire decision-making process. In addition, the predictive power of PTD for subsequent returns is stronger among stocks less subject to arbitrage.

This paper makes marginal contributions in the following three aspects. First, this paper extends the application of prospect theory and proposes an investor decision-making framework that accounts for all preferences. Previous work mostly focuses on certain preferences. Barberis et al. (2001) present a model bases on "loss aversion," in which investors derive direct utility not only from consumption but also from changes in the value of their financial wealth. Grinblatt and Han (2005) find that "diminishing sensitivity" and "reference-dependence" make investors tend to hold on to their losing stocks too long and sell their winners too soon. Kyle et al. (2006) and Henderson (2012) examine how investors make liquidation decisions under "diminishing sensitivity" and "reference-dependence" preferences. Barberis and Huang (2008) research on the pricing implications of "overweighting of small probabilities," showing that stocks with a positive skew are overpriced. Li and Yang (2013) develop an equilibrium model to describe the trading behavior of investors with "loss aversion" and "diminishing sensitivity". Barberis et al. (2016) study investors' decision-making behavior based on value and probability functions. The more closely related paper is Barberis et al. (2021), who examine investors' decision-making process under all prospect theory preferences and propose an asset pricing model for the portfolios. Our paper differs from theirs in that we propose an alternative pricing implication by considering the four preferences as a unified component, and we consider the demand generated by this decision as a firm characteristic for individual stock.

Second, we further analyze the influence of a stock's unrealized past gains or losses. We construct a "backward-forward-looking" framework that incorporates both capital gains overhang and future expectations. In contrast, previous studies typically focus on the capital gains overhang or future expectations, but not both. Grinblatt and Han (2005) first discover a positive cross-sectional relation between a stock's capital gains overhang and its subsequent stock return. Frazzini (2006) shows that capital gains overhang induces underreaction, leading to return predictability. Ben-David and Hirshleifer (2012) find that the selling probability for stocks increases as the magnitude of gains or losses increases. An (2015) shows stocks with both large unrealized gains and unrealized losses tend to experience higher selling pressure. Previous studies also find that capital gains overhang has an impact on investors' risk attitude (Wang et al., 2017; An et al., 2020). Furthermore, capital gains overhang (Grinblatt & Han, 2005) cannot predict future stock returns in the Chinese stock market (Chen & Chen, 2020), making it challenging to characterize investors' decision-making behavior in the Chinese stock market. We extend the research on unrealized past gains and losses to provide a more comprehensive depiction of decision-making behaviors among Chinese investors.

Third, this paper adds to the literature related to the behavioral factors affecting cross-sectional stock returns. We find a novel behavior mispricing variable PTD in both of Chinese and U.S. stock markets. Bali et al. (2011) find that investors exhibit a gambling preference, leading to overpricing of stocks with higher recent returns. Atilgan et al. (2020) find that investors underestimate the persistence of left-tail risk, resulting in stocks with severe recent losses having low subsequent returns. Mohrschladt (2021) argues that investors pay more attention to a stock's recent performance, causing stocks with high recent returns and low past returns to be overpriced. Cakici and Zaremba (2021) discover that investors tend to concentrate their attention on stocks that are salient to the market, resulting in an excessive demand for these stocks. Chen et al. (2022) find that the recent performance of neighboring stocks can positively predict future returns of the focal stock because investors engage in positive feedback trading and exhibit attention spillover.

The rest of the paper is organized as follows. Section 2 introduces the theoretical basis of prospect theory demand. Section 3 provides empirical evidence on the relation between prospect theory demand and future stock returns. Section 4 rules out alternative explanations and establishs that investors make the decision under all prospect theory preferences. Section 5 performs heterogeneity analysis. Section 6 presents empirical evidence from the U.S. stock market. Section 7 reports additional robustness tests. Section 8 concludes.

2. Theoretical Basis and Prospect Theory Demand

This section presents the conceptual framework of prospect theory demand. Since the investors discussed in this paper exhibit prospect theory preferences, subsection 2.1 provides a brief review of prospect theory. Subsequently, subsection 2.2 presents the theory of prospect theory demand, explaining how investors with prospect theory preferences make the decision between immediate-selling and continuous-holding. Subsection 2.3 introduces the method for computing the prospect theory demand variable PTD.

2.1 Prospect theory

We provide a brief overview of prospect theory to facilitate the analysis of PTD in the following subsections. Prospect theory is proposed by Kahneman and Tversky (1979) and extended by Tversky and Kahneman (1992). Prospect theory describes how investors make decisions under risk, and suggests that investors exhibit four preferences: reference-dependence, loss aversion, diminishing sensitivity, and overweighting of small probabilities. Reference-dependence indicates that investors' utility (referred to as value in prospect theory) is derived from wealth changes relative to a reference point rather than total wealth. Loss aversion suggests that investors experience a greater negative value from losses than a positive value from equivalent gains. Diminishing sensitivity indicates that investors are risk-averse when experiencing gains but become risk-seeking when facing losses. Overweighting of small probabilities implies that investors tend to overestimate the probability of extreme events occurring.

We Define a set of $n + m$ returns x_i, $i \in [-m, \ldots, -1, 1, \ldots, n]$, with corresponding objective probabilities p_i. These returns are sorted in increasing order, beginning with the most negative through to the most positive, and the rank-dependent distribution is:

$$(x_{-m}, p_{-m}; \cdots; x_{-1}, p_{-1}; x_1, p_1; \cdots; x_n, p_n), \tag{1}$$

where $x_{-m} < \cdots < x_{-1} < x_1 < \cdots < x_n$. Under the assumption that the reference point is 0, negative subscripts represent losses while positive subscripts indicate gains. To assess the return distributions, investors with prospect theory preferences use the cumulative prospect theory value rather than the expected utility function. The cumulative prospect theory value V of the return distribution is defined as:

$$V = \sum_{i=-m}^{n} v(x_i)\, \pi_i, \tag{2}$$

where $v(x_i)$ is the value function, and π_i is the weight function. The value function $v(x_i)$ is defined as follows:

$$v(x_i) = \begin{cases} x_i^{\alpha} & \\ -\lambda(-x_i)^{\beta} & \end{cases} for \begin{matrix} x_i \geq 0 \\ x_i < 0 \end{matrix}, \tag{3}$$

where the value function $v(x_i)$ is piecewise at the reference point 0. The parameter $\lambda > 1$ reflects loss aversion. Parameters α and β capture the degree of diminishing sensitivity.

The weight function π_i describes that investors form subjective weights based on objective probabilities, and it is represented as follows:

$$\pi_i = \begin{cases} w(p_i + \cdots + p_n) - w(p_{i+1} + \cdots + p_n) & \text{for} \quad x_i \geq 0 \\ w(p_{-m} + \cdots + p_i) - w(p_{-m} + \cdots + p_{i-1}) & \quad\quad\; x_i < 0 \end{cases}, \tag{4}$$

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{\frac{1}{\gamma}}},\ w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{\frac{1}{\delta}}}, \tag{5}$$

The weight function π_i is piecewise at the reference point and depends on the ordering of returns x_i. π_i reflects that investors tend to overweigh low-probability events, where the subjective weight exceeds objective probabilities. Parameters γ and δ determine the degree of overweighting of small probabilities.

2.2 Decision making process and the prospect theory demand

Investors with stockholdings often face a dilemma: selling stocks immediately or holding them on for sale in the future. In this paper, we construct a framework based on prospect theory preferences to describe how investors make such decisions. Generally, investors aim to compare the value of immediate-selling and continuous-holding, and then choose the one of higher value. In order to make such a decision, investors engage a three-step process: first, they form the return distributions for immediate-selling and continuous-holding separately; second, they evaluate these return distributions; and third, they make a choice by comparing the results of their evaluation. Figure 2 provides an overview of the decision-making process. We assume that investors are influenced by narrow framing (Tversky & Kahneman, 1981), where the stock is separated from the portfolio and evaluated in isolation (Barberis et al., 2021; Cosemans & Frehen, 2021). This assumption is also reasonable in the Chinese stock market, where individual investors are the primary participants. According to a survey conducted by the China Household Finance Survey (CHFS) in 2019, households participating in the stock market hold an average of only six stocks, indicating a limited level of diversification.

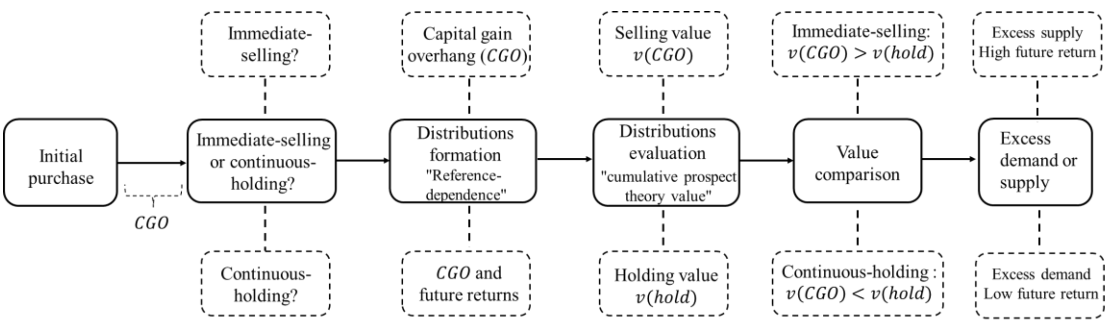

Figure 2. Decision-making process under prospect theory preferences

Investors first form return distributions for immediate-selling and continuous-holding. Investors with the "reference-dependence" preference derive the value of a stock from gains and losses relative to the reference point, which is typically the purchase price (Grinblatt & Han, 2005; Frazzini, 2006). In other words, a stock's value is influenced by its capital gains overhang (unrealized gains and losses). This differs from traditional finance theory, as investors take into account not only the future return distribution but also the capital gains overhang. For immediate-selling, the return distribution corresponds to the capital gains overhang. For continuous-holding, the cumulative return distribution encompasses both capital gains overhang and future return distributions.

Investors need to make forecasts about the future return distribution when forming the return distribution for continuous-holding. Following Barberis et al. (2021) and Cosemans and Frehen (2021), we suggest that investors mentally represent each stock by the distribution of its past returns and infer the set of future return states from past states. We assume that investors use the past 60 months' monthly return distribution as a proxy for the future return distribution, which simplifies the analysis[5]. This is a reasonable assumption in the Chinese stock market. As the primary participants, individual investors with limited financial literacy and restricted access to information about the firm (Hou et al., 2021) may rely on extrapolative expectations to form a future return distribution (Greenwood & Shleifer, 2014; Da et al., 2021). Additionally, individual investors can easily access past return information from widely-used software[6] in China, which mostly shows historical price candlestick charts covering approximately 60 months by default.

Second, after forming return distributions for immediate-selling and continuous-holding, investors proceed to evaluate the values of the two distributions. The evaluation process also involves the investor's preferences formulated in prospect theory. Instead of the expected utility function, investors obtain the return distribution value by using the evaluation function in cumulative prospect theory (Tversky & Kahneman, 1992), which reflects preferences including loss aversion, diminishing sensitivity, and overweighting of small probabilities.

In the final stage, investors simply compare the value of immediate-selling and that of continuous-holding, and then choose the one with the higher value. This stage is straightforward and does not involve prospect theory preferences. Even when stocks are expected to have positive (negative) future returns, investors may choose to sell the stock immediately (maintain stockholding continuously). For instance, consider an investor who has a positive capital gains overhang and

[5] In robustness tests, we further assume that the returns follow either a normal distribution or a log-normal distribution. By doing so, we demonstrate that our results do not depend on the specific method used to form the return distribution.

[6] Tong-hua-shun, Dongfang Caifu and so on.

anticipates positive future returns. However, the investor perceives a probability of unrealized gains turning into losses and a small chance of incurring extreme losses if the investor maintains stockholding. In this case, the overweighting of small probabilities and loss aversion decrease the value of continuous-holding, and as a result investors choose to sell the stock immediately. On the other hand, they may still choose to maintain stockholding continuously, even though they predict future returns to be negative.

Throughout the "distributions formation - distributions evaluation - value comparison" decision-making process, investors are subject to prospect theory preferences. Hence, regardless of whether investors choose to sell the stock immediately or maintain stockholding continuously, their decisions lead to excess supply or demand and stock mispricing. When the value of immediate-selling exceeds that of continuous-holding, investors choose to sell the stock. This results in increased selling pressure, causing the stock to be underpriced, thereby leading to higher future returns. Conversely, when the value of continuous-holding surpasses that of immediate-selling, investors choose to maintain stockholding continuously, causing the stock to be overpriced and consequently yielding lower future returns.

We define prospect theory demand (PTD) as the difference between the value of continuous-holding and the value of immediate-selling. PTD represents the investor's excess demand under prospect theory preferences and is anticipated to negatively predict the subsequent returns of the stock.

2.3 Method for computing PTD

This subsection shows how PTD is calculated. Investors consider the capital gains overhang when they form return distributions. Following Grinblatt and Han (2005), we use CGO to measure the average capital gains overhang for an individual stock. To avoid situations where past gains or losses are less than -100%, we adopt the adjusted method proposed by Barberis et al. (2021). The stock subscript is dropped for brevity. CGO for each individual stock is defined as follows:

$$CGO_t = \frac{P_t - RP_t}{RP_t}, \tag{6}$$

where P_t is the stock price on day t. RP_t denotes the reference price on day t, which is the investor's weighted average purchase price. RP_t is computed as follows:

$$RP_t = \frac{1}{k}\sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}[1 - V_{t-n+\tau}]\right)P_{t-n}, \tag{7}$$

where V_t is the turnover ratio on day t. The weight $V_{t-n}\prod_{\tau=1}^{n-1}[1 - V_{t-n+\tau}]$ measures the fraction of stocks purchased on day $t-n$ that are not traded afterward, and k is a constant that makes the weights sum to one. T is the truncation period used to calculate RP_t. We choose 500 trading days as the truncation period to capture investors' trading behavior as comprehensively as possible. During this time period, approximately 99% of individual investors and mutual funds sell the stocks they hold (Lu et al., 2022).

At the end of month, investors form and evaluate the return distributions for immediate-selling and continuous-holding. The return distribution for immediate-selling is CGO_t. Substituting CGO_t into the value function as described in Equation (3), the value of immediate-selling is $v(CGO_t)$. When forming the return distributions for continuous-holding, investors predict the future return distribution by using the past 60 months' return distribution as a proxy. Investors form the cumulative return distribution as a function of CGO_t and the future return distribution. Specifically, suppose that the stock has a monthly return r_j in one of the past 60 months, where j ranges from 1 to 60. The cumulative return $r_{CGO,j}$ can be calculated as follows:

$$r_{CGO,j} = (1 + CGO_t) \times (1 + r_j) - 1. \tag{8}$$

Given each month's return in the past 60 months, the corresponding cumulative return r_{CGO} can be calculated. Sort these 60 cumulative returns in increasing order, then the rank-dependent cumulative return distribution is:

$$\left(r_{CGO,-m}, \frac{1}{60}; \cdots; r_{CGO,-1}, \frac{1}{60}; r_{CGO,1}, \frac{1}{60}; \cdots; r_{CGO,n}, \frac{1}{60}\right), \tag{9}$$

where m of these returns are negative and n are non-negative. The most negative cumulative return is denoted as $r_{CGO,-m}$, and the maximum cumulative return is represented as $r_{CGO,n}$. Investors evaluate this cumulative return distribution based on the cumulative prospect theory value defined in Equation (2). The value of continuous-holding $v(hold_t)$ is calculated as follows:

$$\begin{aligned} v(hold_t) \ &= \sum_{i=-m}^{-1} v(r_{CGO,i}) \left[w^-\left(\frac{i+m+1}{60}\right) - w^-\left(\frac{i+m}{60}\right)\right] \\ &+ \sum_{i=1}^{n} v(r_{CGO,i}) \left[w^+\left(\frac{n-i+1}{60}\right) - w^+\left(\frac{n-i}{60}\right)\right]. \end{aligned} \tag{10}$$

It is necessary to determine the parameter values of prospect theory preference when evaluating distributions, including the diminishing sensitivity parameters α and β, the risk aversion parameter λ, and the overweighting of small probabilities parameters γ and δ. A well-known set of values for these parameters comes from Tversky and Kahneman (1992). Subsequent studies, however, suggest a potential change in investors' risk attitudes over time, and the degree of loss aversion is lower than that in Tversky and Kahneman's study (Mrkva et al., 2020; Gächter et al., 2021). In line with the research of Barberis et al. (2021), we adopt the parameters $(\lambda, \alpha, \beta, \gamma, \delta) = (1.5, 0.7, 0.7, 0.61, 0.69)$[7]

[7] In robustness tests, we use the preference parameters following Tversky and Kahneman (1992).

