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by

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Abstract

We propose a simple algorithm for the ex-ante valuation based on prospect theory. Our results reveal a strong and robust pricing effect associated with predicted values based on prospect theory (PV) in the US market, that is, higher ex-ante PV stocks associated with higher returns. Our findings indicate no equilibrium exists for ex-ante PV. Our evidence shows liquidity has a limited impact on the ex-ante PV effect, which is mainly on liquid stocks. In general, liquidity, equilibrium, and the limits of arbitrage are crucial to understanding the ex-ante PV effect.

Key words: ex-ante valuation; prospect theory; equilibrium; liquidity; crash; jackpot

1. Introduction

Prospect theory, introduced by Kahneman and Tversky (1979) and Tversky and Kahneman (1992), is wildly regarded as the best and most influential description and framework of individual risk attitudes under uncertainty. Extensive experimental evidence suggests that it elegantly compensates for the systematic discrepancy between expected utility choices and actual risk decision-making behaviors. In recent decades, scholars find that it has an impact on pricing and can explain the cross-section of average returns on risk assets (Barberis et al. 2001; Barberis and Huang, 2008; Levy and Levy, 2004; Barberis et al., 2016; Barberis et al., 2021). The current literature on its role in financial markets is dominated by normative research from an equilibrium perspective, positive investigations of realized (ex-post) returns, and indirect empirical findings. It is still unclear whether the expected value (ex-ante) based on prospect theory can be applied to predict stock returns.

To find out whether the ex-ante value based on prospect theory can be applied to predict stock returns, we develop a straightforward ex-ante forecasting procedure based on prospect theory and provide new findings about the US equity market.

The primary task is to use prospect theory to predict stock returns. The theoretical guides often utilize the framework of equilibrium (Barberis et al., 2001; Barberis and Huang, 2008; Levy and Levy, 2004; Barberis et al., 2016; Barberis et al., 2021). However, the equilibrium structure sometimes involves heterogeneous investors, which also consider individuals with traditional mean-variance preferences. These situations make the application of prospect theory more difficult. According to prospect theory, representative investors give preference to stocks with high valuations. Therefore, it makes sense to exploit a method for representative investors based directly on the expected valuation (ex-ante) of prospect theory. Post and Levy (2005) and Fang (2012) demonstrate that the aggregate investor preferences in the equity market is more inclined to follow prospect theory. Then, the finding of the expected valuation of prospect theory can help us to examine the equilibrium structure and market efficiency of asset pricing. Especially, Kopa and Post (2009) find the market portfolio is significantly first-order stochastic dominance non-optimal. It contradicts all single-period, portfolio-oriented, and representative-investor models of capital market equilibrium.[1] So pay attention to the ex-ante PV, it may discover or excavate some pricing rules based on prospect theory under non-equilibrium.

Then, it is necessary to study how to obtain robust forecasts for representative investors. As far as we are aware, the problem is a critical challenge in applying prospect theory to financial decision-making under uncertainty. The literature on prospect theory implements an exquisite valuation process involving s-shaped risk preference, loss aversion, and weight distortion with probability. They characterize the basic features of individual risk attitudes, namely, risk aversions over gains, risk-seeking over losses, greater sensitivity to losses than gains, and overweighed tails of the distribution. Nevertheless, we still need to excavate a proper procedure to build an ex-ante prediction of stock return distributions. Finding an accurate return distribution is an arduous task, but good distribution approximation can be obtained by traditional methods. For example, Barberis et al. (2016) adopt the stock's empirical distribution, and Barberis et al. (2021) employ generalized hyperbolic skewed t distribution. Both distributions reveal the pricing mechanism resulting from prospect theory.

In this paper, we posit that the aggregate investor preferences are in line with prospect theory first, then propose a simple and novel approach to estimate the expected value based on prospect theory in three steps. First, estimate the probabilities of extreme returns for each stock. The evaluation of the extreme gain (jackpot) and the extreme loss (crash) is critical to an individual's decision-making. Typically, investors can utilize the evaluation to speculate on a stock's return distribution. We propose a dynamic structure of a trinomial logit model of

[1] According to Baberis and Huang (2008), first-order stochastic dominance is necessary to market efficiency referenced to prospect theory.

panel data to measure the occurrences of extreme returns, which is an extension of Campbell et al. (2008), Conrad et al. (2014), Jang and Kang (2019), and Fang et al. (2022). With some differences from their approach, we define extreme return events as occurring at some point in time, rather than over some time period in the future. Because the original definition cannot be applied to compute return distribution. Second, generate ex-ante return distributions of stocks. The prediction information of the logit model can help us estimate the distribution parameters by using the ex-ante probability of price crashes (CRASHP) and the probability of price jackpots (JACKP). Then we implement a numerical grids algorithm to generate the return distributions of stocks. Third, calculate expected stock values according to prospect theory. The valuation is straightforward. We employ the classical formulation and parameters of Tversky and Kahneman (1992) for prospect theory.

In the application part, we investigate the relationship between predicted values based on prospect theory (PV) and the future cross-sectional returns of stocks. Intuitively, using ex-ante PV, the representative investor will choose stocks based solely on PV rank. Therefore, the representative investor would prefer stocks with higher average returns, lower standard deviations (due to loss aversion), and higher skewness (due to probability weighting). Primarily, we find a cross-sectional relationship between ex-ante PV and subsequent returns, that is, the higher the ex-ante PV, the greater the subsequent return. The zero-cost portfolio, buying the highest 10% and selling the lowest 10% of PV, earns statistically significant positive returns per month, even controlling risk factors of Fama and French (2015) and Carhart (1997). According to the equilibrium analysis based on prospect theory, there are trade-off relationships among return, standard deviation, and skewness. However, we don't find a clear trade-off relationship as predicted by Barberis and Huang (2008) and Barberis et al. (2016). Furthermore, our finding indicates that there is no equilibrium in line with prospect theory. Comparing the pricing effects, we find that the zero-cost portfolio based on

PV completely outperforms the zero-cost portfolios based on CRASHP and JACKP.

From the following five aspects, we further explore the potential mechanisms behind the relationship between PV and subsequent returns.

First, we examine the effect of firm characteristics on the cross-sectional returns associated with PV, which is closely related to the extensive literature on pricing anomalies.[2] Our results suggest that PV relates to several firms characteristics. When PV is increasing, JACKP is rising, but there is no clear trend of CRASHP. Companies with high PV keep high book-to-market, illiquidity, and skewness, but small size, low detrend turnover, and low institutional ownership. Our finding of the correlation between skewness and PV is opposite to Barberis et al. (2016). A possible reason is that their PV is an ex-post estimation based on history return. Notable, our evidence implies that ex-ante PV has strong predictive power on cross-sectional stock returns, even after controlling the company characteristics.

Second, to exploit the source of the PV pricing effect, we investigate state-dependent as previous literature by Stambaugh et al. (2012) and Jang and Kang (2019). The outcomes suggest that the cross-sectional returns based on PV are strong and robust regarding the market-wide sentiment and economic status, even if market liquidity has a significant impact on the PV effect.

Third, we examine the influences of arbitrage constraints by using company size, stock price, illiquidity, and institutional ownership related to Bhardwaj and Brooks (1992), Hong et al. (2000), Fama and French (2008), Nagel (2005), and Jang and Kang (2019). We find that the results of company size, stock price, and institutional ownership are mixed or not clear. A strong PV effect is observed in illiquid stocks rather than liquid stocks. Therefore, liquidity is critical to understand the cross-sectional mispricing associated with the PV effect.

Fourth, we further assess the effect of liquidity on PV by analyzing the performance of

[2] See, for example, French et al. 1987; Glosten et al. 1993; Fama and French, 1993; Fama and French, 1996; Gervais et al. 2001; Amihud, 2002; Bali et al., 2011; Conrad et al. 2013; Conrad et al., 2014; Jang and Kang, 2019.

portfolios classified by the ex-ante PV and residual of illiquidity. There is no straightforward relationship between liquidity and PV. The evidence suggests that liquidity-related mispricing is more prominent in highly liquid stocks. This is in line with Black (1986), Odean (1998), Liu (2015), and Shiller (2000) for arbitrage risk generated by bullish investor sentiment and noise trade. Conversely, low liquidity stocks have a more dramatic PV effect, which is expected of Shleifer and Vishny (1997) for high trading costs for trade obstacles. Though liquid stocks have an influential impact on the PV effect, the impact is limited rather than subversive. We can find the correlation coefficient between the average excess return and ex-ante PV is 0.677 (t-value=9.115) for whole portfolios.

Fifth, we inspect institutional investors' trading behavior and characteristics in sub-markets. The evidence suggests that institutional investors don't have a strong picking ability, and their trading isn't the determinate factor of the PV effect. There is an intriguing paradox for institutional investors. The rule-of-thumb based on prospect theory is valid in the sub-markets of the illiquid group, but not in the sub-market of the liquid group. However, institutions prefer stocks with high PV in the liquid group; nevertheless, they tend to use a passive trading strategy in the illiquid group. Interestingly, our results suggest high PV stocks earn a high subsequent return in the illiquid group. This is opposite to Barberis et al. (2016). Distinct return distribution estimations and non-equilibrium based on ex-ante PV may be the reasons for our fundamental disagreement. Comparing the results of the liquid and illiquid groups, the limits of arbitrage should be an important determinant of the PV effect.

The rest of this paper is organized as follows. In Section 2, we put forward a simple algorithm method of the ex-ante PV. In Section 3, we investigate the valuation based on prospect theory in the US equity market. We analyze the cross-sectional returns based on ex-ante PV and further explore the underlying mechanisms behind the relationship. We conclude in Section 4.

2. Algorithm Routine

The judgment of the representative investor with the risk attitudes according to prospect theory via two phases. In the first phase, assessing all stocks by using a variety of heuristics of prospect theory; in the second phase, investing in line with PV. The core issue is the appraisal of prospects and the valuation of expected distributions of stocks. In this section, we will clarify the overall idea and provide valuation supporting details.