After investors obtain the immediate-selling value $v(CGO_t)$ and the continuous-holding value $v(hold_t)$, they make the choice with the higher value. Investors tend to sell the stock when $v(hold_t) < v(CGO_t)$, leading to high future returns. Conversely, when $v(hold_t) > v(CGO_t)$, investors' excess demand leads to lower the stock's future returns. We define the core variable prospect theory demand (PTD) as follows:

$$PTD_t = v(hold_t) - v(CGO_t)\,, \tag{11}$$

PTD_t represents the difference between the holding value and the selling value of a particular stock at the end of month t. PTD has a negative relationship with future returns.

We first regress PTD on short-term reversal and take the residuals from this regression as our main variable. We adopt this approach due to the strong correlation between CGO and short-term reversal, which is a notable asset pricing anomaly observed in the Chinese stock market (Hsu et al., 2018; Jansen et al., 2021; Liu et al., 2023). CGO is a turnover-weighted variable that tends to assign greater weight to recent stock returns. A high CGO usually implies high recent stock returns, thereby indicating a substantial short-term reversal (the stock's return in month t) at the same time. Specifically, the correlations between CGO, $v(CGO)$, and short-term reversal are 0.53 and 0.54, respectively. To prevent that PTD is a rediscovery of short-term reversal, we orthogonalize PTD with respect to short-term reversal. In robustness tests, we examine the results without orthogonalization.

3. Cross-sectional Relation between PTD and Stock Returns

3.1 Data

We use daily and monthly stock data sourced from CSMAR. Our sample covers all A-share stocks from January 2000 to January 2023. All stocks need at least five years of monthly return data to calculate the variable PTD. Special treatment (ST) stocks are excluded from our sample because they have a daily price fluctuation limit of 5%. We also exclude stocks with fewer than 10 trading days in a month.

We include other control variables that have strong explanatory power for cross-sectional returns: CAPM $Beta$, company size ($Size$), earnings-to-price ratio (EP^+) and its corresponding dummy variable $D(EP < 0)$, momentum effect (Mom), $Turnover$, short-term reversal (Rev), illiquidity ($Illiq$), long-term reversal ($Lt\ rev$), idiosyncratic volatility ($Ivol$), maximum daily return (Max), minimum daily return (Min), skewness ($Skew$), coskewness ($Coskew$), and expected idiosyncratic skewness ($Eiskew$). Table 1 presents the descriptive definitions for these control variables, and detailed definitions are given in Appendix A. The sample stocks are required to have at least 60% non-missing values within the measuring window. Continuous explanatory variables are winsorized at the 1st and 99th percentiles.

[Table 1]

Table 2 presents the summary statistics of the variables. Panel A displays the means, standard deviations, and the 10th, 50th, and 90th percentiles for each variable, while Panel B shows the correlations between variables. The statistics are calculated as the time-series averages of the monthly cross-sectional means. The mean of PTD is 0, indicating that, on average, investors exhibit an equal willingness to sell stocks immediately and maintain stockholding continuously. According to Panel B, the coefficients between PTD and most variables are less than 0.1, indicating relatively weak correlations. The coefficient between PTD and $Lt\,rev$ is 0.30. A high $Lt\,rev$ leads to a strong preference for continuous-holding, as investors use past returns as a proxy for future return distributions. The correlation coefficient between PTD and $Skew$ is 0.34. Stocks with positive skewness have a low probability of achieving high positive returns, leading investors to evaluate such stocks highly because of the overweighting of small probabilities.

[Table 2]

3.2 Univariate portfolio sorts

We perform univariate portfolio-level analysis in this subsection. At the end of each month t, stocks are sorted into ten groups based on their PTD values and calculate the equal-weighted (EW) and value-weighted (VW) portfolio returns over the next month $t+1$. In Table 3, we report the average return of each decile in excess of the risk-free rate; the three-factor alpha obtained from the Liu et al. (2019) model that incorporates China-specific factors; the four-factor alpha obtained from the Carhart (1997) model; and the five-factor alpha obtained from Fama and French (2015) model[8].

The results in Table 3 show that PTD is negatively related to subsequent returns. For the equal-weighted portfolios, the lowest PTD and P2 portfolios yield monthly average CH3 alphas of 0.67% (t-statistic = 3.75) and 0.66% (t-statistic = 5.41), respectively. The excess returns and alphas decrease as PTD increases, with the High PTD portfolio having a CH3 alpha of -0.27% (t-statistic = -1.93). The CH3 alpha of Low-High portfolio is equal to 0.94% per month, with a t-statistic of 4.01, which is both economically and statistically significant. The four-factor alpha and five-factor alpha of Low-High portfolio are approximately 1%, and they are also statistically significant. These results indicate that the predictive ability of PTD cannot be explained by fundamental factors such as size, value, momentum, investment, and profitability.

Panel B of Table 3 presents results for the value-weighted portfolios, and the findings are similar to those of Panel A. A slight difference exists where low PTD portfolios and high PTD portfolios are exposed to CH3 factors. Specifically, the CH3 alpha of Low PTD portfolio is 0.5%,

[8] Monthly CH3 factors data from January 2000 to December 2021 are obtained from Robert Stambaugh's website, while the CH3 factors data from January 2022 to January 2023 are derived from our mimic portfolios. We use Financial Report Disclosure Time Database in CNRDS to fill in the missing values in CSMAR. Monthly four-factors and five-factors data are sourced from CSMAR.

which is slightly lower than that of the P2 portfolio. The CH3 alpha of High PTD portfolio is -0.46%, which is slightly higher than that of the P9 portfolio. However, all the return spreads between the lowest and highest PTD deciles remain significant for value-weighted portfolios. For the long-short portfolios, the average monthly alphas are 0.98%, demonstrating that the predictive ability of PTD is not limited to small-cap stocks.

[Table 3]

3.2. Bivariate portfolio sorts

In this subsection, we construct double-sorted portfolios to examine the predictive ability of PTD by controlling for the potential correlation between PTD and other variables, which also have explanatory power for subsequent returns. At the end of each month, we sort stocks into five groups based on one of the control variables, and within each group, we further sort stocks into five groups based on PTD. The returns over the next month of the five PTD groups are then averaged across different groups of the control variable.

[Table 4]

Table 4 presents the results of the bivariate portfolios. Panel A reports CH3 alphas for the equal-weighted portfolios, while Panel B is for value-weighted portfolios. The bottom rows report the average long-short portfolio returns adjusted by the four-factor model and the five-factor model. The results demonstrate that PTD maintains its predictive ability on returns after controlling for various firm characteristics. Average equal-weighted CH3 alphas decline nearly monotonically across the PTD portfolios. All alphas of Low-High portfolios are statistically significant at the 1% level, ranging from 0.68% to 0.96% per month. For the value-weighted portfolios, the results are similar, with all long-short portfolios yielding both statistically and economically significant alphas.

Compared to the results in Table 3, the CH3 alphas for the long-short portfolios exhibit a slight decline. However, the impact of controlling variables is limited, as the monthly average CH3 alpha of Low-High portfolios decreased by only approximately 0.1%. The summary statistics in Table 2 show a certain degree of correlation between PTD and $Lt\ rev$, as well as PTD and $Skew$. After controlling for $Lt\ rev$, the CH3 alpha of long-short portfolio is 0.78% (t-statistic = 4.07). For the $Skew - PTD$ long-short portfolio, the CH3 alpha is 0.84% (t-statistic = 3.85), indicating that the performance of PTD is slightly influenced by these related variables. The outcomes presented in Table 4 suggest that the PTD anomaly is widespread among stocks even after controlling for a large set of characteristics.

3.3 Fama-MacBeth regression analysis

In this subsection, we explore the pricing implications of the prospect theory demand in Fama-MacBeth regressions (Fama & MacBeth, 1973). The advantage of this methodology enables us to examine the predictive ability of PTD while simultaneously controlling for a large number of characteristics. We estimate monthly Fama-MacBeth cross-sectional regressions in the following form:

$$Ret_{i,t+1} = \alpha_t + \beta_t PTD_{it} + X'_{it}\lambda_t + \varepsilon_{it}, \tag{12}$$

where the dependent variable $Ret_{i,t+1}$ represents monthly return in excess of the risk-free rate for stock i in month $t+1$. The core explanatory variable is PTD_{it}, which denotes the prospect theory demand at the end of month t. X_{it} represents a set of control variables. In the baseline regression equation, X_{it} includes: $CAPM\ Beta$, company size ($Size$), earnings-to-price ratio (EP^+) and its corresponding dummy variable $D(EP < 0)$, momentum effect (Mom), $Turnover$, short-term reversal (Rev), illiquidity ($Illiq$), long-term reversal ($Lt\ rev$), idiosyncratic volatility ($Ivol$), maximum daily return (Max), minimum daily return (Min), skewness ($Skew$), coskewness ($Coskew$), and expected idiosyncratic skewness ($Eiskew$). Table 1 provides definitions of each control variable.

[Table 5]

Table 5 presents the results of the Fama-MacBeth regressions, with t-statistics adjusted using the Newey and West (1987) method. All of the coefficients of PTD are negative and statistically significant, indicating that PTD negatively predicts subsequent returns. In column (1), where no control variables are included, the coefficient on PTD is -0.065 and statistically significant at the 1% level. After controlling for size and value characteristics in column (2), the coefficient is -0.058 with a t-statistic of -4.3. Upon adding momentum, turnover ratio and short-term reversal, three characteristics remarkably influence stock prices, in column (3), the predictive power of PTD is similar to that in column (2). The coefficients on PTD remain stable around -0.04 and statistically significant at the 1% level, after controlling for illiquidity and long-term reversal in column (4), adding idiosyncratic volatility and lottery-like stock characteristics in column (5), incorporating three types of skewness variables in columns (6)-(8). In column (9), where all the control variables are included, the coefficient on PTD is -0.047 (t-statistic = -4.75), which is similar to that in column (1), indicating that control variables have little impact on the predictive power of PTD. An increase of a one standard deviation (0.052) in PTD predicts a decrease in next month's stock return of 0.24% when accounting for all the control variables.

Harvey et al. (2016) emphasize the necessity of accounting for multiple tests when assessing statistical significance in asset pricing tests. All t-statistics of PTD are above 3.7 and surpass the hurdle of 2.85 proposed by Hou et al. (2021) for the Chinese stock market, thereby addressing potential concerns related to data mining.

4. Tests of the Decision-Making Process

In this section, we discuss and rule out a variety of alternative explanations. We firmly establish that investors make the decision under all prospect theory preferences, rather than incomplete decision-making process or partial prospect theory preferences. Specifically, the predictive ability of PTD for subsequent returns arises from "forming the return distributions for immediate-selling and continuous-holding based on the capital gains overhang, evaluating these return distributions using the cumulative prospect theory value, and making the value comparison between immediate-selling and continuous-holding".

Subsection 4.1 examines the situation in which investors form return distributions without considering the capital gains overhang. In subsection 4.2, we examine the case in which investors evaluate return distributions without using the cumulative prospect theory value. Subsection 4.3 analyzes the scenario in which investors do not make the value comparison between immediate-selling and continuous-holding.

4.1 Are return distributions formed based on past gains or losses?

We propose that during the decision-making process of "distributions formation - distributions evaluation - value comparison," investors form return distributions based on unrealized past gains and losses. However, two concerns arise: Firstly, whether investors take into account unrealized gains and losses in their decisions. Secondly, whether these unrealized gains and losses directly impact investors' demand, rather than influencing the "distributions formation" stage. This subsection aims to address these concerns and confirms that investors do formulate return distributions based on capital gains overhang.

Investors who do not take the capital gains overhang into account focus only on the value of future return distributions and exhibit prospect theory preferences in the "distributions evaluation" stage, which corresponds to the anomaly TK proposed by Barberis et al. (2016). TK describes investors' behavior of evaluating the future return distribution under prospect theory preferences. Investors who do not consider past gains or losses focus the return distribution $\left(r_{-m}, \frac{1}{60}; \cdots; r_{-1}, \frac{1}{60}; r_1, \frac{1}{60}; \cdots; r_n, \frac{1}{60}\right)$. Note that these returns are different from Equation (9) since they are original monthly returns without the inclusion of CGO. The value of TK is obtained by incorporating this distribution in Equation (10). Stocks with high TK are appealing to investors, causing these stocks to become overvalued and earn low subsequent returns.

If PTD does not reflect investors' consideration of capital gains overhang, its economic implication would be similar to that of TK. Consequently, controlling for TK would lead to a great reduction in the predictive power of PTD. We employ a Fama-MacBeth regression in Table 6 to compare PTD and TK. Column (1) presents the result of Fama-MacBeth regression of excess returns on lagged TK, with a coefficient of -0.204. Column (4) estimates the Fama-MacBeth regression on PTD while controlling for TK. The coefficient on PTD is -0.05 (t- statistic = -3.42), which is similar to the coefficient in the baseline regression (-0.047). Controlling for TK does not lead to a reduction in the predictive ability of PTD. In contrast, comparing the results in columns (1) and (4), the coefficient on TK changes from -0.204 (t-statistic = -2.93) to -0.157 (t-statistic = -2.41). The magnitude and significance of the coefficient on TK decreases when PTD is included, indicating that the predictive ability of TK is partly captured by PTD. The results suggest that investors do indeed consider unrealized past gains or losses in their decision-making process.

We proceed to investigate whether the capital gains overhang influences the "distributions formation" stage. Within the decision-making process, capital gains overhang serves as a factor in forming the cumulative return distributions and do not directly affect investors' demand. We examine the performance of PTD after controlling for CGO and $VNSP$, which capture the excess demand directly generated by unrealized past gains or losses. Grinblatt and Han (2005) find that investors tend to hold on to losing stocks too long and sell winners too soon, and use CGO to quantify the average gains and losses on a particular stock. The definition of CGO is shown in Equation (6). An (2015) suggests that investors' selling probability increases as the magnitude of unrealized gains or losses increases. $VNSP$ measures this selling propensity and is calculated as $VNSP_t = Gain_t - 0.23Loss_t$, where $Gain$ represents the weighted average gain when purchase prices are lower than the current price, and $Loss$ represents the weighted average loss when purchase prices are higher than the current prices. The detailed definition is given in Appendix A.

If the impact of unrealized past gains or losses does not influence the "distributions formation" stage but directly affects investors' demand, then controlling for CGO and $VNSP$ would lead to an insignificant coefficient of PTD. In Table 6, columns (2)-(3) present the results with CGO, and $VNSP$ as the main explanatory variables, where only $VNSP$ exhibits statistically significant predictive power for future returns. Columns (5) and (6) report the results when variables related to unrealized gains or losses are included. In column (5) the coefficient on PTD is -0.045 (t-statistic = -3.85) when CGO is included, showing insignificant change compared to the baseline regression. In column (6), where $VNSP$ is controlled for, the predictive ability of PTD slightly decreases. However, PTD remains statistically significant at the 1% level. This result implies that investors perceive capital gains overhang to be part of return distributions, while also exhibiting V-shaped disposition effects due to the direct impact of capital gains overhang.

[Table 6]

Columns (7) and (8) include TK and unrealized past gains or losses anomalies simultaneously. In column (7), where both TK and CGO are controlled for, PTD's coefficient remains similar to that of the baseline regression. In column (8), after controlling for TK and $VNSP$, the coefficient on PTD is -0.035 with a t-statistic of -2.52, remaining statistically and economically significant. In column (9), we examine the combined effects of "distributions evaluation" bias and the direct impact of "unrealized past gains or losses". By controlling for these three related anomalies concurrently, we find that only PTD remains statistically significant at the 1% level. These results demonstrate that PTD does not simply mix the discrete effects of unrealized past gains or losses with the "distributions evaluation", but rather integrates them as a unified process in decision-making. Investors do formulate return distributions based on capital gains overhang.

4.2 Are return distributions evaluated by the cumulative prospect theory value?

We posit that within the decision-making process of "distributions formation - distributions evaluation - value comparison", investors use the cumulative prospect theory value to "evaluate distributions". However, there might be a concern regarding whether investors exhibit prospect theory preferences when evaluating distributions. If investors do not exhibit prospect theory preferences and use the expected utility function to evaluate return distributions, and such decisions also forecast future stock returns, this implies that "distributions evaluation" through the cumulative prospect theory value is not a necessary component in explaining investors' behavior. Conversely, if such decisions fail to predict future returns, it suggests that prospect theory preferences in "distributions evaluation" do indeed play a critical role. Furthermore, we explore whether investors simultaneously exhibit the three prospect theory preferences, including loss aversion, diminishing sensitivity, and overweighting of small probabilities when evaluating distributions.

We calculate the demand EUD based on the expected utility function. Specifically, investors' behavior remains unchanged in the "distributions formation" and "value comparison" stages. However, when evaluating the return distributions in Equation (9), we use the utility function $u(\cdot)$ instead of the value function $v(\cdot)$, and use the objective probability $\frac{1}{60}$ to replace the subjective weights. EUD is calculated as follows:

$$EUD_t = u(hold_t) - u(CGO_t),$$
$$u(hold_t) = \frac{1}{60}\sum_{j=1}^{60} u\left(1 + r_{CGO,j}\right). \tag{13}$$

We use different parameter settings for CARA and CRRA utility functions:

CARA utility functions: $u(x) = 1 - e^{-ax}$, where $a = 0.5, 1, 2, 4, 5, 10$.

CRRA utility functions: $u(x) = \frac{x^{1-\gamma}}{1-\gamma}$, where $\gamma = 0.5, 1(lnx), 2, 4, 5, 10$.

We sort stocks into decile portfolios based on EUD and calculate the equal-weighted CH3 alphas. The results are shown in Table 7. Across various parameter values, the alphas of long-short portfolios average approximately 0.2%, which is notably smaller compared to that of PTD, and they are not statistically significant at the 10% level. These results demonstrate that decisions based on the expected utility function are unable to predict future returns, confirming that investors do indeed evaluate the return distributions using the cumulative prospect theory value. In untabulated tests, value-weighted portfolios have similar results.

[Table 7]

We further examine whether investors simultaneously exhibit all prospect theory preferences when evaluating distributions. The cumulative prospect theory value includes diminishing sensitivity, loss aversion, and overweighting of small probabilities. If a specific preference indeed influences investors' decision-making behavior, then excluding the preference should reduce the predictive power of PTD for subsequent returns. We preform univariate portfolio analysis when "turning off" one or more prospect theory preferences. Table 8 displays value-weighted CH3 alphas.

The label "DS" in column (1) stands for considering only "diminishing sensitivity," where the parameters α and β remain at 0.7, while the parameters for "loss aversion" and "overweighting of small probabilities" are set to 1, represented as $(\lambda, \alpha, \beta, \gamma, \delta) = (1, 0.7, 0.7, 1, 1)$. Similarly, in the column labeled "LA", we consider only "loss aversion" with parameters $(\lambda, \alpha, \beta, \gamma, \delta) = (1.5,1,1,1,1)$. "PW" indicates that only "overweighting of small probabilities" is incorporated into PTD. The column labeled "LAPW" retains "loss aversion" and "overweighting of small probabilities" but turns off "diminishing sensitivity," with parameters $(\lambda, \alpha, \beta, \gamma, \delta) = (1.5,1,1,0.61,0.69)$. "DSPW" and "DSLA" respectively denote the results without considering "loss aversion" and "overweighting of small probabilities." The label "None" in the last column turns off three preferences simultaneously.

[Table 8]

When investors consider only "diminishing sensitivity" or "loss aversion," the value-weighted alpha of long-short portfolio is not statistically significant. When investors solely consider the "overweighting of small probabilities," the alpha of the long-short portfolio is 0.63%, representing a decrease of 0.32% compared to the benchmark result in Table 3. Such results demonstrate that single prospect theory preference does not adequately capture investors' decision-making behavior, and suggest that investors exhibit multiple preferences when evaluating return distributions.

Columns (4) to (6) represent scenarios where investors simultaneously consider two prospect theory preferences when evaluating return distributions. The long-short portfolios' alphas are lower than the baseline results when "diminishing sensitivity" (LAPW) or "overestimating small probability events" (DSLA) are not incorporated into PTD. These results indicate that "diminishing sensitivity" and “overweighting of small probabilities” play significant roles in distributions evaluation.

When "loss aversion" is not incorporated (DSPW), the long-short portfolio alpha is similar to the benchmark results. However, this does not imply that "loss aversion" does not influence the distributions evaluation. We discuss the impact of "loss aversion" in Appendix B, suggesting two potential reasons for this phenomenon: First, high (low) PTD stocks tend to remain high (low) PTD characteristics across different "loss aversion" parameter values, so the alpha of the long-short portfolio remains similar. We find a negative correlation between PTD and CGO, with high (low) PTD portfolios often having the lowest (highest) CGO. The lowest CGO indicates substantial losses, and it also implies that the cumulative returns of continuous-holding are highly likely to be negative. When investors suffer severe losses and anticipate no possibility of turning these losses into gains by continuous-holding, loss aversion becomes inconsequential as investors only face losses. Similarly, when investors achieve substantial gains and anticipate no possibility of losses from continuous-holding, they are not influenced by "loss aversion" as they only face profits. Second, investors may not exhibit a strong "loss aversion" preference. The predictive power of PTD for subsequent returns is strongest when λ is approximately 1.3. The predictive power remains similar between scenarios that do not consider "loss aversion" ($\lambda = 1$) and the benchmark result ($\lambda = 1.5$).

In general, investors do evaluate return distributions based on the cumulative prospect theory value, and simultaneously exhibit three prospect theory preferences: "diminishing sensitivity," "loss aversion," and "overweighting of small probabilities." Among the three biases, "diminishing sensitivity" and "overweighting of small probabilities" play more significant roles in the “distributions evaluation” stage.

4.3 Do investors make the value comparison between immediate-selling and continuous-holding?

The prospect theory demand reflects investors' value comparison between immediate-selling and continuous-holding, represented as $PTD_t = v(hold_t) - v(CGO_t)$. However, a concern arises as to whether investors focus only on one value, either immediate-selling or continuous-holding, without comparing the two values. If a single variable, either $v(hold)$ or $v(CGO)$, can predict future returns, PTD may only reflect the impact of the predominant variable rather than the value comparison.

In order to demonstrate that PTD does indeed reflect "value comparison", this subsection shows that a single value of either immediate-selling or continuous-holding cannot predict future returns. Specifically, we perform Fama-MacBeth regressions of excess returns on $v(hold)$ or

$v(CGO)$, replacing PTD. For ease of interpretation, $v(hold)$ and $v(CGO)$ are divided by 100 in the regression equation:

$$Ret_{i,t+1} = \alpha_{1t} + \beta_{1t} v(hold)_{it} + X'_{it}\lambda_{1t} + \varepsilon_{it} \quad (14)$$

$$Ret_{i,t+1} = \alpha_{2t} + \beta_{2t} v(CGO)_{it} + X'_{it}\lambda_{2t} + \epsilon_{it} \quad (15)$$

Table 9 presents the regression results. Columns (1) to (4) show that both $v(hold)$ and $v(CGO)$ are not statistically significant, indicating that an individual value lacks predictability for future returns. In addition, we conduct regressions where all continuous independent variables are standardized to have a mean of zero and a standard deviation of one in each month, which allows for a comparison of coefficients on PTD, $v(hold)$, and $v(CGO)$. In column (5), the coefficient on standardized PTD is -0.23 (t-statistic = -4.77), whereas the coefficients of standardized $v(hold)$ and $v(CGO)$ in columns (6) and (7) exhibit much smaller economic magnitudes. These results demonstrate that investors make the value comparison between immediate-selling and continuous-holding,

[Table 9]

5. Heterogeneity Analysis

We perform heterogeneity analysis in subsections 5.1 and 5.2. In Section 5.2, we examine whether the prospect theory demand primarily reflects the decision-making behavior of individual investors rather than institutional investors. Specially, we investigate the interaction between institutional ownership and prospect theory demand. In Section 5.2, we test the hypothesis that investors deviate from the prospect theory demand framework when they exhibit strong speculative tendencies. We estimate Fama-MacBeth regressions that include interaction terms between PTD and speculative characteristics

5.1 Institutional investors and PTD anomaly

Prospect theory demand reflects investors' decision-making behavior under bounded rationality, where decisions are not solely based on fundamental information. Therefore, PTD is more likely to related to the trading of individual investors rather than institutional investors. Prior research demonstrates that institutional investors possess advantages in information acquisition and processing, and they are strongly motivated to explore and accurately process information (Hendershott et al., 2015; Huang et al., 2020). Therefore, when stocks are predominantly held by institutions, the descriptive power of PTD on investor behavior decreases, as PTD reflects the stockholders' decision-making process and their excess demand. We posit that the predictive ability of PTD is expected to be weak for stocks with a higher proportion of institutional ownership.

We estimate Fama-MacBeth regressions that include interaction terms between PTD and institutional ownership ($Hold$)[9]. Column (1) in Table 10 shows that the coefficient on the interaction term is 0.183 with a t-statistic of 1.95. The predictive ability of PTD decreases as institutional ownership increases, indicating that prospect theory demand primarily originates from individual investors' decision-making process.

[Table 10]

5.2 Speculative stocks and PTD anomaly

Prospect theory demand reflects the investors' value comparison between immediate-selling and continuous-holding. Therefore, deviations from this decision-making framework weaken the predictive power of PTD. We suggest that PTD is inadequate for characterizing the trading behavior of short-term speculators. When speculators purchase speculative stocks, they often focus on recent upward trends and expect to achieve substantial returns in the short run (Bali et al., 2011). Speculators tend to engage in frequent short-term trading and are less likely to hold stocks for the long term (Pan et al., 2016). They find opportunities for speculation through frequent short-term trading and often sell stocks quickly after making profits. Therefore, speculative investors' decisions revolve around choosing the timing and targets for speculation, rather than making value comparisons between selling stocks immediately and maintaining stockholding continuously. This strong speculative decision-making process deviates from the prospect theory demand framework. We posit that the predictive ability of PTD is expected to be weak for stocks with strong speculative characteristics.

We estimate Fama-MacBeth regressions that include interaction terms between PTD and speculative characteristics to examine whether the PTD anomaly is weak among speculative stocks. Following previous research, we use idiosyncratic volatility ($Ivol$), maximum daily return (Max), turnover ratio ($Turnover$), and stock price ($Price$) as proxy variables for speculative characteristics. Idiosyncratic volatility reflects the idiosyncratic risk of companies, and speculative investors usually target stocks with higher risk for higher returns (Kumar, 2009). Max measures the lottery-like features of stocks, and speculative investors favor this category of stock under gambling preference (Bali et al., 2011). A high turnover ratio implies short holding periods, reflecting a short-term speculative characteristic, with speculative stocks showing significantly higher turnover ratios than other types of stocks (Pan et al., 2016). The stock price determines the entry threshold for speculators, and highly speculative stocks generally have low prices (Kumar, 2009).

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[9] The proportion of shares held by mutual funds, QFIIs, securities firms, insurance companies, social security funds, trusts, financial companies, and banks.

Columns (2) to (5) in Table 10 present the results. The interaction terms between PTD and $Ivol$, Max, $Turnover$, and $Price$ are all positive, indicating that the predictive power of PTD declines as the speculative characteristic increases, although the interaction term between PTD and $Price$ is not statistically significant at the 10% level. These results confirm that when trading highly speculative stocks, investors tend to engage in short-term and high-frequency trading, thereby deviating from the value comparison framework described by PTD. In addition, PTD continues to negatively predict future returns even when stocks exhibit strong speculative characteristics. When $Ivol$, Max, $Turnover$, and $Price$ are positioned at the 90th percentile (0.03, 0.07, 0.84, and 22.96, respectively), an increase of a one standard deviation in PTD predicts a decrease in next month's stock return of 0.16%, 0.15%, 0.13%, and 0.11%, respectively.

Prior research suggests that investors tend to exhibit optimism and speculative tendencies when market-wide sentiment is high, leading to an increase in speculative trading activities (Baker & Wurgler, 2006; Stambaugh et al., 2012). To further confirm that the decision-making process of speculative traders deviates from the PTD framework, thereby weakening the predictive ability of PTD, we examine the performance of univariate portfolios under high and low sentiment. We use the investor composite sentiment index in the Chinese stock market (CICSI) to measure sentiment, which is constructed based on the approach of Baker and Wurgler (2006)[10]. Months with CICSI values above the median are classified as periods of high sentiment, while those with values below the median are classified as periods of low sentiment.

Table 11 reports the CH3 alphas of each decile under high and low sentiment. Both equal-weighted and value-weighted portfolios exhibit higher alphas for low sentiment than for high sentiment. The average difference is 0.31% for equal-weighted portfolios and 0.62% for value-weighted portfolios. This result confirms that when investors exhibit a stronger speculative tendency due to high sentiment, they are more inclined to engage in short-term speculative trading and deviates from the PTD decision-making process.

[Table 11]

Prior studies on the U.S. stock market suggest that mispricing factors should perform better among stocks less subject to arbitrage. These studies often employ variables such as idiosyncratic volatility as proxies for limits to arbitrage. However, in this subsection, we find that the predictive power of PTD weakens with an increase in such limits to arbitrage proxy variables. We suggest that the conclusions drawn from the U.S. stock market may not necessarily apply to the Chinese stock market. There are significant differences between the Chinese and U.S. stock markets in terms of individual investor participation. The U.S. stock market is influenced primarily by institutional

[10] The data of CICSI comes from CSMAR.

investors, with relatively limited participation from individual investors. On the other hand, the Chinese stock market is influenced mainly by individual investors who exhibit notable cognitive preferences (Pan et al., 2016; Zhu et al., 2021; Chen et al., 2022). Overall, the U.S. stock market tends to be more rational and has a strong ability to correct mispricing, increasing the sensitivity of mispricing factors to arbitrage. In the Chinese stock market, however, persistent individual investors' noise trading risk, coupled with consistently high short-selling costs, makes it challenging to eliminate mispricing in the short term. Therefore, the performance of PTD in the Chinese stock market is predominantly influenced by whether investors adhere to the PTD decision-making framework rather than being contingent on stock-specific arbitrage risk. In subsection 6.2, we discuss the role of limits to arbitrage in the U.S. stock market.

6. Empirical Analysis in the U.S. Stock Market

We suggest that investors make decisions under prospect theory preferences and that the corresponding variable PTD predicts the stock's subsequent return. This section examines whether PTD performs well in the U.S. stock market. Our sample consists of ordinary common stocks listed on the NYSE, Amex, and Nasdaq from January 1926 to December 2022. Stock returns and prices are from CRSP, and financial data are from Compustat. The monthly excess returns on the market, size, value, profitability and investment factors of Fama and French (2015) are obtained from Kenneth French's online data library. In Subsection 6.1, we replicate the study of the Chinese stock market using data from the U.S. stock market. Subsection 6.2 discusses the influence of limits to arbitrage on prospect theory demand.