2.1 General guidelines

An investor with risk preferences according to prospect theory makes decisions relying on two aspects, objective scenarios of risk assets and subjective willingness.

On the objective side, the investor needs to predict occurrences of various scenarios with existing information. Though the accuracy of forecasting is associated with artificial factors, it mainly depends on the technical merit of modeling. We emphasize the estimation of probabilities of extreme returns due to theoretical and empirical significance. According to Kahneman and Tversky (1979) and Tversky and Kahneman (1992), downside protection and upside desire with probability transformation for extreme scenarios is a valued and inherent part of the investor with risk attitudes in line with prospect theory. Empirical researches also indicate that the theoretical econometric model for cumulative response can catch the property of the ex-ante probabilities of extreme stock returns (Conrad et al., 2014; Jang and Kang, 2019). Based on the evaluation of the occurrences of extreme values, the representative investor can deduce or approximate the ex-ante stock distributions succinctly by using common assumptions.

From a subjective point of view, the investor evaluates the stock prospects with preferences according to prospect theory and the ex-ante stock distributions. The appraisal process is driven by an individual’s mental traits under uncertainty. Kahneman and Tversky (1979) abstract the psychological process as coding and editing by the value function and the probability weighting function.

In brief, to obtain PV, the routine consists of three steps, estimating probabilities of extreme returns, generating ex-ante stock distributions, and computing expected stock valuations.

2.2 Concrete procedure

2.2.1 Estimation of probabilities of extreme returns

Conrad et al. (2014) and Jang and Kang (2019) employ the logit specification to capture the extreme stock returns. The evidence shows the method has a satisfactory predictive ability. Conrad et al. (2014) adopt a binary logit model to predict jackpot probability. However, we employ a more general framework in line with Jang and Kang (2019), the trinomial logit model, to predict the ex-ante probability of extreme positive returns and extreme negative returns for individual stocks in one model. There are two potential reasons for our choice. Primarily, Jang and Kang (2019) indicate that the binary logit model might entangle the probabilities of extreme negative returns and extreme positive returns. Next, using the same model to estimate the probabilities of both extreme positive and negative returns, we can have a more reasonable residual distribution and avoid overfitting.

Our stellar estimates depend on the definition of extreme returns. Price crash events are associated with the impact of extremely low returns and the left tail of the return distribution. On the contrary, the jackpot event is strongly associated with extremely high returns and the right tail of a return distribution. Conrad et al. (2014) and Jang and Kang (2019) view a crash (or jackpot) as a stock price fall (or down) sharply over a period in the future. However, if we adopt the definitions, crash and jackpot events can be spotted on a single stock at the same time. In addition, the information about occurrences of returns over a time period cannot clearly describe the ex-ante stock return distribution. Therefore, our trinomial logit model defines extreme events as extreme returns at a point rather than during a time period. Then the model covers three events: extreme negative returns (crash) of $m = -1$, the stock's logarithm return is extremely lower than the percentage of q_C in the next L months; extreme positive returns (jackpot) of $m = 1$, the stock's logarithm return is extremely greater than the percentage of q_J in the next L months; and $m = 0$ is the rest situation of non-extreme return event.

Our explanatory variables selection of the model follows classical literature related to extreme return probability. The variables are related to factors of RM12 (past 12-month market return), EXRET12 (past individual return in excess of the market return), TVOL (total standard deviation), SKEW (total skewness), SIZE (firm capitalization), DTURN (detrended turnover), SALESG (sales growth), TANG (tangible assets), and AGE (company age). The detailed definitions of variables are in the appendix.

These factors are similar to Conrad et al. (2014) and Jang and Kang (2019). We consider EXRET12 because it can isolate future idiosyncratic skewness (Jang and Kang, 2019). Likewise, we follow Conrad et al. (2014) and Jang and Kang (2019) to adopt the term structure of 6-month/18-month for DTURN.

Let the log return $y_{i,t,L}$ as a ternary variable for $m = -1, 0, 1$, with the non-extreme return event as the reference group. Considering the event of extreme return with $m = \pm 1$, the logit model is:

$$\mathrm{Ln}\left(\frac{\mathrm{P}(y_{i,t,L} = m)}{\mathrm{P}(y_{i,t,L} = 0)}\right) = \beta_{0,m} + \sum_{i=1}^{N} \beta_{i,m} x_{i,t} \tag{1}$$

The probability of its occurrence in the next Lth month is:

$$\mathrm{P}(y_{i,t,L} = m) = \frac{\exp\left(\beta_{0,m} + \sum_{i=1}^{N} \beta_{i,m} x_{i,t}\right)}{1 + \sum_{j=-1,1} \exp\left(\beta_{0,j} + \sum_{i=1}^{N} \beta_{i,j} x_{i,t}\right)} \tag{2}$$

In application, we adopt history data to fit the model and obtain parameters $\hat{\beta}_{i,m}$ at time

$t+L$. Then we use the estimated parameters to compute out-sample probabilities of crash and jackpot for stock i at time $t+K\,(K \geq L)$, which is:

$$\hat{\mathrm{P}}(y_{i,t+K,L}=m)=\frac{\exp\left(\hat{\beta}_{0,m}x_{i,t+K}+\sum_{i=1}^{N}\hat{\beta}_{i,m}x_{i,t+K}\right)}{1+\sum_{j=-1,1}\exp\left(\hat{\beta}_{0,j}x_{i,t+K}+\sum_{i=1}^{N}\hat{\beta}_{i,j}x_{i,t+K}\right)} \tag{3}$$

2.2.2 Generation of ex-ante stock distributions

We suppose that the stock's log return $r_{i,t+K,L}$ follows normal distribution $N(\mu_i,\sigma_i^2)$, where μ_i and σ_i are the mean and standard deviation of the log return. It means that the simple return of the stock i abides by log normal distribution. Additionally, after estimation of probabilities of extreme returns, we have $\hat{\mathrm{P}}(y_{i,t+K,L}=m)$, where $m=-1,1$ for crash and jackpot with the logarithm return lower than the percentage of q_C and greater than the percentage of q_J, respectively. According to properties of normal distribution, it is easy to obtain that $\hat{\mu}_i=\dfrac{d_C q_J - d_J q_C}{100(d_C+d_J)}$ and $\hat{\sigma}_i=\dfrac{-q_C-q_J}{100(d_C+d_J)}$, where d_P is the p-th quantile of the standard normal distribution and $C=\hat{\mathrm{P}}(y_{i,t+K,L}=-1)$ and $J=\hat{\mathrm{P}}(y_{i,t+K,L}=1)$.

In application, we consider simple return R_i of stock i for later the assessment of prospects using prospect theory. Because the carriers of value in prospect theory are loss and gain. The domain of simple return $1+R_i$ of stock i is $[0,M]$, and employ a regular grid $R_{i,h}$, $h=0,1,\ldots,H$ with mesh size Δ, $H\in N$ to approximate the ex-ante stock distribution. Transform simple return $R_{i,h}$ into log return $\mathrm{Ln}(R_{i,h}+1)$. It is easy to produce the return distribution of stock i from estimated parameters $\hat{\mu}_i$ and $\hat{\sigma}_i$.

2.2.3 Computation of expected stock valuations

Armed with the information about the estimated distribution, the investor with the preferences according to prospect theory would evaluate the prospects in the light of his subjective psychological response. We assume that the investor's assessment complies with the refined version of prospect theory, known as cumulative prospect theory, which is proposed by Tversky and Kahneman (1992). This revised version incorporates all essential insights and extends the validity of the original theory described by Kahneman and Tversky (1979).[3] Following is the valuation according to the refined version.

We re-label $R_{i,h}(h=0,1,...,H)$ as $\tilde{R}_{i,h}(h=-H_N,...,-1,0,1,...,H_P)$ for gains and losses, where $H_P+H_N=H$ and $\tilde{R}_{i,0}=0$, without changing the sequence order. With the ex-ante distribution, we calculate the probability of $P_{i,h}$ for $\tilde{R}_{i,h}$. Then the prospect of stock i can be viewed as a gamble:

$$(\tilde{R}_{i,-H_N}, P_{i,H_N}; ...; \tilde{R}_{i,-1}, P_{i,-1}; \tilde{R}_{i,0}, P_{i,0}; \tilde{R}_{i,1}, P_{i,1}; ...; \tilde{R}_{i,-H_P}, P_{i,H_P}) \tag{4}$$

Our predictions of stock distribution adopt raw returns. Therefore, the $R_{i,h}$ for gains and losses is based on raw return. We also can construct gains and losses by using returns in excess of the risk-free rate, or returns in excess of the market return. Fortunately, Barberis et al. (2016) show that the finding of prospect theory is robust to different choices of gains and losses.

An investor with risk attitudes of Tversky and Kahneman (1992) assesses the gamble as the value of

$$V_i = \sum\nolimits_{h=-H_N}^{H_P} \pi_h v(\tilde{R}_{i,h}) \tag{5}$$

where

$$\pi_h = \begin{cases} w^+(p_h+...+p_{H_P}) - w^+(p_{h+1}+...+p_{H_P}), & 0 \le h \le H_P; \\ w^-(p_{-H_N}+...+p_h) - w^-(p_{-H_N}+...+p_{h-1}), & -H_N \le h < 0 \end{cases} \tag{6}$$

and where $v(.)$ is known as the value function, and $w^+(.)$ and $w^-(.)$ are used as the

[3] Barberis (2013) stress that prospect theory of Kahneman and Tversky (1979) has two limitations: it can be applied to gambles with at most two nonzero outcomes, and it predicts that people will sometimes choose dominated gambles.

probability weighting functions, respectively. Their functional forms are

$$v(\tilde{R}_{i,h}) = \begin{cases} \tilde{R}_{i,h}^{\alpha}, & \tilde{R}_{i,h} \geq 0; \\ \lambda(-\tilde{R}_{i,h})^{\beta}, & \tilde{R}_{i,h} \leq 0 \end{cases} \tag{7}$$

and

$$w^{+}(p) = \frac{p^{\gamma+}}{(p^{\gamma+} + (1-p)^{\gamma+})^{1/\gamma+}}, \quad w^{-}(p) = \frac{p^{\gamma-}}{(p^{\gamma-} + (1-p)^{\gamma-})^{1/\gamma-}} \tag{8}$$

where $\alpha, \beta, \gamma+, \gamma- \in (0,1)$ and $\lambda > 1$.