6.1 Cross-sectional relation in the U.S. stock market

We first perform Fama-MacBeth regressions of excess return on PTD to examine whether PTD predicts the subsequent return in the U.S. stock market. We include the same control variables as those used in the Chinese stock market analysis, except for EP^+ and $D(EP < 0)$, which are replaced by the book-to-market ratio (BM) following Fama and French (1992). Table 12 presents the results. In columns (1) to (5), the coefficients on PTD are all negative and statistically significant at the 1% level, with t-statistics surpassing the threshold of 3 proposed by Harvey et al. (2016). In column (5), when all the control variables are included, an increase of a one standard deviation (0.056) in PTD predicts a decrease in next month's stock return of 0.17%, slightly lower than 0.24% in the Chinese stock market. These results indicate that PTD has a strong predictive power for future returns in the U.S. stock market as well.

[Table 12]

Following subsection 4.1, we include TK, CGO and $VNSP$ in the Fama-MacBeth regression to explore whether investors in the U.S. stock market consider the capital gains overhang during the "distributions formation" stage. In column (6) of Table 13, where TK is controlled for, the coefficient on PTD is -0.029 (t-statistic = -8.01). With the inclusion of CGO in column (7), the coefficient becomes -0.033. Column (8) shows that, after adding $VNSP$, the coefficient is -0.014 with a t-statistic of -2.47, indicating a slightly reduced predictive power. When all variables are controlled, PTD remains statistically significant at the 1% level. These results are consistent with findings in the Chinese stock market, demonstrating that PTD is not merely an aggregation of similar anomalies but rather characterizes investors' decision-making behavior.

Referring to subsection 4.2, we discuss whether investors in the U.S. stock market evaluate return distributions based on the cumulative prospect theory value. We first perform univariate portfolio analysis by "turning off" specific prospect theory preferences. Panel A in Table 13 displays equal-weighted Fama and French (2015) five factor alphas. The label "PTD" in column (1) represents the baseline result. The labels "DS", "LA", and "PW" indicate "diminishing sensitivity", "loss aversion", and "overweighting of small probabilities", respectively, and are incorporated into PTD. When investors solely consider a single prospect theory preference, alphas of long-short portfolios are not statistically significant. For portfolios when "diminishing sensitivity" (LAPW) or "overestimating small probability events" (DSLA) is not incorporated into PTD, long-short portfolios' alphas are 0.25% and 0.48%, lower than the baseline result 0.85%. When "loss aversion" is not incorporated (DSPW), the long-short portfolio alpha is similar to the benchmark results. Overall, these results are consistent with findings in the Chinese market.

[Table 13]

We employ varying parameter settings for the CRRA and CARA utility functions to compute the expected utility demand (EUD) according to Equation (13), and then sort stocks into decile portfolios based on EUD. Panels B and C in Table 13 represent equal-weighted Fama and French (2015) five factor alphas, with corresponding to the CARA EUD and the CRRA EUD, respectively. In terms of the CARA utility function, all factor alphas of long-short portfolios are not statistically significant. For the CRRA utility function, the alpha of long-short portfolio is statistically significant when the loss aversion parameter is set to 10. However, it negatively predicts future stock returns, contradicting our hypothesis, and its economic magnitude is smaller than that of the PTD portfolio. Generally, the results from Panels A to C confirm that investors do evaluate return distributions based on the cumulative prospect theory value.

We proceed to discuss whether investors in the U.S. stock market make the value comparison between immediate-selling and continuous-holding following subsection 4.3. Panel D in Table 13 reports the Fama-Macbeth regression results using $v(hold)$ or $v(CGO)$ as the main explanatory variable. In columns (2) and (4), after adding control variables, the coefficients of $v(hold)$ and $v(CGO)$ are not statistically significant at the 10% level. We also conduct regressions where all independent variables are standardized, which allows for a comparison of coefficients on PTD, $v(hold)$, and $v(CGO)$. In column (5), the coefficient on standardized PTD is -0.18 with a t-statistic of -8.05. The coefficients of standardized $v(hold)$ and $v(CGO)$ in columns (6) and (7) exhibit much smaller economic magnitudes. These results confirm that investors indeed make the value comparison between immediate-selling and continuous-holding.

6.2 Impact of limits to arbitrage

Prior research suggests that in the U.S. stock market, anomalies are more pronounced when the arbitrage cost and risk are higher (Shleifer & Vishny, 1997; Barberis & Thaler, 2003). We expect the predictive power of PTD to be stronger for stocks less subject to arbitrage. We present the Fama-MacBeth regression results, which include four interaction terms between PTD and proxies for limits to arbitrage: PTD interacts with $Size$, PTD interacts with $Illiq$, PTD interacts with $Ivol$, and PTD interacts with $Turnover$. Stocks with smaller market capitalization, higher idiosyncratic volatility, and greater illiquidity often have higher arbitrage costs and risks (Brav et al., 2010). On the other hand, turnover reflects investor sentiment (Liu et al., 2019), and higher sentiment leads to more noise traders participating in the market, resulting in higher arbitrage risk (Stambaugh et al., 2012).

The coefficients on the interaction terms in Table 14 confirm our hypothesis. The interaction term between PTD and $Size$ exhibits a positive coefficient, indicating that PTD performs better for small-cap stocks. The coefficients on the remaining interaction terms are negative, suggesting that the predictive ability of PTD becomes more pronounced as illiquidity, idiosyncratic volatility, and turnover increase. Overall, PTD performs better for stocks with higher arbitrage risk in the U.S. stock market, which aligns with evidence from prior research.

[Table 14]

7. Robustness Tests

7.1 Prospect theory preference parameters

In our empirical analysis, we set the prospect theory preference parameter values following Barberis et al. (2021), which is $(\lambda, \alpha, \beta, \gamma, \delta) = (1.5, 0.7, 0.7, 0.61, 0.69)$. A well-known set of parameter values comes from Tversky and Kahneman (1992), who estimate $(\lambda, \alpha, \beta, \gamma, \delta) = (2.25, 0.88, 0.88, 0.61, 0.69)$, which differs in the extent of risk aversion and diminishing sensitivity. To examine whether PTD is sensitive to parameter values, this subsection recalculates PTD using the parameter setting from Tversky and Kahneman (1992). We perform a Fama-MacBeth regression where all continuous independent variables are standardized to have a mean of zero and a standard deviation of one in each month, which allows for a comparison of coefficients on the baseline result (-0.234 according to column (5) of Table 9). In column (1) of Table 15, the coefficient on PTD

is -0.211 with a t-statistic of -5.0, demonstrating that prospect theory preference parameter settings do not affect the explanatory power of PTD.

[Table 15]

7.2 PTD without handling short-term reversals

When constructing the PTD variable, we consider the strong correlation between PTD and short-term reversal. We first regress PTD on Rev and take the residuals as our core variable. This subsection recalculates PTD without dealing with the short-term reversal. The regression result is shown in column (2) of Table 15. Standardized PTD remains statistically significant at the 1% level, and the coefficient is similar to the that of baseline regression.

7.3 Form distributions considering risk-free returns

Our core variable PTD is defined as the difference between $v(hold)$ and $v(CGO)$, where $v(CGO)$ represents the value of selling the stock immediately, and $v(hold)$ represents the value of maintaining stockholding until the next month. Investors can reinvest the profits from selling stocks into risk-free assets to earn a one-month risk-free return. Since investors may allocate stocks and risk-free assets to different mental accounts (Thaler, 1985), our main analysis does not consider the risk-free return. In this subsection, we further investigate the influence of risk-free returns on return distributions. Specifically, if investors sell the stock immediately, they realize the return CGO and benefit from the one-month risk-free return r_f. Thus, the return on immediate-selling can be calculated as follows:

$$CGO_{rf,t} = (1 + CGO_t) \times (1 + r_{f,t}) - 1$$

We recalculate $PTD_t = v(hold_t) - v(CGO_{rf,t})$ and examine its predictive ability via the Fama-MacBeth regression analysis. Column (3) of Table 15 presents the result. The coefficient on standardized PTD is -0.233 (t-statistic = -4.79). PTD remains statistically and economically significant.

7.4 Impact of small-cap stocks

The sample used in the Chinese stock market comprises all A-share stocks excluding ST stocks. Liu et al. (2019) suggest that small companies have additional shell value for "backdoor listing" due to the protracted IPO process in China. In this subsection, we investigate whether PTD is affected by the shell value. We follow the approach of Liu et al. (2019) and exclude the smallest 30% of firms each month, subsequently running Fama-MacBeth regressions on the remaining sample. The coefficient on standardized PTD in column (4) is -0.229 with a t-statistic of -4.59, demonstrating that PTD is not influenced by shell value.

7.5 Extrapolative expectation time horizon

We assume that investors use the past 60-months return distributions as a proxy for the future return distribution. Given the possibility that investors may adopt varying time horizons for their extrapolative expectations, we recalculate $v(hold)$ and PTD by considering the use of past 36-month and 48-month return distributions as proxies. Columns (5) and (6) in Table 15 present the results of the Fama-MacBeth regressions. All the coefficients on standardized PTD are statistically significant at the 1% level, thereby indicating that adjusting the time horizon for extrapolative expectations does not alter the predictive capability of PTD.

7.6 Formation methods of future return distributions

We assume that investors form future return distributions based on a uniform distribution to simplify our analysis. It is crucial to emphasize that the predictive ability of PTD rests solely on investors' prospect theory preferences, and remains independent of the approach used for forming return distributions. To illustrate this point, we assume that investors believe that stock returns follow either a normal distribution or a log-normal distribution. Investors estimate the mean and standard deviation based on the past 60-month returns and subsequently employ these parameters to formulate future return distributions. Building upon this assumption, we recalculate $v(hold)$ and PTD. Columns (7) and (8) in Table 15 report the regression results. The coefficients on standardized PTD remain statistically significant at the 1% level, and are similar to those in the benchmark regression.

8. Conclusion

We examine investors' decision-making behavior based on all prospect theory preferences. Investors face a decision dilemma between selling a stock immediately or maintaining stockholding for a future sale. Unlike rational agents, investors with prospect theory preferences exhibit the "reference-dependent" preference, and form return distributions based on their unrealized past gains or losses. Subsequently, investors use the cumulative prospect theory value to evaluate these distributions. Ultimately investors compare the value of immediate-selling and the one of continuous-holding, then make the choice with a higher value. Regardless of the specific choice made by investors, their decisions lead to noise trading and result in stock mispricing. Prospect theory demand, defined as the continuous-holding value minus the immediate-selling value, exhibits significant predictive power for future stock returns. The empirical results for both the Chinese stock market and the U.S. stock market support our hypotheses. Furthermore, our findings suggest that the predictive ability of prospect theory demand depends on the entire decision-making process, rather than being solely determined by a single stage of the process. Prospect theory demand tends to exhibit stronger predictive ability for future returns in stocks with lower institutional ownership and weaker speculative characteristics.

We integrate all the components of prospect theory to construct a straightforward yet comprehensive decision-making framework. This framework exhibits flexibility, allowing new cognitive preferences to be incorporated into the processes of distributions formation, distributions evaluation, and value comparison. We provide a novel perspective for comprehending investor decision-making processes based on behavioral finance.

Our research, as a behavioral finance study, inherently involves a close examination of the investors themselves. In this paper, the reference point is set as the initial purchase price. Recent studies propose that investors' reference points could exhibit time-varying characteristics (Riley et al., 2020). Therefore, dynamic models may offer a more insightful understanding of investors' decision-making behavior in the future research.

Table 1 Definitions for control variables

Variables	Definitions
$Beta$	The stock's CAPM beta computed using daily returns of the previous 250 trading days
$Size$	The logarithm of a firm's market capitalization at the end of month t.
EP^{+}	Equal to the earnings-price ratio (EP) when EP is positive, and zero otherwise, following Liu et al. (2019).
$D(EP < 0)$	Equal to 1 when earnings-price ratio is negative, and 0 otherwise.
Mom	The cumulative return from the start of month $t-11$ to the end of month $t-1$.
$Turnover$	The number of shares traded divided by the total number of outstanding shares in month t.
Rev	The stock's return in month t.
$Illiq$	The absolute daily return divided by the daily trading volume, averaged over all trading days in a month, as in Amihud (2002). $Illiq$ is scaled by 10^{8} in the Chinese stock market and 10^{5} in the U.S. stock market.
$Lt\ rev$	The cumulative return from the start of month $t-59$ to the end of month $t-12$.
$Ivol$	At the end of month t, we regress daily returns on the Fama-French three factors over a one-month window, and $Ivol$ is the standard deviation of the residuals, following Ang et al. (2006).
Max	The average of the highest three daily returns in month t, following Bali et al. (2011).
Min	The average of the negative of lowest three daily returns in month t, following Bali et al. (2011).
$Skew$	The skewness of a stock's monthly returns over the previous five years.
$Coskew$	The coskewness of monthly stock returns with market returns over the previous five years, computed using the approach of Harvey and Siddique (2000).
$Eiskew$	At the end of month t, we regress daily returns on the Fama-French three factors over a one-month window, and $Eiskew$ is the expected idiosyncratic skewness of the residuals, following Boyer et al. (2010).
BM	The logarithm of a firm's book-to-market ratio. The book-to-market ratio is book equity for the fiscal year ending in preceding calendar year, divided by market equity at the end of December of the previous year, following Fama and French (1993).

Table 2 Statistic summary

Panel A: Means, standard deviations and quantiles

	PTD	$Beta$	$Size$	EP^{+}	$D(EP < 0)$	Mom	$Turnover$	Rev	$Illiq$	$Lt\ rev$	$Ivol$	Max	Min	$Skew$	$Coskew$	$Eiskew$
mean	0.00	1.10	22.57	0.01	0.15	0.18	0.44	0.02	0.07	0.70	0.02	0.04	0.04	0.65	-0.12	0.94
std	0.05	0.24	1.00	0.01	0.35	0.31	0.33	0.10	0.06	0.59	0.01	0.02	0.01	0.78	0.24	0.12
p10	-0.07	0.80	21.47	0.00	0.00	-0.17	0.14	-0.09	0.01	0.01	0.01	0.02	0.03	-0.13	-0.40	0.78
p50	0.00	1.11	22.36	0.01	0.00	0.14	0.36	0.00	0.06	0.64	0.02	0.04	0.04	0.49	-0.14	0.95
p90	0.06	1.40	23.92	0.02	0.84	0.59	0.84	0.14	0.14	1.51	0.03	0.07	0.06	1.60	0.20	1.07

Panel B: Correlations

	PTD	$Beta$	$Size$	EP^{+}	$D(EP < 0)$	Mom	$Turnover$	Rev	$Illiq$	$Lt\ rev$	$Ivol$	Max	Min	$Skew$	$Coskew$	$Eiskew$
PTD	1.00															
$Beta$	0.12	1.00														
$Size$	0.04	-0.18	1.00													
EP^{+}	-0.03	-0.19	0.40	1.00												
$D(EP < 0)$	0.00	0.06	-0.19	-0.37	1.00											
Mom	-0.06	0.04	0.15	0.00	-0.08	1.00										
$Turnover$	0.04	0.27	-0.22	-0.18	0.08	0.20	1.00									
Rev	-0.01	-0.02	0.05	-0.01	-0.03	-0.03	0.24	1.00								
$Illiq$	-0.04	-0.03	-0.56	-0.21	0.13	-0.18	-0.18	-0.02	1.00							
$Lt\ rev$	0.30	0.09	0.29	0.04	-0.11	-0.09	0.01	-0.02	-0.23	1.00						
$Ivol$	0.01	0.14	-0.05	-0.19	0.07	0.25	0.58	0.39	-0.05	0.07	1.00					
Max	0.03	0.23	-0.03	-0.16	0.05	0.18	0.56	0.58	-0.06	0.05	0.83	1.00				
Min	0.03	0.36	-0.17	-0.22	0.10	0.24	0.49	-0.21	-0.01	0.05	0.56	0.43	1.00			
$Skew$	0.34	0.08	0.07	-0.05	0.01	0.13	0.09	0.01	-0.04	0.22	0.10	0.09	0.09	1.00		
$Eiskew$	0.12	-0.01	0.16	0.07	0.00	-0.03	-0.06	0.00	-0.08	0.02	-0.03	-0.03	-0.05	0.33	1.00	
$Coskew$	0.03	-0.06	-0.15	0.01	0.08	-0.73	-0.04	0.06	0.13	-0.04	-0.14	-0.08	-0.15	-0.10	0.03	1.00

The table presents the time-series averages of the cross-sectional mean, standard deviation, 0.1-quantile, median, and 0.9-quantile of each variable (panel A) and the correlations between them (panel B). PTD is the prospect theory demand (see Section 2). $Beta$ is a stock's CAPM beta computed using daily returns of the previous 250 trading days. $Size$ is the logarithm of a firm's market capitalization at the end of month t. EP^{+} equal to the earnings-price ratio (EP) when EP is positive, and zero otherwise, following Liu et al. (2019). $D(EP < 0)$ equals 1 when EP is negative, and 0 otherwise. Mom is the cumulative return from the start of month $t-11$ to the end of month $t-1$. Rev is the stock's return in month t. $Illiq$ is the illiquidity measure following Amihud (2002), scaled by 10^{8}. $Lt\ rev$ is the cumulative return from the start of month $t-59$ to the end of month $t-12$. $Ivol$ is the volatility of the stock's daily idiosyncratic returns over month t, as in Ang et al. (2006). Max (Min) is the average of the highest (negative of lowest) three daily returns in month t. $Skew$ is the skewness of a stock's monthly returns over the previous five years. $Coskew$ is the coskewness of monthly stock returns with market returns over the previous five years, following Harvey and Siddique (2000). $Eiskew$ is the expected idiosyncratic skewness of the residuals from a Fama-French three-factor model regression, as in Boyer et al. (2010). The sample period is January 2000 to January 2023.

Table 3 Returns on PTD-sorted portfolios

Decile	Equal-Weighted portfolios				Value-Weighted portfolios			
	Average return	CH3 alpha	4F alpha	FF5 alhpa	Average return	CH3 alpha	4F alpha	FF5 alhpa
Low PTD	1.889	0.668	0.529	0.506	1.485	0.496	0.450	0.492
P2	1.865	0.664	0.498	0.491	1.504	0.666	0.339	0.488
P3	1.796	0.595	0.465	0.378	1.304	0.464	0.327	0.340
P4	1.838	0.525	0.496	0.427	1.361	0.198	0.321	0.313
P5	1.696	0.369	0.340	0.265	1.451	0.427	0.500	0.483
P6	1.652	0.343	0.308	0.212	1.335	0.328	0.394	0.406
P7	1.592	0.287	0.262	0.145	1.246	0.020	0.340	0.263
P8	1.258	0.040	-0.106	-0.176	0.794	-0.226	-0.254	-0.256
P9	1.021	-0.246	-0.291	-0.360	0.558	-0.630	-0.360	-0.445
High PTD	0.870	-0.268	-0.476	-0.540	0.521	-0.455	-0.536	-0.525
Low-High	1.019	0.936	1.005	1.047	0.964	0.951	0.986	1.017
	(4.32)	(4.01)	(3.83)	(4.45)	(4.39)	(3.43)	(3.71)	(4.06)

This table reports monthly raw excess returns and alphas for decile portfolios formed on the prospect theory demand variable PTD. At the end of each month, all stocks are sorted into deciles based on PTD and are rebalanced at the end of the next month. For each decile portfolio, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess returns, Chinese three-factor alphas (Liu et al., 2019), four-factor alphas (Carhart, 1997), and five-factor alphas (Fama & French, 2015). The average PTD increases across the ten portfolios. Low PTD represents the portfolio with the smallest PTD, and High PTD denotes that with the largest PTD. Low-High reports the returns of the zero-cost strategy that buys the stocks in the lowest PTD decile and shorts the stocks in the highest PTD decile. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 4 Returns on double-sorted PTD portfolios

Panel A: Equal-weighted portfolios														
Decile	$Beta$	$Size$	EP^{+}	Mom	$Turnover$	Rev	$Illiq$	$Lt\ rev$	$Ivol$	Max	Min	$Skew$	$Coskew$	$Eiskew$
Low PTD	0.689	0.537	0.624	0.504	0.634	0.785	0.619	0.888	0.622	0.670	0.716	0.483	0.645	0.592
P2	0.568	0.501	0.534	0.514	0.547	0.516	0.511	0.842	0.550	0.595	0.507	0.562	0.551	0.570
P3	0.350	0.366	0.380	0.378	0.378	0.402	0.324	0.707	0.399	0.367	0.363	0.379	0.349	0.399
P4	0.144	0.182	0.183	0.209	0.133	0.267	0.143	0.502	0.145	0.141	0.139	0.147	0.155	0.169
High PTD	-0.244	-0.144	-0.262	-0.172	-0.252	-0.145	-0.173	0.106	-0.205	-0.220	-0.246	-0.352	-0.219	-0.263
Low-High	0.932	0.681	0.886	0.676	0.886	0.930	0.792	0.782	0.828	0.889	0.962	0.835	0.864	0.855
	(5.47)	(4.16)	(4.71)	(3.78)	(5.61)	(4.90)	(4.27)	(4.07)	(4.70)	(5.05)	(5.06)	(3.85)	(4.63)	(4.14)
4F alpha	0.846	0.729	0.853	0.699	0.792	0.930	0.816	0.661	0.833	0.871	0.941	0.731	0.864	0.800
	(4.54)	(3.90)	(4.06)	(3.92)	(5.25)	(4.75)	(3.62)	(3.43)	(4.32)	(4.72)	(4.92)	(3.25)	(4.08)	(4.05)
FF5 alpha	0.900	0.814	0.896	0.764	0.847	0.968	0.891	0.730	0.871	0.904	0.978	0.810	0.913	0.866
	(5.37)	(4.75)	(4.68)	(4.38)	(5.24)	(5.35)	(4.48)	(3.83)	(4.81)	(5.25)	(5.56)	(3.97)	(4.71)	(4.57)

Panel B: Value-weighted portfolios														
Decile	$Beta$	$Size$	EP^{+}	Mom	$Turnover$	Rev	$Illiq$	$Lt\ rev$	$Ivol$	Max	Min	$Skew$	$Coskew$	$Eiskew$
Low PTD	0.523	0.501	0.620	0.314	0.427	0.763	0.673	0.613	0.530	0.556	0.663	0.569	0.682	0.436
P2	0.340	0.465	0.367	0.265	0.354	0.411	0.469	0.510	0.369	0.407	0.456	0.406	0.369	0.321
P3	0.318	0.365	0.449	0.287	0.372	0.341	0.427	0.476	0.354	0.389	0.430	0.414	0.367	0.358
P4	-0.087	0.172	-0.045	-0.061	-0.103	0.029	0.067	0.165	-0.093	-0.039	-0.055	-0.074	-0.022	-0.120
High PTD	-0.496	-0.184	-0.463	-0.469	-0.426	-0.338	-0.348	-0.127	-0.462	-0.431	-0.406	-0.513	-0.373	-0.597
Low-High	1.020	0.685	1.082	0.782	0.853	1.101	1.020	0.741	0.992	0.987	1.069	1.082	1.054	1.033
	(3.96)	(4.20)	(4.13)	(3.23)	(3.56)	(4.19)	(4.75)	(2.76)	(4.41)	(4.07)	(4.43)	(3.74)	(4.32)	(3.81)
4F alpha	0.718	0.698	0.841	0.552	0.478	0.814	0.939	0.503	0.689	0.691	0.809	0.703	0.801	0.725
	(3.66)	(3.88)	(3.62)	(3.15)	(2.47)	(3.31)	(4.25)	(1.90)	(3.73)	(3.63)	(4.23)	(2.71)	(4.16)	(3.86)
FF5 alpha	0.835	0.794	0.952	0.703	0.589	0.935	1.029	0.617	0.814	0.820	0.917	0.914	0.931	0.853
	(3.79)	(4.85)	(3.87)	(3.39)	(2.47)	(3.86)	(4.98)	(2.41)	(3.88)	(3.79)	(4.47)	(3.59)	(4.17)	(4.05)

At the end of each month, stocks are sorted into quintiles based on one of the control variables defined in Table 1. Then, within each quintile, stocks are further sorted into quintiles based on PTD. All portfolios are rebalanced at the end of the next month. The Chinese three-factor alphas (Liu et al., 2019) of the five PTD portfolios over the next month are averaged across the five control variable quintiles. We also report the four-factor alpha (Carhart, 1997) and five-factor alpha (Fama & French, 2015) of the Low PTD minus High PTD long-short portfolios. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 5 Fama-MacBeth regression analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTD	-0.065	-0.050	-0.048	-0.041	-0.043	-0.047	-0.042	-0.042	-0.047
	(-3.70)	(-4.30)	(-3.94)	(-4.51)	(-4.82)	(-4.38)	(-4.82)	(-4.80)	(-4.20)
$Beta$		0.001	0.006	0.008	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.34)	(1.39)	(1.81)	(-0.05)	(-0.09)	(-0.01)	(-0.07)	(-0.09)
$Size$		-0.006	-0.006	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
		(-3.95)	(-4.26)	(-3.83)	(-3.83)	(-3.86)	(-3.75)	(-3.78)	(-3.81)
EP^{+}		0.545	0.490	0.492	0.459	0.460	0.460	0.457	0.460
		(4.32)	(4.22)	(4.14)	(4.40)	(4.41)	(4.44)	(4.41)	(4.45)
$D(EP < 0)$		-0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
		(-0.25)	(0.08)	(-0.09)	(0.13)	(0.10)	(0.12)	(0.10)	(0.10)
Mom			0.005	0.005	0.005	0.005	0.005	-0.006	-0.006
			(2.24)	(1.96)	(2.39)	(2.55)	(2.38)	(-0.88)	(-0.82)
$Turnover$			-0.019	-0.018	-0.020	-0.020	-0.020	-0.009	-0.010
			(-8.92)	(-7.86)	(-6.70)	(-6.73)	(-6.68)	(-1.04)	(-1.12)
Rev			-0.029	-0.034	-0.007	-0.007	-0.009	-0.007	-0.009
			(-3.15)	(-3.60)	(-0.64)	(-0.65)	(-0.86)	(-0.69)	(-0.92)
$Illiq$				0.061	0.063	0.062	0.063	0.064	0.062
				(2.79)	(2.70)	(2.63)	(2.66)	(2.74)	(2.60)
$Lt\ rev$				-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
				(-0.44)	(-0.48)	(-0.44)	(-0.53)	(-0.68)	(-0.63)
$Ivol$					-0.827	-0.826	-0.829	-0.820	-0.819
					(-5.90)	(-5.90)	(-5.93)	(-5.85)	(-5.85)
Max					0.162	0.165	0.164	0.159	0.163
					(2.63)	(2.72)	(2.69)	(2.59)	(2.71)
Min					0.431	0.428	0.430	0.418	0.412
					(6.85)	(6.88)	(6.91)	(6.99)	(7.06)
$Skew$						0.000			0.001
						(0.66)			(1.15)
$Coskew$							-0.002		-0.002
							(-0.97)		(-0.99)
$Eiskew$								-0.022	-0.027
								(-0.59)	(-0.75)

This table reports the results of Fama-MacBeth regressions. Monthly cross-sectional regressions are run for excess stock returns in month $t+1$ on a firm's prospect theory demand (PTD_{it}) and a vector of control variables X_{it} measured at the end of the previous month t: $Ret_{i,t+1} = \alpha_t + \beta_t PTD_{it} + X_{it}'\lambda_t + \varepsilon_{it}$. X_{it} includes the firm characteristics market beta ($Beta$), $Size$, earnings-price ratio (EP^{+}), earnings-price ratio dummy ($D(EP < 0)$) momentum (Mom), turnover ratio ($Turnover$), short-term reversal (Rev), illiquidity ($Illiq$), long-term reversal ($Lt\ rev$), idiosyncratic volatility ($Ivol$), maximum daily return (Max), minimum daily return (Min), skewness ($Skew$), coskewness ($Coskew$), and expected idiosyncratic skewness ($Eiskew$). All the control variables are defined in Table 1. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 6 Fama-MacBeth regression analysis including TK, CGO and $VNSP$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTD				-0.051	-0.045	-0.030	-0.048	-0.034	-0.035
				(-3.42)	(-3.85)	(-3.09)	(-3.09)	(-2.52)	(-2.87)
TK	-0.204			-0.157			-0.139	-0.151	-0.142
	(-2.93)			(-2.41)			(-2.22)	(-2.36)	(-2.29)
CGO		-0.009			-0.015		-0.012		0.002
		(-0.99)			(-1.66)		(-1.44)		(0.28)
$VNSP$			0.039			0.035		0.035	0.013
			(2.34)			(2.11)		(2.13)	(0.56)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the results of Fama-MacBeth regressions that explore whether investors consider the capital gains overhang in the "distributions formation" stage. We run horse races between PTD and similar anomalies (TK, CGO, and $VNSP$). TK (Barberis et al., 2016) characterizes investors' behavior of using cumulative prospect theory value to evaluate future return distributions without considering past gains or losses. CGO (Grinblatt & Han, 2005) and $VNSP$ (An, 2015) measure investors' demand directly affected by unrealized past gains or losses, but do not influence the "distributions formation" stage. All the control variables defined in Table 1 are included in the regressions. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 7 Returns on EUD-sorted portfolios

	Panel A: CARA EW					
$a =$	0.5	1	2	4	5	10
Low EUD	0.440	0.493	0.507	0.512	0.528	0.624
P2	0.530	0.480	0.512	0.458	0.462	0.241
P3	0.447	0.424	0.417	0.422	0.338	0.203
P4	0.255	0.430	0.365	0.339	0.330	0.330
P5	0.386	0.294	0.261	0.218	0.192	0.140
P6	0.296	0.218	0.173	0.210	0.294	0.190
P7	0.151	0.139	0.208	0.140	0.066	0.278
P8	0.240	0.089	0.007	0.120	0.099	0.285
P9	0.015	0.181	0.181	0.239	0.287	0.226
High EUD	0.212	0.226	0.340	0.316	0.376	0.456
Low-High	0.227	0.267	0.167	0.195	0.151	0.168
	(0.62)	(0.77)	(0.55)	(0.54)	(0.37)	(0.38)

	Panel B: CRRA EW					
$\gamma =$	0.5	1	2	4	5	10
Low EUD	0.434	0.512	0.650	0.685	0.685	0.518
P2	0.586	0.547	0.468	0.359	0.289	0.042
P3	0.403	0.423	0.496	0.316	0.292	0.096
P4	0.301	0.319	0.394	0.379	0.223	0.123
P5	0.391	0.317	0.205	0.229	0.291	0.215
P6	0.268	0.190	0.249	0.231	0.265	0.240
P7	0.122	0.229	-0.002	0.042	0.136	0.387
P8	0.225	0.113	0.068	0.142	0.144	0.428
P9	0.038	0.075	0.105	0.232	0.284	0.352
High EUD	0.204	0.247	0.340	0.357	0.364	0.570
Low-High	0.229	0.265	0.311	0.328	0.320	-0.052
	(0.64)	(0.76)	(0.84)	(0.72)	(0.73)	(-0.13)

This table reports the result of univariate portfolio analysis that explore whether investors use cumulative prospect theory in the "distributions evaluation" stage. We report the equal-weighted (EW) average monthly Chinese three-factor alpha (Liu et al., 2019) for decile portfolios formed on the EUD. $EUD_t = u(hold_t) - u(CGO_t)$, where $u(hold_t) = 1/60 \sum_{j=1}^{60} u(1 + r_{CGO,j})$. $u(\cdot)$ represents the constant absolute risk aversion (CARA) utility function in Panel A, and the constant relative risk aversion (CRRA) function in Panel B. Each column represents different risk aversion coefficients. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 8 univariate portfolio analysis using different prospect theory preferences