The above process of valuation is quite different from the traditional expected utility. The latter provides a simple way to assess prospects by combining objective probabilities of gain or loss levels and risk aversion degrees. However, the former involves several inventive and vital phenomena of subjective mental state for decision-making under uncertainty. Primarily, the valuation based on prospect theory is derived from gains and losses, measured relative to a reference point, rather than wealth level as the expected utility. Moreover, while the expected utility is globally differentiable, the value function is kinked at the intersection of gains and losses. More importantly, the investor with the preferences according to prospect theory has distinctive risk appetites of concavity/convexity (CC) on gains and losses, loss aversion (LA), and probability distortion (PW).

The value function includes the ingredients of CC and LA. From $\alpha, \beta \in (0,1)$, we find that the CC of the investor in line with prospect theory is S type, which implies the property of local risk-seeking, that is, risk aversion (concavity) for gains and risk seeking (convexity) for losses. Meanwhile, the risk attitudes with the expected utility are risk aversion (concavity) everywhere. The degree of LA is governed by $\lambda > 1$. This reflects the general tendency of individual psychology that we prefer avoiding losses to making equal gains.

PW is implied by $\gamma+$ and $\gamma-$ of the probability weighting function. The weighting function allows having distinct magnitudes of probability distortion in gains and losses. It can capture a prominent subjective trait that an individual's decision-making does not fully follow objective probabilities, but focus more on the extreme cases by overweighting the tails of any return distribution.

3. Application

We investigate the valuation based on prospect theory in the US equity market in this section.

3.1 Data

We select the monthly and daily stock data from the Center for Research in Security Prices (CRSP) database over the period June 1952 through December 2020. Our sample includes NYSE, AMEX, and NASDAQ common stocks with CRSP share codes 10 and 11, excluding stocks with month-end prices below $5 per share. We obtain accounting variables for various firm characteristics from Compustat annual data and match annual accounting data at the end of year t-1 with monthly CRSP data from June of year t to May of year t+1. The sample is from January 1972 to December 2020. We also collect all institutional ownership data from the Thomson Reuters Institutional (13F) Holdings database, which begins in the first quarter of 1980. So the analysis associated with accounting data is confined to the period after 1980.

3.2 Estimation of logit model

This section adopts a logit model to estimate extreme probabilities of both crash and jackpot events.

3.2.1 Definitions of extreme events

While Conrad et al. (2014) focus on jackpot and Jang and Kang (2019) pay attention to crash, our analysis examines both crash and jackpot events. Our cutoffs of extreme events follow Jang and Kang (2019). Meanwhile, distinct from Conrad et al. (2014) and Jang and Kang (2019), we specify our events as the occurrences of price fluctuation at a point rather than overtime periods. Therefore, a price crash $(m=-1)$ is defined as logarithmic returns declines by 70% $(q_C = 70)$ in the next 12 months $(L = 12)$, which amounts to a 50% drop in the capital gains. Analogously, a jackpot return $(m = 1)$ is defined as a logarithmic yield climbs by 70% $(q_J = 70)$ in the next 12 months $(L = 12)$. The loss corresponds approximately to a 100% increase in capital gains.

3.2.2 Parameter estimates

[Insert Table 1 Here]

Table 1 reports the parameter estimates for predicting extreme stock returns. The z-statistics based on the standard error are calculated. The results show that most variables are significant at the 1% statistical level apart from DTURN and TANG of the crash. In the multinomial logit model, the coefficient doesn't capture the variable's marginal effect. Therefore, we also report the percentage change in the odds ratio for a 1σ change (PCO) in the variable. TVOL acts an essential role in probability predicting. Because PCO means that the biggest consequence of a crash (or jackpot) comes from TVOL. AGE, SIZE, and RM12 also play important parts in predicting the probability of extreme return, whose PCO is greater than 10% for crash or jackpot. Comparing models of crash and jackpot, we find the signs of RM12 and EXRET12 are opposite. Crashes are more likely to occur when EXRET12 is down, but RM12 is up. Conversely, jackpots become more likely as RM12 decreases, but EXRET12 increases.

3.2.3 Predictive accuracy and validity

To explore the reliability and predictive power of our trinomial logit models, we adopt a rolling window procedure to re-estimate the model and generate out-of-sample predicted crash probabilities and jackpot probabilities. Then we use the accuracy ratio proposed by Moody, following the definition used by Vassalou and Xing (2004) to evaluate the validity of our model's predictions. The ratio evaluates the ability of the model to predict actual crashes or jackpots in the next six months. The ratio range is [-1,1]. The zero information model has an accuracy ratio of zero. If the model has the predictive ability, the ratio would be greater than zero. The perfect model has an accuracy ratio of one.

Following Conrad et al. (2014), we re-estimate the model using all available data (expanding annual rolling windows), and then we use each set of estimated parameters for t to calculate out-of-sample predictions of the probabilities of crash and jackpot of t+12. Then, the out-of-sample predictors are not observed until the period of extreme future returns is measured. The first out-of-sample forecasts are in November 1971, and the last out-of-sample predictions are in December 2020. The model achieves accuracy ratios of 0.503 on crash and 0.378 on jackpot. The predictive accuracy of the jackpot is lower than that of the crash. Because the extreme events in the right tail of return distribution are harder to detect (Conrad et al., 2014), and the majority of cross-sectional anomalies are caused by the underperformance of securities classified as relatively overvalued (Nagel, 2005; Stambaugh et al. 2012; Avramov et al. 2013).

3.3 Cross-section of stock returns for values based on prospect theory

In this section, we compute the ex-ante PV of stocks and clarify the relationship between predicted PV. Our calculation of ex-ante PV is based on out-of-sample parameters of the logit model for extreme returns, and the algorithm follows the procedure in section 2. To ensure accurate estimates, we choose $\Delta = 0.01$ and $M = 12$ to generate distribution estimates. For the parameters of prospect theory, we adopt Tversky and Kahneman (1992), that is,

$$\alpha = 0.88, \beta = 0.88, \ \gamma + = 0.61, \ \gamma - = 0.69, \text{ and } \ \lambda = 2.25$$

Though these parameters are based on a small number of participants, they are widely used in financial market (Barberis et al. 2016). We also employ the parameters from an extensive survey on risk attitudes of Rieger et al. (2017) and Barberis et al. (2021). The results are similar to those obtained by Tversky and Kahneman (1992), and there is no material impact.

We divide all stocks into ten groups and form deciles P01 to P10 in ascending order of PV at the end of month t. The weighting methods include value-weighted (VW) and equal-weighted (EW). PV is predicted by using the procedure above. Portfolios are rebalanced every month. To account for the effect of short-term reversals, we compute the monthly portfolio returns for each decile realized at month t+2 as Conrad et al. (2014) and Jang and Kang (2019). The out-of-sample returns begin in January 1972 and end in December 2020.

3.3.1 Descriptive statistics

[Insert Table 2 Here]

Table 2 presents descriptive statistics for the returns of VW and EW portfolios sorted by the ex-ante CRASHP and JACKP, and PV. At the end of month t, we sort portfolios according to CRASHP, JACKP, or PV in ascending order. The average excess return relative to the risk-free rate, standard deviation (Std), skewness, and Sharpe ratio are reported. The portfolios of panels A, B, and C are grouped by the ex-ante CRASHP, JACKP, and PV, respectively. C01-C10, J01-J10, and P01-P10 are decile portfolios. Column C01 (J01 or P01) presents the results for the bottom 10% portfolio of CRASHP (JACKP or PV). Column C10 (J10 or P10) provides the results for the top 10% portfolio of CRASHP (JACKP or PV). Column DC10 (DJ10 or DP10) exhibits the results for the zero-cost portfolio buying the highest 10% and selling the lowest 10% of CRASHP (JACKP or PV).

An investor with risk attitudes of prospect theory will make heuristic decisions relying on the order of the ex-ante PV. The stocks with higher returns, lower standard deviation, and higher skewness are priorities. Nonetheless, there are possible trade-off relationships among return, standard deviation, and skewness driven by the market equilibrium mechanism. Barberis et al. (2001) and Levy and Levy (2004) suggest that when diversification between stocks is allowed, the mean-variance and prospect theory efficient sets are nearly identical. Barberis et al. (2008) further imply that positive skewness earns a lower risk premium. The simulation of Barberis et al. (2021) shows, in equilibrium, there is a perfectly positive correlation between return and standard deviation, and negative correlations between return and skewness and between standard deviation and skewness. Our results show a trend that higher ex-ante PV corresponds to higher average returns. But the pattern of our results doesn't suggest trade-off relationships of classical equilibrium theories, which involve higher average return with higher standard deviation illustrated by Barberis et al. (2001) and Levy and Levy (2004), and higher Sharper ratio with lower skewness predicted by Barberis and Huang (2008) and Barberis et al. (2021). Figure 1 plots scatterplots of VW and EW portfolios classified by ex-ante PV, suggesting an instant judgment. Therefore, a possible reason for the cross-sectional anomaly of ex-ante PV is that the imperfect equilibrium mechanism in the US equity market. The research in the following sections will further explore the drivers of asset pricing, that is, the equilibrium force or the thumb rule of investors.