	DS	LA	PW	LAPW	DSPW	DSLA	None
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low PTD	0.312	0.199	0.441	0.393	0.517	0.432	0.229
P2	0.517	0.145	0.181	0.167	0.702	0.192	0.234
P3	0.390	0.238	0.356	0.442	0.156	0.646	-0.002
P4	0.224	0.198	0.097	0.048	0.499	0.210	-0.032
P5	0.126	0.260	0.250	0.177	0.179	0.265	0.231
P6	0.306	-0.002	0.323	0.343	0.170	0.308	0.209
P7	0.019	-0.144	0.046	0.256	0.134	0.182	-0.332
P8	-0.184	-0.242	-0.067	-0.126	-0.255	-0.189	-0.146
P9	0.021	-0.148	-0.083	-0.074	-0.543	-0.076	-0.149
High PTD	-0.249	0.229	-0.188	-0.241	-0.554	-0.244	0.181
Long-Short	0.561	-0.030	0.628	0.634	1.070	0.676	0.048
	(1.43)	(-0.07)	(2.06)	(1.86)	(4.63)	(1.55)	(0.10)

This table reports monthly value-weighted CH3-alphas for decile portfolios formed on PTD using different prospect theory preferences. At the end of each month, all stocks are sorted into deciles based on PTD and are rebalanced at the end of the next month. The seven specifications vary by which prospect theory preferences are incorporated into PTD. “DS,” “LA,” and “PW” indicate that only diminishing sensitivity, loss aversion, and overweighting of small probabilities are incorporated into PTD, respectively. “LAPW” indicates that only "loss aversion" and "overweighting of small probabilities" are incorporated into PTD. "DSPW" and "DSLA" denote the results without considering "loss aversion" and "overweighting of small probabilities", respectively. “None” turns off three preferences simultaneously. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 9 Fama-MacBeth regression on holding or selling value

	$v(hold)$		$v(cgo)$		*Normalized* *PTD*	*Normalized* $v(hold)$	*Normalized* $v(cgo)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Value	-0.436	-0.307	-0.170	-0.070	-0.234	-0.065	-0.005
	(-0.69)	(-0.64)	(-0.31)	(-0.17)	(-4.77)	(-0.81)	(-0.07)
Beta		-0.001		-0.001	0.010	-0.005	-0.004
		(-0.20)		(-0.19)	(0.12)	(-0.05)	(-0.05)
Size		-0.005		-0.005	-0.508	-0.517	-0.515
		(-3.66)		(-3.68)	(-3.96)	(-3.81)	(-3.83)
Ep^{+}		0.469		0.466	0.361	0.369	0.367
		(4.59)		(4.57)	(5.87)	(6.08)	(6.02)
$D(EP < 0)$		0.000		0.000	0.011	0.005	0.007
		(0.04)		(0.06)	(0.10)	(0.04)	(0.06)
Mom		-0.005		-0.006	-0.202	-0.163	-0.174
		(-0.71)		(-0.77)	(-0.84)	(-0.70)	(-0.76)
Turnover		-0.009		-0.009	-0.368	-0.355	-0.347
		(-1.10)		(-1.11)	(-1.50)	(-1.48)	(-1.47)
Rev		-0.008		-0.008	-0.155	-0.145	-0.146
		(-0.83)		(-0.85)	(-1.56)	(-1.49)	(-1.49)
Illiq		0.059		0.060	0.139	0.135	0.136
		(2.56)		(2.57)	(3.05)	(3.03)	(3.03)
Lt rev		-0.002		-0.002	-0.052	-0.106	-0.116
		(-1.52)		(-1.58)	(-0.71)	(-1.55)	(-1.64)
Ivol		-0.800		-0.800	-0.666	-0.649	-0.650
		(-5.60)		(-5.62)	(-6.00)	(-5.77)	(-5.79)
Max		0.150		0.151	0.297	0.278	0.277
		(2.55)		(2.57)	(3.10)	(2.94)	(2.96)
Min		0.403		0.404	0.521	0.508	0.511
		(7.23)		(7.25)	(7.32)	(7.45)	(7.53)
Skew		-0.000		-0.000	0.036	-0.027	-0.031
		(-0.34)		(-0.45)	(0.85)	(-0.65)	(-0.80)
Coskew		-0.002		-0.002	-0.047	-0.047	-0.051
		(-0.97)		(-1.07)	(-1.03)	(-1.02)	(-1.12)
Eiskew		-0.022		-0.021	-0.375	-0.336	-0.325
		(-0.64)		(-0.61)	(-1.29)	(-1.20)	(-1.18)

This table reports the results of Fama-MacBeth regressions that explore whether investors make the value comparison between immediate-selling and continuous-holding. We run Fama-Macbeth regressions with $v(hold)$ or $v(CGO)$ as the main explanatory variable separately, replacing PTD. To facilitate observation, $v(hold)$ and $v(CGO)$ are divided by 100. $Ret_{i,t+1} = \alpha_t + \beta_t Value_{it} + X'_{it}\lambda_t + \varepsilon_{it}$. $Value$ is denoted as $v(hold)$ in columns (1)-(2) and represented as $v(CGO)$ in columns (3)-(4). In columns (5)-(7), all the independent variables are standardized. The control variables include includes firm characteristics market beta ($Beta$), $Size$, earnings-price ratio (EP^{+}), earnings-price ratio dummy ($D(EP < 0)$) momentum (Mom), turnover ratio ($Turnover$), short-term reversal (Rev), illiquidity ($Illiq$), long-term reversal ($Lt\ rev$), idiosyncratic volatility ($Ivol$), maximum daily return (Max), minimum daily return (Min), skewness ($Skew$), coskewness ($Coskew$), and expected idiosyncratic skewness ($Eiskew$). All the control variables are defined in Table 1. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 10 Fama-MacBeth analysis of institutional investors and speculative stocks

	(1)	(2)	(3)	(4)	(5)
PTD	-0.060	-0.095	-0.091	-0.071	-0.068
	(-3.92)	(-4.22)	(-3.93)	(-3.53)	(-2.82)
$PTD * Hold$	0.148				
	(1.95)				
$PTD * Ivol$		2.125			
		(3.34)			
$PTD * Max$			0.873		
			(2.88)		
$PTD * Turnover$				0.053	
				(2.32)	
$PTD * Price$					0.002
					(1.48)
$Hold$	0.015				
	(3.04)				
$Price$					0.000
					(0.08)
$Beta$	0.001	-0.000	-0.000	-0.000	0.001
	(0.19)	(-0.06)	(-0.06)	(-0.06)	(0.16)
$Size$	-0.005	-0.005	-0.005	-0.005	-0.005
	(-3.80)	(-3.77)	(-3.84)	(-3.82)	(-4.14)
$Ep+$	0.457	0.455	0.455	0.454	0.470
	(4.38)	(4.43)	(4.42)	(4.48)	(4.54)
$D(EP < 0)$	0.000	0.000	0.000	0.000	0.000
	(0.08)	(0.10)	(0.12)	(0.08)	(0.07)
Mom	-0.010	-0.006	-0.007	-0.002	-0.005
	(-1.38)	(-0.75)	(-0.84)	(-0.28)	(-0.74)
$Turnover$	-0.007	-0.010	-0.010	-0.011	-0.011
	(-0.89)	(-1.17)	(-1.14)	(-1.19)	(-1.43)
Rev	-0.013	-0.010	-0.010	-0.009	-0.011
	(-1.24)	(-0.97)	(-0.98)	(-0.83)	(-1.05)
$Illiq$	0.068	0.062	0.061	0.061	0.057
	(2.66)	(2.61)	(2.59)	(2.53)	(2.45)
$Lt\ rev$	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.11)	(-0.59)	(-0.64)	(-0.64)	(-1.10)
$Ivol$	-0.817	-0.824	-0.824	-0.821	-0.808
	(-5.81)	(-5.81)	(-5.79)	(-5.87)	(-5.90)
Max	0.169	0.163	0.162	0.160	0.161
	(2.78)	(2.71)	(2.63)	(2.73)	(2.76)
Min	0.388	0.410	0.410	0.410	0.412
	(6.78)	(6.94)	(6.95)	(6.99)	(7.02)
$Skew$	0.001	0.001	0.001	0.001	0.001
	(1.30)	(1.14)	(1.10)	(1.07)	(1.27)
$Coskew$	-0.002	-0.002	-0.002	-0.002	-0.002
	(-1.07)	(-0.88)	(-0.90)	(-0.94)	(-0.78)
$Eiskew$	-0.040	-0.026	-0.028	-0.019	-0.020
	(-1.09)	(-0.74)	(-0.79)	(-0.51)	(-0.60)

This table reports the results of Fama-MacBeth regressions that include interaction terms to explore the impact of institutional ownership and speculative characteristics on PTD. Column (1) includes PTD interacted with institutional ownership ($Hold$). Columns (2) – (6) include PTD interacted with five variables that proxy for speculative characteristics: $Ivol$, Max, $Turnover$, and stock price ($Price$). All the control variables defined in Table 1 are included in the regressions. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 11 Returns on PTD-sorted portfolios under high and low sentiment

		Low PTD	P2	P3	P4	P5	P6	P7	P8	P9	High PTD	Low - High
	High	0.812	0.690	0.470	0.346	0.225	0.249	0.152	0.152	0.115	-0.022	0.834
Equal	sentiment	(4.01)	(3.45)	(3.31)	(2.04)	(1.89)	(1.99)	(1.23)	(1.12)	(0.78)	(-0.13)	(2.84)
Weighted	Low	0.573	0.710	0.775	0.716	0.531	0.483	0.465	-0.048	-0.609	-0.567	1.140
	sentiment	(2.18)	(3.72)	(3.73)	(3.04)	(2.19)	(2.47)	(2.94)	(-0.24)	(-3.05)	(-2.45)	(3.15)
	High	0.434	0.669	0.393	0.115	0.178	-0.085	-0.066	-0.190	-0.107	-0.220	0.654
Value	sentiment	(1.56)	(2.25)	(1.81)	(0.50)	(0.88)	(-0.46)	(-0.33)	(-0.98)	(-0.47)	(-0.92)	(1.48)
Weighted	Low	0.626	0.763	0.498	0.405	0.718	0.773	0.177	-0.196	-1.195	-0.647	1.273
	sentiment	(1.46)	(2.25)	(1.50)	(1.07)	(2.41)	(2.07)	(0.73)	(-0.65)	(-4.44)	(-2.22)	(2.58)

This table reports the decile portfolios formed on the PTD under high and low sentiment. Months with CICSI values above the median are categorized as high sentiment, while those below the median are categorized as low sentiment. For each decile portfolio, we report the equal-weighted (EW) and value-weighted (VW) average monthly Chinese three-factor alpha (Liu et al., 2019). The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 12 Fama-MacBeth analysis in the U.S. stock market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTD	-0.043	-0.044	-0.034	-0.032	-0.031	-0.029	-0.033	-0.014	-0.015
	(-7.25)	(-9.76)	(-8.89)	(-8.97)	(-8.12)	(-8.01)	(-8.07)	(-3.99)	(-4.39)
TK						-0.073			-0.050
						(-1.94)			(-1.42)
CGO							-0.004		-0.004
							(-2.47)		(-2.01)
$VNSP$								0.029	0.035
								(7.21)	(7.71)
$Beta$		0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	-0.001
		(0.31)	(-0.44)	(0.28)	(0.13)	(-0.51)	(-0.06)	(0.10)	(-0.59)
$Size$		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(-3.64)	(-3.36)	(-4.75)	(-5.10)	(-5.09)	(-5.04)	(-5.36)	(-5.48)
BM		0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
		(3.10)	(3.74)	(2.58)	(2.65)	(2.69)	(2.56)	(2.82)	(2.80)
Mom			0.007	0.007	0.008	0.010	0.009	0.008	0.009
			(4.96)	(5.08)	(5.95)	(6.44)	(6.92)	(5.83)	(6.10)
$Turnover$			0.000	0.018	0.019	0.020	0.019	0.020	0.019
			(0.05)	(2.18)	(1.97)	(2.01)	(1.90)	(2.05)	(1.97)
Rev			-0.064	-0.069	-0.069	-0.069	-0.067	-0.070	-0.067
			(-15.71)	(-15.28)	(-15.12)	(-14.75)	(-14.49)	(-15.82)	(-14.54)
$Illiq$				0.004	0.003	0.003	0.003	0.003	0.003
				(4.37)	(4.12)	(4.17)	(4.04)	(3.92)	(3.86)
$Lt\ rev$				-0.001	-0.001	0.001	-0.000	-0.001	0.000
				(-1.49)	(-1.11)	(1.15)	(-1.01)	(-2.07)	(0.17)
$Ivol$				-0.031	-0.052	-0.049	-0.050	-0.070	-0.069
				(-0.54)	(-0.90)	(-0.85)	(-0.86)	(-1.23)	(-1.23)
Max				-0.016	-0.025	-0.026	-0.026	-0.033	-0.035
				(-0.68)	(-1.14)	(-1.17)	(-1.18)	(-1.50)	(-1.60)
Min				-0.064	-0.072	-0.077	-0.076	-0.084	-0.093
				(-2.48)	(-2.96)	(-3.19)	(-3.14)	(-3.49)	(-3.90)
$Skew$					-0.001	0.000	-0.001	-0.001	-0.000
					(-1.95)	(0.16)	(-1.77)	(-2.50)	(-0.55)
$Coskew$					0.001	0.001	0.001	0.001	0.001
					(0.98)	(0.85)	(1.13)	(0.89)	(0.86)
$Eiskew$					0.007	0.007	0.008	0.005	0.005
					(2.39)	(2.35)	(2.51)	(1.65)	(1.83)

This table reports the results of Fama-MacBeth regressions in the U.S. stock market. Monthly cross-sectional regressions are run for excess stock returns in month $t+1$ on a firm's prospect theory demand (PTD) and control variables at the end of the previous month t. The control variables are defined in Table 1. In columns (6)-(9), we run horse races between PTD and similar anomalies (TK, CGO, and $VNSP$). The sample period is January 1931 to December 2022. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 13 Further analysis in the U.S. stock market

	Panel A: Prospect Theory Parameter Values							
	PTD	DS	LA	PW	LAPW	DSPW	DSLA	None
Low PTD	0.360	0.138	-0.094	0.051	0.088	0.356	0.102	-0.170
P5	0.223	0.165	0.072	0.212	0.167	0.201	0.166	0.142
High PTD	-0.485	-0.339	0.223	-0.178	-0.158	-0.503	-0.378	0.199
Long-Short	0.845	0.477	-0.316	0.230	0.246	0.859	0.480	-0.368
	(6.39)	(3.40)	(-1.55)	(1.68)	(1.92)	(6.65)	(3.49)	(-1.82)

	Panel B: CARA EW					
$a =$	0.5	1	2	4	5	10
Low EUD	0.093	0.194	0.220	0.195	0.173	0.289
P5	0.100	0.073	0.080	0.056	0.039	0.028
High EUD	0.084	0.004	0.027	0.226	0.293	0.378
Low-High	0.010	0.189	0.193	-0.031	-0.120	-0.090
	(0.04)	(0.79)	(0.78)	(-0.13)	(-0.51)	(-0.39)

	Panel C: CRRA EW					
$\gamma =$	0.5	1	2	4	5	10
Low EUD	0.105	0.421	0.463	0.214	0.146	0.049
P5	0.087	0.006	-0.057	-0.017	0.008	0.001
High EUD	0.123	0.133	0.177	0.420	0.479	0.600
Low-High	-0.018	0.288	0.286	-0.207	-0.333	-0.551
	(-0.08)	(1.05)	(1.04)	(-0.95)	(-1.60)	(-2.71)

	Panel D: Holding or selling value						
	$v(hold)$		$v(cgo)$		$Normalized$ PTD	$Normalized$ $v(hold)$	$Normalized$ $v(cgo)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Value	0.318	-0.016	0.374	0.098	-0.176	-0.012	0.031
	(1.58)	(-0.12)	(1.90)	(0.78)	(-8.05)	(-0.31)	(0.83)
Controls	No	Yes	No	Yes	Yes	Yes	Yes