Additionally, our evidence is different from Barberis et al. (2016). They find equity with a higher PV value earns a low subsequent return. Their computation is substantially different from ours. They use history return distribution to calculate PV, which can be viewed as ex-post PV.

Monthly average returns based on the predicted probability of a crash tend to decrease, but monthly average returns based on the predicted probability of a jackpot have a tendency to increase. The pattern of changes in portfolio returns based on the extreme probability of jackpot is also opposite of that of Conrad et al. (2014). Among all portfolios of C01-C10, J01-J10, and P01-P10, for the VW portfolios, portfolio C10 has the lowest monthly return (=0.17%) for concentrating on the biggest crash, and portfolio J10 gets the highest monthly return (=1.03%) for focusing on the biggest jackpot. However, for EW portfolios, portfolio P01 and P10 gain the lowest monthly return (=0.03%) and the highest monthly return (=1.10%), respectively.

Remarkably, the discernability of PV is the most outstanding. Compared with DC10 and DJ10, the corresponding monthly absolute return of DP10 of VW or EW is increased by at least 58.1%. Any excess return of DC10 and DJ10 is not statistically significant, but both VW and EW portfolios of DP10 are significant at the 1% statistical level. Furthermore, the Sharpe ratio of DP10 also improved dramatically. For example, the monthly absolute return of EW DP10 is 1.06%, which is more than 200% of that of DC10 (or DJ10); the Sharpe ratio of EW DP10 is 0.23, but that of DC10 is only -0.08 (or that of DJ10 is 0.07). It is only that the skewness of EW DP10 (=0.47) is lower than that of EW DJ10 (=0.88).

3.3.2 Adjusted return with risk factors

We examine the excess returns using the five-factors model (FF5) proposed by Fama and French (2015) to control risk factors. The model improves the description of a cross-section of stock returns based on the three-factor model developed by Fama and French (1993). To account for the momentum effect on asset pricing, we also adopt FF6, an augmented form of FF5 by adding the factor of Carhart (1997), to investigate the excess returns.

[Insert Table 3 Here]

Table 3 presents the average of excess return relative to the market return and the risk-adjusted alpha on VW and EW portfolios sorted by the ex-ante PV.

Regarding VW portfolios, conspicuous monotonic increasing trends can be found in both the excess returns and alphas from P01 to P10. The findings of EW portfolios are observed in a similar way to those of VW portfolios. For long-short portfolios, the performance of DP10 based on prospect theory is statistically significant at 1% level. Any t-value of alphas of DP10 is greater than 3, which is the critical value recommended by Harvey et al. (2016). The strong evidence suggests that there are positive excess returns even after controlling for conventional risk factors.

[Insert Figure 2 Here]

Figure 2 plots the loadings on the factor of the excess market return (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profitability factor (RMW), and the momentum factor (UMD) for value-weighted portfolios from January 1972 to December 2020. The portfolios are sorted by CRASHP, JACKP, and PV.

The loadings on MKT (or SMB) of portfolios sorted by CRASHP are gradually increasing with rising CRASHP. The portfolios sorted by JACKP or PV display similar variations in the factor loading on MKT (or SMB) as those of CRASHP. These suggest that the prevalence of high market beta and small-size firms are in the greatest CRASHP (JACKP or PV) portfolio of C10 (J10 or P10).

The loadings on HML (CMA or RMW) of portfolios sorted by CRASHP show a declining trend as CRASHP increases. The behaviors of the loadings on HML (CMA or RMW) of portfolios sorted by JACKP and the loadings on RMW of portfolios sorted by PV are in a like manner. These reflect that the greatest CRASHP (JACKP) portfolio of C10 (or J10) is largely comprised of stocks with low HML, small CMA, and low RMW, and the largest PV portfolio of P10 has low RMW stocks.

The loadings on HML (or CMA) of portfolios sorted by PV have no tendency.

Additionally, the loadings on UMD of portfolios sorted by CRASHP (JACKP or PV) also do not exhibit a clear trend. Therefore, compared with FF5, FF6 does not provide a significant and distinct improvement in its ability to explain the cross-sectional market anomalies related to PV in table 3.

In general, the significant anomalies after controlling the risk factors further stimulate us to analyze the imperfections of market efficiency.

3.3.3 Illustration of equilibrium

This section illustrates market efficiency related to the effect of PV on asset pricing in a straightforward way from the perspective of equilibrium. Using the parameterized model of prospect theory, we plot the ex-post PV of portfolios constructed by the market portfolio and the EW long-short portfolio of DP10 in figure 3. We allocate 100% weight to the market portfolio and $\lambda \times 100\%$ weight to the EW long-short portfolio of DP10.

[Insert Figure 3 Here]

The relationship between PV and λ shows a single peak shape. As we decrease the allocation to DP10 from zero, the ex-post PV declines. Meanwhile, when we increase the allocation to DP10 from zero, the ex-post PV rises first and then falls. The ex-post PV of the combination is the highest (=-0.018) when the weight of DP10 is 90%. We find that stocks with extremely high ex-ante PV are overpriced, but stocks with extremely low ex-ante PV are underpriced. These suggest that there exists no homogeneous holdings equilibrium or heterogeneous holdings equilibrium for our given parameter values. Therefore, we cannot find perfect trade-off relationships described by Barberis et al. (2001), Levy and Levy (2004), Barberis and Huang (2008) and Barberis et al. (2021).

Obviously, the market efficiency analysis will be affected by parameter values. Based on the extensive survey of risk attitudes by Rieger et al. (2017), we specify parameter ranges with 95% confidence intervals. Then examine market efficiency by using the grid search method. We are unable to find market efficiency with any set of parameters in our range. Those indicate there is no market equilibrium with normal parameters. The findings are consistent with Kopa and Post (2009), who conclude no nonsatiable investor would hold the market portfolio for violation of the concept of first-order stochastic dominance optimality.

3.4 Mechanism and source

We find a cross-sectional relationship between PV and subsequent returns. This section further explores the underlying mechanisms behind the relationship and discusses the source of the PV-induced cross-sectional gain.

3.5.1 Firm characteristics

The cross-section of equity returns is associated with various firm characteristics, which are closely related to pricing anomalies. Therefore, we inspect the effect of firm characteristics on the cross-sectional returns associated with PV.

[Insert Table 4 Here]

Table 4 provides firm characteristics and variables related to VW portfolios P01 to P10 sorted by PV. These include PV, CRASHP, JACKP, TVOL, SKEW, maximum (MAX) and minimum (MIN) daily returns in month t, the price per share (PRC), SIZE, the book-to-market ratio (BM), DTURN, illiquidity (ILLIQ), and institutional ownership (IO). Same as to Jang and Kang (2019), we also separate variables for three sets, but with some different variables. The sample period is from November 1971 to October 2020.

In the first set, we have variables related to TVOL, SKEW, MAX, MIN, CRASHP, and JACKP. When PV increases monotonically, JACKP is similar to its trend. Meanwhile, the relationship between PV and CRASHP is not clear. The trend of SKEW is also monotonically increasing with rising of PV. Barberis et al. (2016) find that stocks with high afterward skewness earn lower excess returns. However, our results associated with SKEW are opposite to those of Barberis et al. (2016). Possible reasons are: first, their PV is ex-post estimation rather than ex-ante estimation; second, portfolios constructed on ex-ante PV don't be driven by an equilibrium mechanism. Although the TVOL of P01 (=0.032) is less than that of P10 (=0.037), there is no obvious trend of TVOl when PV increases, and the lowest value of TVOL (=0.024) is at P05. As the PV increases, MAX and MIN also don't show any trend with the variation of PV.

In the second set, we only choose PRC and IO as traditional measures of limits to arbitrage. Interestingly, our results show that stocks with higher PV maintain lower PRC and lower IO. The evidence is supported by existing documents. For example, Nagel (2005) and Lewellen (2011) find that firms with low IO earn a higher return.

In the last set, we have SIZE, BM, DTURN, and ILLIQ, also known as cross-sectional stock return determinants (Jang and Kang, 2019). Table 4 illustrates that companies with high PV have high BM, small SIZE, low DTURN, and high ILLIQ. Interestingly, Conrad et al. (2014) show stocks with higher JACKP are smaller SIZE. The relationship between JACKP and PV indicate our finding of company size is consistent with Conrad et al. (2014).

The relationships among CRASHP, JACKP, and PV indicate that our finding of company size is consistent with Conrad et al. (2014), but are opposite to Jang and Kang (2019).

The results in table 4 confirm that PV is strongly associated with various firm characteristics. Then, an interesting question is whether PV can forecast the cross-section of stock returns even after controlling for firm characteristics. We orthogonalize PV with each firm characteristic and construct portfolios sorted by the orthogonalized residuals. If PV, compared to the firm characteristics, contains additional information for predicting future returns, the orthogonalized residuals can still predict returns. Additionally, the orthogonal residuals based on the cross-sectional regression can dissipate the effect caused by state dependencies. At the end of each month t, the orthogonalized residuals of PV are generated from the cross-sectional regression of PV on each of the firm characteristics, then decile portfolios are constructed by sorting stocks based on the residuals. We build both VW and EW portfolios, and also calculate monthly returns on each portfolio in month t+2. P01 and P10 are the bottom 10% and top 10% of the residual of PV, while DP10 is a zero-cost portfolio, buying P10 and selling P01.

[Insert Table 5 Here]

Table 5 shows the risk-adjusted returns sorted by the orthogonalized residual of PV to various firm characteristics. It reports alpha estimations and t-values of two types of factor models, FF5 and FF6, for two weighted methods of P01, P10, and DP10. In all cases, after controlling for company traits, the alpha of P10 is greater than P01, while the alpha of DP10 is greater than 0. Furthermore, any alpha is significant at least at the 5% statistical level. These results provide strong evidence that the PV residual is orthogonal to firm characteristics keeping predictive power for asset returns, and we are able to use this residual to generate a cross-sectional significant excess return. Controlling for company characteristics does not appear to fundamentally eliminate PV's predictive power and portfolio anomaly.

The findings of table 4 and table 5 prompt us to explore the mechanism of anomaly formation from other perspectives.

3.5.2 Effect across different sub-periods

To investigate whether the pricing effect resulting from PV is state dependent as in previous literature, we examine the cross-sectional returns of portfolios based on PV with variations in market-wide sentiment and economic status. It allows us to understand whether this pricing effect stems from various states. Furthermore, it also gives us a clear picture of whether this pricing effect is robust.

To differentiate the states of investor sentiment, our investigation adopts the monthly market-wide sentiment index (MSI) constructed by Baker and Wurgler (2006), which considers pervasive irrational speculation and binding arbitrage constraints in the US equity market. For economic status, we use market return over the past 24 months (RM24), the National Bureau of Economic Research recession indicator (NRI), and the liquidity innovation (LII) introduced by Pastor and Stambaugh (2003). We obtained investor sentiment data MSI from the Department of Finance(https://pages.stern.nyu.edu/~jwurgler/) and NRI from Federal Reserve Economic Data (https://fred.stlouisfed.org).

Based on MSI, RM24, NRI, and LII, we categorize each month into high- and low-sentiment periods, Up- and Down- market periods, expansion and recession periods, and high- and low-liquidity periods, respectively. High- and low-sentiment periods are classified by the median of MSI. Up- and Down-market periods, expansion and recession periods, and high- and low-liquidity periods are sorted by the signs of RM24, NRI, and LII, respectively. The sentiment index of MSI is from January 1972 to December 2018, and the rest of the sample period is from January 1972 to December 2020.

The multi-factor models are used to obtain the risk-adjusted average return rate for each sub-period as following:

$$R_t - R_f = \alpha_1 D_{1,t-1} + \alpha_2 D_{2,t-1} + \sum_{i=1}^{K} \beta_i f_i + \varepsilon_t \tag{9}$$

In equation (9), $D_{1,t-1}$ and $D_{2,t-1}$ are two dummy variables, which represent two different sub-periods in month t-1, respectively; f_i involves asset pricing factors.

[Insert Table 6 Here]

Table 6 shows the average risk-adjusted returns categorized by PV for both VW and EW portfolios over diffident sub-periods.

In panel A, regardless of the VW portfolios, alphas of P01 are significant at least at the 5% statistical level for FF5 and FF6 during high-sentiment periods, but those are not statistically significant during low-sentiment periods. A similar pattern is also observed in the portfolio of VW P10. The alpha of the VW DP10 (=0.84) is positively significant for FF5 at the 5% statistical level. The t-value of that for FF6 is 1.94, which exceeds the critical value at the 10% statistical level. For the EW portfolios, all of the alphas of P01, P10, and DP10 are significant at the 1% statistical level, and the alphas of DP10 are positive. Although alphas of the VW or EW portfolios are more significant during high-sentiment periods, the difference in distinct sentiment states is not statistically significant based on any pricing factors of FF5 or FF6, which is not consistent with Stambaugh et al. (2012).[4] Stambaugh et al. (2012) investigate extensive cross-sectional anomalies and find serious mispricing in a high-sentiment

[4] Stambaugh et al. (2012) find the broad set of cross-sectional anomalies reflects market-wide sentiment-driven mispricing, at least partially.

environment. Our findings indicate that PV effects on mispricing are robust across different sentiment periods. Though there are variations in prospect theory value effects on various sentiment periods, market-wide sentiment is not the determining factor in this pricing bias. Other factors rather than market-wide sentiment substantially drive the prospect theory value effect of the cross-section of stock returns.

Similarly, when we focus on economic status following up- and down- market periods or expansion and recession periods, the results of panel B and C also suggest that prospect theory value effects are strong across economic status and independent of changes in economic status, while the vast majority of differences in the distinct sub-periods are not statistically significant. These also rule out that the cross-sectional returns based on prospect theory value effects are driven by Up- and Down- market state or economic trends.

During high-liquidity periods, the alphas of P01, P10, and DP10 are all statistically significant at the 1% level, and mispricing is more severe. Furthermore, the differences in returns of the long-short portfolio of DP10 between high- and low-liquidity periods are greater than zero. All of those differences but the difference associated with VW DP10 for FF6 are significant at least at the 5% statistical level. Therefore, PV effects are stronger during high-liquidity periods. However, all alphas of DP10 are statistically significant at the 1% level during both low- and high-liquidity periods. It can be seen that market liquidity will affect the mispricing of the PV effect to a certain extent, but there are other factors at the root of the PV effect.

Overall, the evidence implies that the cross-sectional returns based on PV are strong and robust relative to the market-wide sentiment and economic status, even if market liquidity significantly affects the PV effect.

3.5.3 Limits to arbitrage

The literature proposes that stock performance is related to arbitrage behavior. The section investigates the impact of arbitrage constraints on cross-sectional stock returns associated with PV. Four variables are adopted as measurements of arbitrage restrictions: company size (SIZE), price (PRC), illiquidity (ILLIQ), and institutional ownership (IO). The first three of them are common indicators as trading costs in previous researches. Stocks with smaller size, lower price, or higher illiquid are typically more expensive (Bhardwaj and Brooks, 1992; Jang and Kang, 2019; Hong et al., 2000; Fama and French, 2008). The indicator ILLIQ is the inverse measurement of liquidity level. The larger the ILLIQ, the less liquidity it is. Stocks with higher IO are easier to short and have lower short-selling limits (Nagel, 2005).

To separate the impact of company size on limits of arbitrage, we regress the log of PRC, the log of ILLIQ, and the log of IO on the variables of SIZE and squared SIZE in the cross-section, and get the residuals of price (RPRC), liquidity (RILLIQ), and institutional ownership (RIO), respectively.

We classify stocks by decile of SIZE, RPRC, RILLIQ, and RIO at the end of month t, respectively. The bottom 10% stocks with the smallest SIZE, the lowest RPRC, the highest RILLIQ, and the lowest RIO are categorized into the group of small size, low price, illiquid, and low institutional ownership, respectively. According to classical literature, these groups are high limits-to-arbitrage groups. Correspondingly, the top 10% stocks with the largest SIZE, the highest RPRC, the lowest RILLIQ, and the highest RIO are sorted into the group of big size, high price, liquid, and high institutional ownership, respectively. These groups can be viewed as low limits to arbitrage groups. Then, within each of the eight groups, decile VW or EW portfolios are constructed by classifying stocks based on PV.

[Insert Table 7 Here]

Table 7 reports the average excess returns relative to the risk-free rate and alphas estimated by extensive factor models of the zero-cost portfolios buying the highest and selling the lowest PV for subgroups divided by arbitrage constraint, and the difference in alphas between the high and low limits-to-arbitrage groups.

Though the average excess returns on the zero-cost portfolios constructed by small firms are significant for both VW and EW methods, there is no consistent evidence for those portfolios for large enterprises. The excess return of the zero-cost EW portfolio with large enterprises is insignificant. Furthermore, the alpha difference and excess return of the zero-cost EW portfolio between large and small size groups is significant at the 1% statistical level, while the t-value of the excess return of the zero-cost VW portfolio is only 0.55, which is not significant.

Consistent with the statistically significant of alpha, the PV effect can be found in low-price stocks, but not in high-price stocks. The PV effect is sensitive to weighting method of the portfolio. Only EW portfolios with high-price stocks yield significant excess return and alphas. Moreover, there is no strong and robust evidence that the differences in excess returns between low- and high-price groups are insignificant for both VW and EW portfolios, which have opposite signs.

From the results based on the illiquidity measure adjusted for firm size, we are surprised to find that all excess returns and the alphas of VW and EW for the illiquid stocks group are significant at the 1% statistical level, while those of liquid stocks are insignificant. More importantly, the differences between the illiquid and liquid groups are statistically significantly positive, which is consistent with almost all existing literature (Stambaugh et al., 2015; Han et al., 2022). The stronger and more robust evidence suggests that illiquidity has a fundamental impact on the PV effect of mispricing. Theoretically, the more liquid the stock, the less arbitrage constraint it has. This also prompts us to further explore investors' trading behavior and emphasizes the importance of analyzing the role of arbitrage from the perspective of liquidity.

The results associated with the IO factor are mixed. For VW portfolios of low- and high-IO, the excess returns and differences of the zero-cost portfolios are not significant. The results of EW portfolios indicate that the low-IO portfolios achieve higher returns than the high-IO portfolio, and the difference between the low- and high-IO groups is significant.

The above findings suggest that illiquidity is crucial to cross-sectional mispricing related to the PV effect. As Shleifer and Vishny (1997), high illiquidity implies a high trading cost for trade obstacles. In the meantime, Odean (1998) and Liu (2015) find high liquidity with bullish investor sentiment. Though there are few trade barriers, Black (1986) and Shiller (2000) deem that bullish investor sentiment affects liquidity through noise traders and irrational market makers, which also create arbitrage risk.

3.5.4 PV with liquidity

To further assess the effect of liquidity on PV, we analyze the performance of EW portfolios classified by the ex-ante PV and RILLIQ. At the end of month t, we sort decile portfolios based on RILLIQ. We classify stocks contained in the lowest 10% RILLIQ decile as the highest liquid group, and stocks contained in the highest 10% RILLIQ decile as the lowest liquid group. Then, within each of the ten groups, decile portfolios are constructed by classifying stocks based on PV, and the monthly returns of EW portfolios are calculated in month t+2.

Table 8 exhibits excess returns and alphas on the 10×10 EW portfolios. Column Low presents the results for the portfolio at the bottom 10% of PV sorted by liquidity. Column High provides the results for the portfolio at the top 10% of PV sorted by liquidity. Column High-Low presents the results for the long-short portfolio that long the highest 10% PV stocks and short the lowest 10% PV stocks sorted by liquidity. The table also provides the results of decile portfolios sorted by liquidity in column All. Row Low presents the results for the portfolio at the highest 10% RILLIQ. Row High provides the results for the portfolio at the lowest 10% RILLIQ. The out-of-sample returns begin in March 1980 and end in

December 2020. The average excess return (mean) relative to the risk-free rate and alphas of FF6 are reported.