This table tests the pricing implications of PTD in the U.S. stock market. Panel A reports monthly FF5-alphas for decile portfolios formed on PTD using different prospect theory preferences. The eight specifications vary by which prospect theory preferences are incorporated into PTD. The label “PTD” indicates that all preferences are incorporated. “DS,” “LA,” and “PW” indicate that only diminishing sensitivity, loss aversion, and overweighting of small probabilities are incorporated into PTD, respectively. “LAPW” indicates that only "loss aversion" and "overweighting of small probabilities" are incorporated into PTD. "DSPW" and "DSLA" denote the results without considering "loss aversion" and "overweighting of small probabilities", respectively. “None” turns off three preferences simultaneously. Panels B and C report the alphas for decile portfolios formed on the EUD. $EUD_t = u(hold_t) - u(CGO_t)$, where $u(hold_t) = 1/60\sum_{j=1}^{60} u(1 + r_{CGO,j})$. $u(\cdot)$ represents the constant absolute risk aversion (CARA) utility function in Panel B, and the constant relative risk aversion (CRRA) function in Panel C. Each column represents different risk aversion coefficients. We report the five-factor alpha (Fama & French, 2015) of the long-short portfolios. Panel D explores whether investors judge the value between immediate-selling or continuous-holding. We run Fama-Macbeth regressions with $v(hold)$ or $v(CGO)$ as the main explanatory variable separately, replacing PTD. The main explanatory variables are $v(hold)$ in columns (1)-(2) and $v(CGO)$ in columns (3)-(4). In columns (5)-(7), all the independent variables are standardized. All the control variables are defined in Table 1. The sample period is July 1963 to December 2022 for Panels A, B, and C, and January 1931 to December 2022 for Panel D. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 14 Fama-MacBeth analysis of limits to arbitrage

	(1)	(2)	(3)	(4)
PTD	-0.189	-0.027	0.000	-0.019
	(-6.93)	(-7.48)	(0.08)	(-4.64)
$PTD \times Size$	0.009			
	(6.05)			
$PTD \times Illiq$		-0.024		
		(-2.23)		
$PTD * Ivol$			-1.156	
			(-3.94)	
$PTD \times Turnover$				-0.273
				(-3.48)
$Beta$	0.000	0.000	0.000	0.000
	(0.14)	(0.09)	(0.10)	(0.14)
$Size$	-0.001	-0.001	-0.001	-0.001
	(-4.72)	(-4.99)	(-4.80)	(-5.05)
BM	0.001	0.001	0.001	0.001
	(2.67)	(2.62)	(2.62)	(2.63)
Mom	0.008	0.008	0.009	0.008
	(6.06)	(6.23)	(6.44)	(5.99)
$Turnover$	0.018	0.019	0.017	0.019
	(1.88)	(1.99)	(1.81)	(1.82)
Rev	-0.069	-0.068	-0.067	-0.070
	(-15.07)	(-15.10)	(-14.96)	(-15.37)
$Illiq$	0.003	0.004	0.003	0.003
	(4.21)	(4.37)	(4.14)	(4.11)
$Lt\ rev$	-0.000	-0.001	-0.000	-0.001
	(-0.97)	(-1.04)	(-1.02)	(-1.06)
$Ivol$	-0.049	-0.041	-0.038	-0.053
	(-0.84)	(-0.70)	(-0.66)	(-0.91)
Max	-0.027	-0.030	-0.026	-0.026
	(-1.19)	(-1.34)	(-1.16)	(-1.14)
Min	-0.074	-0.076	-0.078	-0.073
	(-3.04)	(-3.19)	(-3.22)	(-2.97)
$Skew$	-0.001	-0.001	-0.000	-0.001
	(-1.62)	(-1.77)	(-1.46)	(-1.97)
$Coskew$	0.001	0.001	0.001	0.001
	(0.87)	(0.95)	(0.84)	(0.98)
$Eiskew$	0.008	0.007	0.007	0.007
	(2.41)	(2.33)	(2.32)	(2.34)

This table reports results of a Fama-MacBeth analysis of the impact of limits to arbitrage on PTD. Monthly cross-sectional regressions are run for excess stock returns in month $t+1$ on the interaction terms between PTD and proxies for limits to arbitrage. Proxies for limits to arbitrage include $Size$, $Illiq$, $Ivol$, and $Turnover$. The control variables are defined in Table 1. The sample period is January 1931 to December 2022. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Table 15 Robustness tests

	Parameter	Include Rev	Rf	Shell	36 months	48 months	Normal	Lognormal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Value$	-0.050	-0.050	-0.048	-0.047	-0.049	-0.046	-0.053	-0.050
	(-4.43)	(-4.03)	(-4.22)	(-3.50)	(-4.35)	(-4.19)	(-4.02)	(-4.57)
$Beta$	-0.001	-0.001	-0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(-0.20)	(-0.11)	(-0.10)	(0.02)	(-0.11)	(-0.10)	(-0.09)	(-0.04)
$Size$	-0.005	-0.005	-0.005	-0.003	-0.005	-0.005	-0.005	-0.005
	(-3.73)	(-3.81)	(-3.80)	(-3.07)	(-3.82)	(-3.80)	(-3.80)	(-3.87)
Ep^{+}	0.463	0.461	0.460	0.430	0.459	0.461	0.465	0.476
	(4.47)	(4.45)	(4.45)	(4.10)	(4.55)	(4.49)	(4.41)	(4.37)
$D(EP < 0)$	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
	(0.08)	(0.09)	(0.10)	(-0.67)	(0.02)	(0.08)	(0.09)	(0.06)
Mom	-0.006	-0.006	-0.006	-0.008	-0.007	-0.006	-0.006	-0.006
	(-0.78)	(-0.80)	(-0.82)	(-0.85)	(-0.89)	(-0.83)	(-0.81)	(-0.82)
$Turnover$	-0.011	-0.010	-0.010	-0.007	-0.009	-0.009	-0.010	-0.009
	(-1.25)	(-1.14)	(-1.14)	(-0.77)	(-1.04)	(-1.09)	(-1.13)	(-1.04)
Rev	-0.010	-0.015	-0.009	0.000	-0.009	-0.009	-0.009	-0.010
	(-0.95)	(-1.61)	(-0.92)	(0.00)	(-0.92)	(-0.90)	(-0.89)	(-0.95)
$Illiq$	0.063	0.062	0.062	0.020	0.062	0.062	0.061	0.059
	(2.65)	(2.61)	(2.60)	(0.64)	(2.58)	(2.59)	(2.57)	(2.51)
$Lt\ rev$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.52)	(-0.57)	(-0.62)	(-0.99)	(-0.77)	(-0.72)	(-0.62)	(-0.79)
$Ivol$	-0.815	-0.821	-0.819	-0.698	-0.811	-0.813	-0.813	-0.823
	(-5.89)	(-5.89)	(-5.85)	(-4.31)	(-5.82)	(-5.82)	(-5.80)	(-5.90)
Max	0.165	0.163	0.163	0.123	0.161	0.161	0.163	0.162
	(2.73)	(2.72)	(2.72)	(1.73)	(2.69)	(2.68)	(2.71)	(2.73)
Min	0.418	0.413	0.412	0.400	0.408	0.411	0.412	0.411
	(7.22)	(7.04)	(7.06)	(5.30)	(7.09)	(7.11)	(7.07)	(7.08)
$Skew$	0.001	0.001	0.001	0.000	0.001	0.001	-0.000	-0.000
	(1.33)	(1.20)	(1.15)	(0.52)	(1.10)	(1.07)	(-0.30)	(-0.26)
$Coskew$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.92)	(-1.00)	(-0.99)	(-1.06)	(-1.06)	(-1.09)	(-1.08)	(-1.13)
$Eiskew$	-0.025	-0.026	-0.027	-0.057	-0.034	-0.028	-0.026	-0.027
	(-0.71)	(-0.73)	(-0.74)	(-1.40)	(-0.94)	(-0.77)	(-0.72)	(-0.76)

This table presents the results of Fama-MacBeth regressions of robustness tests in the Chinese stock market. Column (1) utilizes the prospect theory preference parameters of Tversky and Kahneman (1992) to compute PTD. Column (2) conducts regressions using PTD without excluding short-term reversal. Column (3) considers the influence of the risk-free rate r_f, and PTD is defined as $PTD_t = v(hold_t) - v(CGO_{rf,t})$, where $CGO_{rf,t} = (1 + CGO_t) \times (1 + r_{f,t}) - 1$. Column (4) accounts for the shell value (Liu et al., 2019) in the Chinese stock market by removing the 30% smallest stocks. Columns (5) and (6) run regressions where investors use the past 36 months and 48 months, respectively, to form return distributions, respectively. Column (7) computes the residual PTD from firm-by-firm regressions of the origin prospect theory demand on the control variables. Columns (8) and (9) test situations where investors form future return distributions based on normal and log-normal distributions, respectively. All columns incorporate control variables defined in Table 1. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

Appendix A:

(1) CAPM Beta ($Beta$): The stock's beta is computed using daily returns of the previous 250 trading days.

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + e_{i,t},$$

where β_i is the $Beta$ of stock i. $r_{i,t}$ is the stock's return on day t. $r_{f,t}$ is the risk-free rate on day t. $r_{m,t}$ represents the market return on day t, and the market portfolio is the Shanghai Composite Index.

(2) $Size$: The log of the market value at the end of month t, where the market value is the daily close price multiplied by total shares outstanding.

(3) Earnings-to-price ratio (EP): Following Liu et al. (2019),

$$EP_{i,t} = Earnings_{i,t}/Size_{i,t},$$

where $Earnings_{i,t}$ represents the net profit excluding non-recurring gains and losses in the most recent financial statement. $Size_{i,t}$ is the market value at the end of month t. When $EP \geq 0$, EP^{+} takes the value of EP, and the dummy variable $D(EP < 0)$ takes the value of 0. When $EP < 0$, EP^{+} takes the value of 0, and $D(EP < 0)$ takes the value of 1.

(4) Momentum effect (Mom): Following Carhart (1997), Mom is the stock's cumulative return from the start of month $t-11$ to the end of month $t-1$.

(5) Turnover ratio ($Turnover$): The number of shares traded divided by the total number of outstanding shares in month t.

(6) Short-term reversal (Rev): The stock's return in month t.

(7) Illiquidity ($Illiq$): The absolute daily return divided by the daily trading volume, averaged over all trading days in a month, as in Amihud (2002):

$$Illiq_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|ret_{i,d}|}{Vol_{i,d}},$$

where $D_{i,t}$ represents the total trading days of stock i in month t, $ret_{i,d}$ is the return on stock i on day d, and $Vol_{i,d}$ represents the trading volume on day d. In the Chinese stock market, $Illiq$ is multiplied by 10^8, while in the U.S. stock market, $Illiq$ is multiplied by 10^5.

(8) Long-term reversal ($Lt\ rev$): The stock's cumulative return from the start of month $t-59$ to the end of month $t-12$.

(9) Idiosyncratic volatility ($Ivol$): Following Ang et al. (2006), at the end of month t, we regress daily returns on the Fama-French three factors over a one-month window:

$$ret_{i,d} = \alpha_i + \beta_{mkt} MKT_d + \beta_{smb} SMB_d + \beta_{hml} HML_d + e_{i,d}$$

where $ret_{i,d}$ represents stock i's excess return on day d. MKT_d, SMB_d and HML_d represent the market factor, size factor, and value factor on day d, respectively. $e_{i,t}$ denotes the residual from the regression. $Ivol$ is defined as follows:

$$Ivol_{i,t} = \sqrt{\frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} e_{i,d}^2},$$

where $D_{i,t}$ represents the total trading days of stock i in month t.

(10) Max and Min: Following Bali et al. (2011), Max (Min) is the average of the highest (negative of lowest) three daily returns in month t.

(11) Skewness ($Skew$): The skewness of a stock's monthly returns over the previous five years.。

(12) Coskewness ($Coskew$): Following Harvey and Siddique (2000), $Coskew$ is computed using the monthly returns of the previous five years:

$$Coskew_{i,t} = \frac{E(e_{m,t}^2 e_{i,t})}{E(e_{m,t}^2)\sqrt{E(e_{i,t}^2)}},$$

where $e_{i,t} = (r_{i,t} - r_{f,t}) - \alpha_i - \beta_i(r_{m,t} - r_{f,t})$. $e_{i,t}$ represents the residual from regressing individual stock excess returns on market excess returns. $e_{m,t}$ is calculated as the difference between the market excess return in month t and the average market excess return over the past five years: $e_{m,t} = r_{m,t} - E(r_m)$.

(13) Expected idiosyncratic skewness ($Eiskew$): Following Boyer et al. (2010), we regress daily returns on the Fama-French three factors over a one-month window:

$$ret_{i,d} = \alpha_i + \beta_{mkt}MKT_d + \beta_{smb}SMB_d + \beta_{hml}HML_d + e_{i,t}.$$

The stock's idiosyncratic volatility ($Ivol$) and idiosyncratic skewness ($Iskew$) can be calculated. $Ivol$ is defined as mentioned earlier. $Iskew$ is defined as follows:

$$Iskew_{i,t} = \frac{1}{D_{i,t}} \frac{\sum_{d=1}^{D_{i,t}} e_{i,d}^3}{Ivol_{i,t}^3},$$

where $D_{i,t}$ represents the total trading days of stock i in month t, and $e_{i,t}$ denotes the residual from the regression. In order to obtain the expected idiosyncratic skewness ($Eiskew$), the following regression needs to be conducted:

$$Iskew_{i,t} = \beta_{0,t} + \beta_{1,t}Iskew_{i,t-24} + \beta_{2,t}IV_{i,t-24} + \gamma_t X_{i,t-24} + \varepsilon_{i,t}$$

where $X_{i,t-24}$ represents control variables, including Mom and $Turnover$ in month $t-24$. After estimating the coefficients $\hat{\beta}_{1,t}$, $\hat{\beta}_{2,t}$, and $\hat{\gamma}_t$, $Eiskew$ can be calculated as follows:

$$Eiskew_{i,t+24} = \beta_{0,t} + \hat{\beta}_{1,t}Iskew_{i,t} + \hat{\beta}_{2,t}IV_{i,t} + \hat{\gamma}_t X_{i,t}$$

(14) Prospect theory value (TK): Following Barberis et al. (2016), TK measures the excess demand generated by evaluating the return distributions using the cumulative prospect theory value. Investors extrapolate future return distributions based on past 60 months' returns. The rank-dependent distribution for the past 60 months' returns is:

$$\left(r_{-m}, \frac{1}{60}; \cdots; r_{-1}, \frac{1}{60}; r_1, \frac{1}{60}; \cdots; r_n, \frac{1}{60}\right).$$

TK is calculated as follows:

$$TK = \sum_{i=-m}^{-1} v(r_i)\left[w^-\left(\frac{i+m+1}{60}\right) - w^-\left(\frac{i+m}{60}\right)\right] + \sum_{i=1}^{n} v(r_i)\left[w^+\left(\frac{n-i+1}{60}\right) - w^+\left(\frac{n-i}{60}\right)\right],$$

where $v(\cdot)$ represents the value function defined in Equation (3), and $w(\cdot)$ represents the weighting function defined in Equation (4).

(15) Capital gains overhang (CGO): Following Grinblatt and Han (2005) and Barberis et al. (2021), CGO measures the investors' weighted average capital gains overhang for an individual stock.

$$CGO_{i,t} = \frac{P_{i,t} - RP_{i,t}}{RP_{i,t}}$$

where $P_{i,t}$ is the stock i's price at date t. $RP_{i,t}$ denotes the reference price at time t, which is the investor's weighted average purchase price. $RP_{i,t}$ is computed as follows:

$$RP_{i,t} = \frac{1}{k}\sum_{n=1}^{T}\left(V_{i,t-n}\prod_{\tau=1}^{n-1}[1 - V_{i,t-n+\tau}]\right)P_{i,t-n},$$

where $V_{i,t}$ is the turnover ratio at date t. The weight $V_{i,t-n}\prod_{\tau=1}^{n-1}[1 - V_{i,t-n+\tau}]$ is a proxy for the portion of stock purchased on day $t-n$ that is not traded afterward, and k is a constant that sets the weights on past prices sum to one. T is the truncation period used to calculate RP_t, and we select 500 trading days as the truncation period.

(16) V-shaped net selling propensity ($VNSP$): Following An (2015), $VNSP$ measures investors' net selling propensity under the V-shaped disposition effect. V-shaped-disposition-prone investors tend to sell more when their unrealized gains and losses increase in magnitude; the gain side of this effect is approximately 4.3 times as strong as the loss side. $VNSP$ is defined as:

$$VNSP_{i,t} = Gain_{i,t} - 0.23Loss_{i,t}.$$

$Gain$ is measured as the weighted average capital gains overhang if the purchase price is lower than the current price.

$$Gain_{i,t} = \sum_{n=1}^{\infty}\omega_{i,t-n}\, gain_{i,t-n}$$

$$gain_{i,t-n} = \frac{P_{it} - P_{i,t-n}}{P_{it}} \cdot 1_{\{P_{it}>P_{i,t-n}\}}$$

$$\omega_{i,t-n} = \frac{1}{k}V_{i,t-n}\prod_{\tau=1}^{n-1}[1 - V_{i,t-n+\tau}]$$

$Loss$ is measured as the weighted average capital gains overhang if the purchase price is higher than the current price.

$$Loss_{i,t} = \sum_{n=1}^{\infty}\omega_{i,t-n}\, loss_{i,t-n}$$

$$loss_{i,t-n} = \frac{P_{it} - P_{i,t-n}}{P_{i,t}} \cdot 1_{\{P_{it}<P_{i,t-n}\}}$$

$$\omega_{i,t-n} = \frac{1}{k}V_{i,t-n}\prod_{\tau=1}^{n-1}[1 - V_{i,t-n+\tau}]$$

(17) Institutional ownership ($Hold$): The proportion of shares held by mutual funds, QFIIs, securities firms, insurance companies, social security funds, trusts, financial companies, and banks.

(18) Book-to-market ratio (BM): The logarithm of a firm's book-to-market ratio. Following Fama and French (1993), the book-to-market ratio is book equity for the fiscal year ending in the preceding calendar year, divided by market equity at the end of December of the previous year. Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. Market equity is the firm's market capitalization.

Appendix B:

Subsection 4.2 explores whether investors simultaneously exhibit the three prospect theory preferences, including loss aversion, diminishing sensitivity, and overweighting of small probabilities when evaluating distributions. However, in Table 8, when "loss aversion" is not incorporated into PTD, the long-short portfolio alpha is similar to the benchmark result. There might be concern regarding whether PTD adequately reflects investors' "loss aversion" preference. In this appendix, we demonstrate that PTD indeed captures investors' "loss aversion" preference, and that the impact of "loss aversion" on PTD is related to investors' capital gains overhang.

We demonstrate that high (low) PTD stocks tend to retain their high (low) PTD characteristics across different "loss aversion" parameter values. Altering the value of the loss aversion parameter minimally affects composition of stocks within the high (low) PTD portfolios, resulting in relatively stable portfolio returns. This explains why the alpha of long-short portfolio excluding "loss aversion" $(\lambda = 1)$ aligns closely with the benchmark results $(\lambda = 1.5)$ in Table 8. Our discussion begins with the calculation method of PTD:

$$PTD_t = v(hold_t) - v(CGO_t).$$

According to Equation (10), the continuous-holding value $v(hold_t)$ is calculated as follows:

$$v(hold_t) = \sum_{i=-m}^{-1} v(r_{CGO,i}) \left[w^-\left(\frac{i+m+1}{60}\right) - w^-\left(\frac{i+m}{60}\right)\right]$$

$$+\sum_{i=1}^{n} v(r_{CGO,i}) \left[w^+\left(\frac{n-i+1}{60}\right) - w^+\left(\frac{n-i}{60}\right)\right].$$

Suppose that all stocks have extremely small capital gains overhang. Investors experience unrealized past severe losses ($CGO_t < 0$), and the 60 months' cumulative returns of continuous-holding are all negative ($r_{CGO,j} < 0,\ \ \forall j \in [1,2,\dots,60]$). Since only negative returns exist, the value function $v(x_i)$ becomes:

$$v(x_i) = -\lambda(-x_i)^\beta,$$

and the formula for PTD can be rewritten as:

$$-\lambda\left(\sum_{i=-60}^{-1} (-r_{CGO,i})^\beta \left[w^-\left(\frac{i+61}{60}\right) - w^-\left(\frac{i+60}{60}\right)\right] - (-CGO_i)^\beta\right).$$

In this situation, the loss aversion parameter λ affects only the value of PTD, and has no influence on the rank of PTD. Stocks in the high (low) PTD portfolios remain in their respective portfolios despite different parameter settings. An intuitive explanation is that when investors have incurred substantial losses and predict no possibility of turning these losses into gains by continuous-holding, loss aversion becomes inconsequential as investors only face losses. Similarly, when investors achieve substantial gains ($CGO_t > 0$) and anticipate no possibility of losses form continuous-holding ($r_{CGO,j} \geq 0,\ \ \forall j \in [1,2,\ldots,60]$), they are not influenced by "loss aversion" as they only face profits.

As long as the majority of $r_{CGO,j}$ are negative (or positive), the impact of loss aversion on the ordering of PTD is minor. The values of $r_{CGO,j}$ are largely dependent on CGO. The 60 months' cumulative returns $r_{CGO,j}$ are more likely to be mostly negative (positive) when CGO is sufficiently small (large). Furthermore, we find a negative correlation between PTD groups and CGO; on average, CGO decreases as PTD increases. Table B1 reports this relationship. At the end of each month, we sort stocks into ten groups based on their PTD values, and calculate the means, standard deviations, and 25th, 50th, 75th percentiles of CGO for each decile group. We report the time-series averages of the monthly statistics.

Table B1 Summary statistics for CGO

Decile	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10
mean	-0.009	-0.047	-0.060	-0.069	-0.074	-0.079	-0.084	-0.087	-0.094	-0.106
std	0.108	0.109	0.110	0.101	0.093	0.089	0.087	0.083	0.082	0.083
p25	-0.070	-0.110	-0.124	-0.128	-0.129	-0.131	-0.134	-0.134	-0.141	-0.150
p50	-0.011	-0.045	-0.064	-0.076	-0.080	-0.085	-0.087	-0.088	-0.097	-0.108
p75	0.056	0.014	0.000	-0.015	-0.024	-0.032	-0.039	-0.045	-0.053	-0.066

This table presents the time-series averages of the cross-sectional mean, standard deviation, 0.25-quantile, median, and 0.75-quantile of CGO for portfolios formed on PTD. At the end of each month, we sort stocks into decile portfolios based on their PTD value and compute summary statistics for CGO. CGO measures the investors' weighted average capital gains overhang for an individual stock (Grinblatt & Han, 2005).

For the high PTD portfolio (p10), the average CGO stands at -10.6%. Corresponding to this CGO, $r_{CGO,j}$ becomes positive only when monthly returns exceed 11.9%, which is roughly at the 83rd percentile of monthly returns. This implies that most $r_{CGO,j}$ values are negative, so the impact of loss aversion is limited. Stocks in high PTD portfolios have a high probability of remaining there after the loss aversion parameter value changes, leading to insignificant changes in the alphas of high PTD portfolios. The low PTD portfolio (p1) exhibits the highest average CGO among the deciles. The 75th percentile of CGO is 5.6%. After adjusting the loss aversion parameter values, some stocks still remaining a higher probability of staying within the low PTD portfolio. As a result, the alphas for long-short portfolios are insensitive to loss aversion parameter values. The alpha of long-short portfolio without incorporating "loss aversion" ($\lambda = 1$) is similar to the benchmark results ($\lambda = 1.5$).

For other portfolios with CGO values closer to 0, there is a greater likelihood of experiencing both positive and negative returns when maintaining stockholding continuously. Investors need to evaluate potential gains and losses, where "loss aversion" preference is truly reflected in investors decision-making process. Overall, the influence of loss aversion on PTD depends on the investors' capital gains overhang. When investors have a small number of unrealized gains or losses, loss aversion has a significant impact. However, when they experience substantial unrealized gains or losses, they become less sensitive to loss aversion.

To establish that PTD indeed captures investors' "loss aversion" preference, we conduct Fama-MacBeth regressions after excluding stocks that are less affected by “loss aversion.” We investigate whether the coefficients on PTD change with variations in "loss aversion" parameter values, and whether the predictive power of PTD for future returns is weak when "loss aversion" is not considered. We employ four methods to filter out stocks insensitive to "loss aversion": (1) Monthly exclusion of the lowest 10% of stocks based on CGO. The time-series average of the cross-sectional 0.1-quantile is -20%. (2) Monthly exclusion of the lowest 20% of stocks based on CGO. The time-series average of the cross-sectional 0.2-quantile is -15.6%. (3) Monthly exclusion of both the lowest and highest 10% of stocks based on CGO, while considering scenarios of "only gains" and "only losses." (4) Monthly exclusion of the lowest and highest 10% of stocks based on PTD. According to the results in Table B1, these stocks are more likely to exhibit great unrealized gains or losses.

Table B2 reports the results of Fama-MacBeth regressions under various "loss aversion" parameter values. For each month, we standardize continuous independent variables to have zero mean and unit variance to make it easier to compare across different specifications. We include all the control variables in regressions and solely report the coefficients on PTD for clarity.

The results across panels A to D, representing the four filter methods, exhibit the same trend. As the "loss aversion" parameter increases, the coefficients on PTD follow a U-shaped pattern. With λ gradually increasing from 0.4, the predictive ability of PTD for subsequent returns improves steadily. The strongest predictive power is observed at approximately $\lambda = 1.3$, after which the predictive power diminishes as λ increases. This indicates that PTD indeed reflects investors' "loss aversion" preference. Setting the "loss aversion" parameter values too high or too low deviates from the actual way investors evaluate return distributions, thereby weakening the explanatory power of PTD for future returns. The results also confirm that investors indeed exhibit "loss aversion" in their decision-making behavior. PTD's predictive power is weaker when "loss aversion" is considered ($\lambda = 1$) than when "loss aversion" exists ($\lambda = 1.2$ to 1.5). However, the difference in PTD's coefficients is not substantial, indicating that investors do not exhibit a high degree of "loss aversion."

Table B2 Fama-MacBeth regressions on PTD that vary the degree of loss aversion

	Panel A: Exclude CGO P10												
	0.4	0.6	0.8	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	2
PTD	-0.130	-0.153	-0.170	-0.183	-0.189	-0.193	-0.195	-0.196	-0.196	-0.195	-0.192	-0.190	-0.184
	(-2.32)	(-2.81)	(-3.26)	(-3.60)	(-3.71)	(-3.79)	(-3.84)	(-3.86)	(-3.85)	(-3.83)	(-3.81)	(-3.78)	(-3.73)
	Panel B: Exclude CGO P20												
	0.4	0.6	0.8	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	2
PTD	-0.114	-0.139	-0.164	-0.187	-0.197	-0.204	-0.207	-0.207	-0.204	-0.200	-0.194	-0.189	-0.178
	(-1.92)	(-2.32)	(-2.72)	(-2.99)	(-3.07)	(-3.12)	(-3.15)	(-3.17)	(-3.19)	(-3.21)	(-3.22)	(-3.24)	(-3.26)
	Panel C: Exclude CGO P10 & P90												
	0.4	0.6	0.8	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	2
PTD	-0.125	-0.148	-0.163	-0.176	-0.181	-0.186	-0.189	-0.190	-0.190	-0.189	-0.187	-0.185	-0.180
	(-2.38)	(-2.83)	(-3.19)	(-3.42)	(-3.47)	(-3.51)	(-3.52)	(-3.52)	(-3.49)	(-3.45)	(-3.41)	(-3.37)	(-3.30)
	Panel D: Exclude PTD P10 & P90												
	0.4	0.6	0.8	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	2
PTD	-0.192	-0.216	-0.230	-0.238	-0.239	-0.239	-0.237	-0.234	-0.231	-0.228	-0.225	-0.222	-0.217
	(-3.27)	(-3.80)	(-4.21)	(-4.44)	(-4.49)	(-4.52)	(-4.55)	(-4.55)	(-4.55)	(-4.55)	(-4.55)	(-4.55)	(-4.55)
	Panel E: TK												
	0.4	0.6	0.8	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	2
TK	0.108	0.027	-0.135	-0.329	-0.395	-0.429	-0.439	-0.431	-0.416	-0.398	-0.380	-0.362	-0.333
	(0.88)	(0.20)	(-1.07)	(-2.64)	(-2.90)	(-2.92)	(-2.91)	(-2.91)	(-2.92)	(-2.93)	(-2.94)	(-2.95)	(-2.94)

This table reports the results of Fama-MacBeth regressions that explore whether PTD indeed captures investors' "loss aversion" preference. The eleven specifications differ in the values of the loss aversion parameters λ. In Panel A, each month we exclude the lowest 10% of stocks based on CGO. In Panel B, each month we exclude the lowest 20% of stocks based on CGO. In Panel C, each month we exclude the lowest and highest 10% of stocks based on CGO. In Panel D, each month we exclude the lowest and highest 10% of stocks based on PTD. All continuous independent variables are standardized to have zero mean and unit variance in each month. Control variables include the firm characteristics market beta ($Beta$), $Size$, earnings-price ratio (EP$^+$), earnings-price ratio dummy ($D(EP < 0)$) momentum (Mom), turnover ratio ($Turnover$), short-term reversal (Rev), illiquidity ($Illiq$), long-term reversal ($Lt\ rev$), idiosyncratic volatility ($Ivol$), maximum daily return (Max), minimum daily return (Min), skewness ($Skew$), coskewness ($Coskew$), and expected idiosyncratic skewness ($Eiskew$). Panel E reports the results of ten Fama-MacBeth regressions on prospect theory variable TK (Barberis et al., 2016). The ten specifications differ in the values of the loss aversion parameters λ. All the control variables are defined in Table 1. The sample period is January 2000 to January 2023. t-statistics in parentheses are Newey-West adjusted with 12 lags.

We employ another variable related to prospect theory, TK (Barberis et al., 2016), to complement our findings. Panel E reports Fama-MacBeth regressions results using standardized TK as the main independent variable under various "loss aversion" parameter values. As the "loss aversion" parameter increases, the coefficients on TK also exhibit a U-shaped pattern, with the strongest predictive power of TK for future returns observed at $\lambda = 1.3$. Additionally, when "loss aversion" is not incorporated into TK ($\lambda = 1$), the coefficient on TK remains statistically significant and is similar to the baseline result ($\lambda = 1.5$). These results also indicate that investors do not exhibit a strong degree of "loss aversion" and $\lambda = 1.3$ might better reflect investors' decision-making behavior.

Overall, this appendix offers two explanations for why the alpha of the long-short portfolio in Table 10 resembles the benchmark results when "loss aversion" is not considered. First, the impact of "loss aversion" on PTD depends on investors' capital gains overhang. Stocks with little unrealized gains or losses are significantly affected by "loss aversion." However, stocks in high and low PTD portfolios often exhibit substantial unrealized gains or losses, resulting in a lower sensitivity to "loss aversion." High (low) PTD stocks tend to retain high (low) PTD characteristics across different "loss aversion" parameter values, so the alpha of the long-short portfolio remains similar. Second, investors in the Chinese stock market do not exhibit a strong "loss aversion" preference. The predictive power of PTD for subsequent returns is strongest when λ is approximately 1.3, whereas the predictive power remains similar between scenarios that do not consider "loss aversion" ($\lambda = 1$) and the benchmark result ($\lambda = 1.5$).

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