[Insert Table 8 Here]

Column All shows the monotonically increasing trend of excess return and alpha of FF6 with increasing liquidity. Decile 6 to high portfolios of liquidity have significantly positive alphas, which are in line with Black (1986) and Shiller (2000). If we view RILLIQ as a proxy of trading volume, the finding also is consistent with the volume amplification effect of Han et al. (2022). A possible reason for this phenomenon is that noise trading and investor sentiment result in great risk premiums as De Long et al. (1990a). Though alphas of decile 2 to 5 portfolios of liquidity are not significant, the alpha of the low liquidity portfolio is 0.18 which is significant at the 5% statistical level.

The results of the 10×10 EW portfolios show that there is no direct relationship between PV and liquidity. For the highest 20% liquidity stocks, the excess return and alpha of the zero-cost portfolio, buying the highest 10% and selling the lowest 10% of values based on PV, are not significant at the 5% statistical level, but those of other zero-cost portfolios of low liquidity stocks are significant. Strikingly, the zero-cost portfolio of the lowest 10% liquidity stocks earns a 1.27% return per month. This means that the PV effect is not observed in extremely highly liquid stocks, but exists in all other stocks. This is the same as the prediction of Shleifer and Vishny (1997) that the limits of arbitrage lead to the mispricing of low liquid stocks. And the excess returns and alphas of the highest 20% long-short portfolio based on PV and liquidity are the lowest compared with the rest of the portfolios, which also shows that no PV effect can be observed under high liquidity. High liquidity stocks have fewer trading restrictions and have no significant PV effect. Conversely, low liquidity stocks are with more limit of arbitrage for trading barriers and have a significant PV effect. It is interesting that alphas of Decile 2 to 5 portfolios of liquidity are not significant. Therefore, the arbitrage limits of trading constraints generate a stronger mispricing effect on PV rather than liquidity.

To further understand the cross-sectional stock returns associated with ex-ante PV, we analyze relationships between ex-ante PV and excess return to explore the impact of liquidity. According to table 8, the PV effect exists in stocks with the highest RILLIQ of 80%, but doesn't in stocks with the lowest RILLIQ of 20%. Then, we investigate the impact on stocks with the lowest RILLIQ of 20%. Using 10×10 EW portfolios classified by the ex-ante values based on PV and RILLIQ, figure 4 plots a scatterplot of the average excess return and ex-ante PV. Part (a) is for all 10×10 EW portfolios, and part (b) is for 8×10 EW portfolios excluding the lowest 20% RILLIQ portfolios.

[Insert Figure 4 Here]

The graph of part (b) of figure 4 exhibits a high linear correlation between the average excess return and ex-ante PV in those portfolios constructed by stocks with the highest RILLIQ of 80%. Its correlation coefficient achieves 0.808, and the t-value is 12.103. Again, the relationship is distinct from Barberis et al. (2016). The curve in part (a) with all 10×10 EW portfolios also shows a strong linear pattern similar to that in part (b). Its correlation coefficient is 0.677 (t-value=9.115). Though the correlation coefficient dropped by a whopping 16.1%, we cannot conclude that the impact of the lowest 20% RILLIQ portfolios has changed the linear relationship between the average excess return and ex-ante PV.

3.5.5 Institutional investor behavior

Our evidence implies liquidity and arbitrage are key to understanding the PV effect. We don't find a clear relationship between liquidity and PV. Section 3.3.3 has suggested that there is no homogeneous holdings equilibrium or heterogeneous holdings equilibrium in the equity market. Is it possible that the market can be divided into different sub-markets and investors adopt distinct trading strategies in line with liquidity for the limits of arbitrage?

To explore the question, we investigate institutional investors' behavior towards stocks with various liquidity levels. We adopt the measure of change in IO as Edelen et al. (2016) and Jang and Kang (2019). We classify stocks contained in the lowest 10% RILLIQ decile as the liquid group, and stocks contained in the highest 10% RILLIQ decile as the illiquid group. In each group, we construct decile portfolios (P01-P10) sorted by PV. Figure 3 provides the holding behavior of institutional investors for liquidity and illiquidity stocks. In part (a), we plot the time-series and cross-sectional average of the change in IO between the end of quarter t and the end of quarter t-6 for each decile. Parts (b) and (c) display changes in IO around the entry into stocks of the bottom 10% and top 10% of values based on PV, respectively. For the stocks that enter into P01 (or P10) at the end of quarter t, we present the average number of IO of the stocks in excess of the mean of each measure for all stocks in the same quarter, for six quarters before and after the entry into P01 (or P10). The sample is from the fourth quarter of 1980 to the first quarter of 2020.

[Insert Figure 5 Here]

In figure 5 (a), we can find the change in institutional investors' holdings and PV portfolios shows a U-shape in firms with liquidity groups. For the liquidity group, institutional investors will increase their holdings for P10 and P01 portfolios. For the illiquid group, the ownership change of institutional investors shows a decreasing trend, with the highest increase in the P01 portfolio and the lowest increase in P10. Overall, institutional investors increase their holdings during the formation period. Obviously, the behavior patterns of institutional investors between liquid stocks and illiquid stocks have striking differences.

Nagel (2005) and Lewellen (2011) find that firms with low institutional ownership earn higher returns. The change of holdings also indicates that institutional investors don't have strong picking ability. For stocks in the liquidity group, they assign heavy weights on both the lowest and highest ex-ante PV stocks. But the stocks' returns are not significantly better than other stocks. At the same time, for stocks in the illiquidity group, institutions invest a larger proportion of their money in low PV stocks with low subsequent yielding rather than subsequent high PV stocks with high subsequent yielding.

The current results also raise a question of whether institutional investors are rationally speculating on the bubble as De Long et al. (1990b), Shiller (2000), and Stambaugh et al. (2012) or correcting mispricing. To clarify these issues, we investigate the trading behavior of institutional investors on P01 and P10 portfolios for the preceding and following six quarters in graphs of Figure 5 (b) and (c).

The visual impact also makes us realize that institutional investors adopt very different trading strategies between stocks of the liquidity group and the illiquidity group.

Institutions' investments are conservative for the illiquidity group. The distance between the peak and valley of the average excess IO of P01 only is 0.032 (=0.100-0.068), and that of P10 also is 0.021 (=-0.218-(-0.239)).

Compared with passive trading of stocks in the illiquidity group, the trading strategies of institutional investors in high liquidity are proactive. The average excess IO of the liquidity group changes significantly. The distance between the top and bottom of the average excess IO of P01 rises to 0.071 (=0.083-0.012), and that of P10 reaches 0.069 (=-0.163+0.233). For P01 with low ex-ante PV, institutional investors show continuous buying behavior from the sixth quarter to the second quarter before the entry. Then institutional investors keep reducing their positions on P01 sharply until the fourth quarter after the entry begins to purchase P01. For P10, which has high ex-ante PV, institutional investors have dramatically increased their allocations since the third quarter prior to the entry. In all but the fourth quarter since the entry, institutional investors have slightly increased their positions on P10.

We also analyze whether PV has an impact on the cross-sectional average of the change in IO between the end of quarter t and the end of quarter t-6 (DIO). Table 9 provides the regression coefficients of ex-ante PV on DIO for the liquidity and illiquidity groups. We adopt the following three regression models:

$$DIO_t = \alpha + \beta_0 PV_t + \varepsilon_t \tag{10}$$

$$DIO_t = \alpha + \beta_0 RPV_t + \sum_{i=1}^{I} \beta_i CV_{i,t} + \varepsilon_t \tag{11}$$

where CV is the control variable including SIZE, AGE, DTURN, SKEW, TVOL, EXRET, SALE, and TANG; RPV is the residual of cross-sectional regressions of PV on SIZE, AGE, DTURN, SKEW, TVOL, EXRET, SALE, and TANG in each month t.

[Insert Table 9 Here]

PV is a complex composition of various firm characteristic variables. An interesting question is whether the PV effect associated with institutional trading behavior can be explained by the firm characteristic variables directly. So we introduce regression (11) involving the control variables of CV, which synthesize PV. To eliminate the multicollinearity effect and obtain a reliable statistical inference, we utilize RPV instead of PV in regression (11). RPV is a nonlinear component relative to the firm characteristic variables. Therefore, RPV also reflects the nonlinear mechanism of investment decisions contributed by prospect theory. Table 9 exhibits the results. As we expected, β_0 of PV and that of RPV are positive and significant at the 1% statistical level for the liquidity group. In the meanwhile, any β_0 for the illiquidity group is not significant. The statistical evidence further confirms that there are clear differences in the trading strategies of institutions between liquidity and illiquidity groups. A possible reason is distinct liquid stocks with different investor structures. Institutional investors don't correct mispricing. They want to ride bubbles in the liquidity group by chasing the high PV stocks, killing the low PV stocks, and adopting a passive trading strategy due to the limits of arbitrage in the illiquidity group.

The evidence manifests that institutional investors adopt the rule-of-thumb based on prospect theory and the ex-ante PV is the key determinant for their trading decision on the liquidity group. Institutions attempt to ride the bubble in line with the ex-ante PV. The finding provides an explanation for vanish of the PV effect in the liquidity group. Institutions are a huge group of investments in the market, and Lewellen (2011) shows that institutions allocate high weight to high-turnover stocks. Therefore, their trading behaviors of the pursuit of high PV stocks naturally eliminate the potential high subsequent returns in the liquidity group. However, with regard to the illiquidity group, institutional investors tilt passive trading strategy and their business behavior on stocks doesn't hinge on the ex-ante PV.

The above results suggest that investors adopt distinct trading strategies in different sub-markets according to liquidity. It is interesting to further explore the characteristics of the sub-markets. Figure 6 plots scatterplots of excess return and ex-ante PV, and the alpha of the FF6, for decile portfolios sorted by PV in both the liquid and illiquid groups.

[Insert Figure 6 Here]

Impressively, in the illiquidity group, excess return and PV show a high positive linear correlation. Its correlation coefficient is 0.910 (t-value=6.19). These suggest that the rule-of-thumb based on prospect theory is optimal for investors. High PV stocks also gain high returns. However, in the liquidity group, excess return and PV don't exhibit a clear linear correlation. Its correlation coefficient is negative, which is -0.020 (t-value=-0.06). For the decile portfolios in the liquidity group, table 8 shows the portfolio with the highest 10% PV is 1.08% and the portfolio with the lowest 10% PV is 1.00%. The gap is only 0.08% and doesn't significant. Therefore, the sub-market of the liquidity group is closer to equilibrium based on prospect theory, and the rule-of-thumb is not valid in this case.

Amazingly, our results suggest that high PV stocks also gain high returns in the illiquidity group, which is opposite to Barberis et al. (2016). There may be the following reasons for our fundamental disagreement. First, Barberis et al. (2016) adopt ex-post PV for some chart investors who make an investment decision in terms of historical return distributions; however, our ex-ante PV mainly aims at sophisticated investors who build trading strategy according to forward-looking stock valuations based on a wide range of firm characteristics. Second, Barberis et al. (2016) explain their results under an equilibrium framework; meanwhile, we find that ex-ante PV does not exist in equilibrium. Comparing the results of the liquidity and illiquidity groups, the limits of arbitrage should be an important determinant of the PV effect.

The above evidence seems to suggest an intriguing paradox for institutional investors. The rule-of-thumb based on prospect theory works in the sub-markets of the illiquidity group, but not in the sub-market of the liquidity group. However, institutional investors bet on high PV stocks in the liquidity group, while they adopt a passive trading strategy in the illiquidity group. Therefore, institutions' trading behavior doesn't the decisive driving force of the PV effect. The curves in figure 4 have shown that the liquidity stocks have some influence on the PV effect but only to a limited extent. We suspect that institutions evaluate stocks based on information in the entire market, but make decisions on trading in line with the limits of arbitrage. They deem that the rule-of-thumb based on prospect theory is profitable for the strong evidence derived from the whole market, but ignore the striking differences in sub-markets divided by liquidity.

Institutions tend to stay away from low-turnover stocks (Lewellen, 2011). Therefore, the decision of institutions on the liquidity group has a great impact on their performance. In the liquidity group, institutional investors chase high PV stocks and kill low PV stocks; however, the differences among distinct PV stocks have close yields. In figure 5, we also can find their changes of allocations on the stocks with the highest 10% PV and with the lowest 10% are almost equal. Therefore, institutional investors' portfolio gain does not have a large deviation from the sub-market return in the liquidity group. In addition, low holdings and passive trading strategy make the institutional portfolio performance close to that of the sub-market portfolio of the illiquidity group. Overall, our findings confirm the view of Lewellen (2011) that institutions as a whole don't appear to have strong stock-picking capabilities, with aggregate portfolio performance approaching the market portfolio.

4. Conclusion

We investigate the predictive ability of ex-ante PV to future stock returns. Based on the predictions of the extreme events developed by Campbell et al. (2008), Conrad et al. (2014), and Jang and Kang (2019) and the classical formulations proposed by Tversky and Kahneman (1992), we build a simple algorithm for ex-ante valuation of prospect theory. Even when we consider firms' characteristics, market-wide sentiment, economic status, and the limits of arbitrage, our results show a strong and robust pricing effect associated with ex-ante PV in the US market.

At the same time, we also get that there is no direct relationship between liquidity and PV. Our evidence implies that liquidity-related mispricing is more prominent in highly liquid stocks. Conversely, illiquid stocks have a more significant PV effect. The evidence suggests that the rule-of-thumb based on prospect theory works in the sub-markets of the illiquidity group, but not in the sub-market of the liquidity group. However, there is an intriguing paradox for institutional investors. Institutional investors bet on high PV stocks in the liquidity group, but adopt a passive trading strategy in the illiquidity group.

For the whole market, the liquidity stocks have an influential but limited impact on the PV effect. We can find the correlation coefficient between the average excess return and ex-ante PV is 0.677 (t-value=9.115) for the whole market. Institutions may infer that the rule-of-thumb based on prospect theory is profitable for drawing robust conclusions from the whole market. But their decision on trading regarding the limits of arbitrage while ignoring significant differences in sub-markets divided by liquidity.

Our evidence exhibits that high PV stocks also gain high returns, especially for illiquidity stocks, which doesn't show a clear trade-off relationship proposed by Barberis and Huang (2008) and Barberis et al. (2016). Barberis et al. (2016) compute ex-post PV based on historical return of chart investors and adopt an equilibrium framework. However, we construct ex-ante PV for sophisticated investors based on broad firm characteristics and find no equilibrium exists for ex-ante PV.

In general, liquidity, equilibrium, and the limits of arbitrage are crucial to understanding the ex-ante PV effect.

Appendix. Definitions of key variables

Following are definitions of key variables

AGE: The number of years since the company's first appearance on the CRSP monthly stock file.

BM: The ratio of the monthly book equity to market equity. Book-to-market ratio at the end of June in year t to May in year t+1 is the ratio of book equity for the end of year t-1 to market equity at the end of December in year t-1.

CRASHP: The probability of stock log returns less than -70% from month t+1 to month t+12.

DIO: The change in the ratio of the shares owned by institutions between the end of quarter t and the end of quarter t-6.

DTURN: The detrended stocks turnover is defined as average past six-month turnover minus average past 18-month turnover.

EXRET12: The cumulative return of individual stocks over the past 12 months minus the market return over the past 12 months (RM12).

GEBDUM: Nasdaq dummy variable, 1 if the stock is Nasdaq, 0 otherwise.

ILLIQ: The illiquidity index proposed by Amihud (2002), which is defined as the average of the ratio of absolute daily return to transaction amount in month t.

IO: The ratio of the shares owned by institutions, obtained from the Thomson Reuters Institutional (13F) Holdings database.

JACKP: The probability of stock log returns greater than 70% from month t+1 to month t+12.

LII: The liquidity index following the procedure proposed by Pastor and Stambaugh (2003).

MAX: The maximum daily return within month t. We exclude stocks with fewer than 15 daily returns each month.

MIN: The minimum daily return within month t. We exclude stocks with fewer than 15 daily returns each month.

MSI: The market-wide sentiment index of Baker and Wurgler (2006).

NRI: the National Bureau of Economic Research recession indicator.

PV: The value based on prospect theory.

PRC: The stock price.

PS: The price-to-sales ratio is defined as the log of the market value divided by the previous year's operation revenue.

RILLIQ: The residuals of liquidity by regressing the log of ILLIQ with the variables of SIZE and squared SIZE on the cross-section.

RIO: The residuals of institutional ownership by regressing the log of IO with the variables of SIZE and squared SIZE on the cross-section.

RPRC: The residuals of price by regressing the log of price with the variables of SIZE and squared SIZE on the cross-section.

RM12: Measured at the end of month t as the log return of the CRSP value-weighted index over the past 12 months.

RM24: Measured at the end of month t as the log return of the CRSP value-weighted index over the past 24 months.

RPRC: The residuals of price by regressing the log of PRC with the variables of SIZE and squared SIZE on the cross-section.

SALESG: The sales growth at the end of June in year t to May in year t+1 is defined as the log difference between sales(Compustat annual item SALE) at the end of year t-1 and sales at the end of year t-2.

SIZE: The log of price per share times the number of shares outstanding.

SKEW: The skewness of daily log returns over the past 6 months. We exclude stocks with fewer than 50 daily log returns in six months.

TANG: Tangible assets at the end of June in year t to May in year t+1 are property, plant, and equipment (Compustat annual item PPEGT) divided by total assets (item AT) for the end of year t-1.

TVOL: The standard deviation of daily log returns over the past 6 months. We exclude stocks with fewer than 50 daily log returns in six months.

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Table 1

Parameter estimates.

This table reports the parameter estimates of the logit model for predicting extreme stock returns. A price crash is defined as logarithmic returns declines by -70% in the next 12 months, and a jackpot return is defined as logarithmic yield climbs by 70% in the next 12 months. The model selects eight explanatory variables, including past market return (RM12), past excess return (EXRET12), standard deviation (TVOL), skewness (TSKEW), market capitalization (SIZE), detrended turnover rate (DTURN), sales growth over the prior year (SALESG), tangible assets divided by total assets (TANG), and company age (AGE). PCO is the percentage change in the odds ratio for a 1σ change in a variable. The z-statistics based on the standard error are calculated. ** and * report significance at 1% and 5%, respectively.

	Crash			Jackpot		
Variable	Coefficient	z-Statistics	PCO	Coefficient	z-Statistics	PCO
Intercept	-4.32**	-201.27		-2.82**	-129.03	
RM12	1.02**	35.66	17.10%	-1.00**	-35.58	-14.30%
EXRET12	-0.09**	-9.40	-3.40%	0.13**	11.81	5.10%
TVOL	47.35**	163.43	87.40%	33.25**	102.52	55.50%
SKEW	0.03**	8.59	3.50%	0.02**	5.58	2.70%
SIZE	0.05**	20.84	11.50%	-0.15**	-54.86	-27.40%
DTURN	-3.0e-05	-0.86	-0.30%	-5.9e-04**	-10.98	-4.40%
SALESG	0.36**	35.47	12.30%	0.24**	18.99	8.10%
TANG	-0.02	-1.69	-0.70%	-0.11**	-9.53	-4.80%
AGE	-0.03**	-59.74	-33.70%	-0.02**	-35.77	-22.50%
Log likelihood	-372973.97					
Pseudo R^2	0.06					

Table 2

Descriptive statistics on sorted portfolios

This table shows descriptive statistics of the returns on value-weighted (VW) and equal-weighted (EW) portfolios sorted by the ex-ante probability of price crashes (CRASHP), ex-ante probability of price jackpots (JACKP), and values based on prospect theory (PV). At the end of month t, we sort portfolios based on CRASHP, JACKP, or PV. The monthly out-of-sample return of all portfolios in month t+2 is calculated. The out-of-sample returns begin in January 1972 and end in December 2020. The average excess return relative to the risk-free rate (Mean), standard deviation (Std), skewness (Skew), and Sharpe ratio (SR) of excess return are reported. The portfolios of panels A, B, and C are grouped by the ex-ante probabilities CRASHP, JACKP, and PV, respectively. C01-C10, J01-J10, and P01-P10 are decile portfolios. Column C01 (J01 or P01) presents the results for the portfolio at the bottom 10% of CRASHP (JACKP or PV). Column C10 (J10 or P10) provides the results for the portfolio at the top 10% of CRASHP (JACKP or PV). Column DC10 (DJ10 or DP10) shows the results for the zero-cost portfolio buying the highest 10% and selling the lowest 10% of CRASHP (JACKP or PV). ** and * report significance at 1% and 5%.

Panel A Returns on CRASHP-sorted portfolios												
		C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	DC10
VW	Mean	0.59**	0.57**	0.82**	0.87**	0.88**	0.69**	0.67**	0.57*	0.74*	0.17	-0.42
	Std	3.96	4.52	4.71	5.19	5.32	5.80	6.28	6.89	7.95	9.26	7.45
	Skew	-0.50	-0.44	-0.33	-0.39	-0.23	-0.44	-0.17	-0.36	-0.16	0.03	0.46
	SR	0.15	0.13	0.17	0.17	0.17	0.12	0.11	0.08	0.09	0.02	-0.06
EW	Mean	0.81**	0.84**	0.99**	1.09**	1.06**	1.02**	1.02**	0.85**	0.77*	0.31	-0.50
	Std	4.01	4.40	4.65	5.01	5.31	5.67	6.03	6.59	7.31	8.69	6.46
	Skew	-0.71	-0.77	-0.85	-0.77	-0.62	-0.74	-0.57	-0.46	-0.36	0.07	0.86
	SR	0.20	0.19	0.21	0.22	0.20	0.18	0.17	0.13	0.11	0.04	-0.08
Panel B Returns on JACKP-sorted portfolios												
		J01	J02	J03	J04	J05	J06	J07	J08	J09	J10	DJ10
VW	Mean	0.59**	0.71**	0.77**	0.92**	1.02**	0.78**	0.81**	0.99**	0.94**	1.03**	0.43
	Std	4.14	5.15	5.57	5.99	6.65	6.81	7.32	7.55	8.36	8.87	6.99
	Skew	-0.33	-0.47	-0.55	-0.53	-0.45	-0.58	-0.47	-0.28	-0.04	-0.38	-0.12
	SR	0.14	0.14	0.14	0.15	0.15	0.11	0.11	0.13	0.11	0.12	0.06
EW	Mean	0.67**	0.75**	0.75**	0.85**	0.92**	0.88**	0.89**	0.99**	0.99**	1.06**	0.40
	Std	4.29	4.82	5.05	5.32	5.68	5.76	6.07	6.45	6.89	7.78	5.99
	Skew	-0.37	-0.55	-0.60	-0.65	-0.52	-0.55	-0.51	-0.45	-0.42	-0.17	0.88
	SR	0.16	0.16	0.15	0.16	0.16	0.15	0.15	0.15	0.14	0.14	0.07
Panel C Returns on PV-sorted portfolios												
		P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	DP10
VW	Mean	0.31	0.67**	0.69**	0.67**	0.75**	0.90**	0.81**	0.97**	1.02**	0.99**	0.68**
	Std	5.26	4.89	4.96	4.83	4.91	5.42	5.62	6.12	7.03	8.03	5.89
	Skew	-0.31	-0.22	-0.33	-0.44	-0.53	-0.71	-0.60	-0.73	-0.13	-0.40	-0.05
	SR	0.06	0.14	0.14	0.14	0.15	0.17	0.15	0.16	0.15	0.12	0.12
EW	Mean	0.03	0.46	0.64**	0.69**	0.76**	0.85**	0.86**	0.97**	1.02**	1.10**	1.06**
	Std	6.29	5.64	5.60	5.47	5.46	5.47	5.67	5.87	6.21	7.02	4.71
	Skew	-0.35	-0.58	-0.54	-0.54	-0.56	-0.58	-0.50	-0.59	-0.45	-0.16	0.47
	SR	0.01	0.08	0.11	0.13	0.14	0.16	0.15	0.16	0.16	0.16	0.23

Table 3

Alpha on sorted portfolios

This table presents alphas on value-weighted (VW) and equal-weighted (EW) portfolios sorted by the ex-ante values based on prospect theory (PV). At the end of month t, we sort portfolios based on PV. The monthly out-of-sample return of all portfolios in month t+2 is calculated. The out-of-sample returns begin in January 1972 and end in December 2020. The average excess return (mean) relative to the risk-free rate and alphas of Fama-French five-factor (FF5) and six-factor (FF6) are reported. P01-P10 are decile portfolios. Column P01 presents the results for the portfolio at the bottom 10% of PV. Column P10 provides the results for the portfolio at the top 10% of PV. Column DP10 shows the results for the zero-cost portfolio buying the highest 10% and selling the lowest 10% of PV. Our inference is based on t-statistics. ** and * report significance at 1% and 5%.

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	DP10
VW mean	0.31	0.67**	0.69**	0.67**	0.75**	0.90**	0.81**	0.97**	1.02**	0.99**	0.68**
	(1.41)	(3.33)	(3.38)	(3.34)	(3.70)	(4.03)	(3.52)	(3.85)	(3.53)	(2.98)	(2.80)
VW α of FF5	-0.26**	0.07	0.04	-0.04	0.01	0.15	0.10	0.28**	0.37**	0.44**	0.70**
	(-3.07)	(0.87)	(0.47)	(-0.51)	(0.16)	(1.44)	(1.04)	(2.61)	(3.09)	(2.84)	(3.64)
VW α of FF6	-0.20*	0.02	0.02	-0.01	0.03	0.21*	0.15	0.30**	0.34**	0.40*	0.60**
	(-2.37)	(0.28)	(0.30)	(-0.13)	(0.35)	(2.12)	(1.48)	(2.81)	(2.79)	(2.52)	(3.08)
EW mean	0.03	0.46	0.64**	0.69**	0.76**	0.85**	0.86**	0.97**	1.02**	1.10**	1.06**
	(0.12)	(1.96)	(2.76)	(3.06)	(3.38)	(3.77)	(3.69)	(4.00)	(3.97)	(3.78)	(5.48)
EW α of FF5	-0.76**	-0.40**	-0.27**	-0.21**	-0.14*	-0.03	0.01	0.16**	0.34**	0.57**	1.32**
	(-6.88)	(-5.25)	(-4.25)	(-3.68)	(-2.49)	(-0.63)	(0.19)	(2.60)	(4.29)	(5.32)	(7.55)
EW α of FF6	-0.59**	-0.33**	-0.20**	-0.15**	-0.08	0.00	0.07	0.20**	0.36**	0.53**	1.12**
	(-5.70)	(-4.33)	(-3.30)	(-2.66)	(-1.47)	(0.05)	(1.16)	(3.17)	(4.47)	(4.92)	(6.57)

Table 4

Firm characteristics of sorted portfolios based on the Prospect Value

This table provides average individual firm characteristics for portfolios sorted on values based on prospect theory (PV). The variables are defined in Appendix A. P01-P10 are decile portfolios. Column P01 presents the results for the portfolio at the bottom 10% of PV. Column P10 provides the results for the portfolio at the top 10% of PV. The sample period is from January 1980 to October 2020.

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10
PV	-0.052	0.027	0.056	0.079	0.099	0.118	0.140	0.167	0.205	0.321
CRASHP	0.106	0.056	0.047	0.042	0.039	0.038	0.038	0.041	0.045	0.070
JACKP	0.029	0.028	0.029	0.030	0.032	0.035	0.039	0.045	0.055	0.087
TVOL	0.032	0.026	0.025	0.024	0.024	0.025	0.025	0.027	0.029	0.037
SKEW	-0.169	-0.002	0.031	0.047	0.074	0.104	0.135	0.188	0.276	0.416
MAX	0.066	0.054	0.051	0.051	0.051	0.052	0.055	0.059	0.064	0.088
MIN	-0.059	-0.048	-0.046	-0.045	-0.045	-0.045	-0.046	-0.049	-0.051	-0.063
PRC	42.477	39.374	38.633	34.531	32.074	31.091	28.408	23.351	19.353	13.976
SIZE	7.425	7.183	6.914	6.665	6.409	6.083	5.723	5.292	4.757	3.940
BM	0.043	0.039	0.045	0.054	0.067	0.090	0.114	0.158	0.245	0.364
DTURN	32.231	6.672	4.130	1.694	0.186	-0.458	-0.637	-0.375	-0.402	-1.031
ILLIQ	0.003	0.003	0.003	0.003	0.004	0.005	0.006	0.008	0.012	0.032
IO	0.551	0.585	0.580	0.570	0.556	0.531	0.498	0.451	0.382	0.244

Table 5

Alphas on portfolios sorted by PV orthogonalized to other characteristics

This table exhibits the risk-adjusted returns on decile portfolios sorted by the residual of PV orthogonalized to various firm characteristics. The variables of firm characteristics are defined in Appendix A. At the end of each month t, the orthogonalized residuals of PV are generated from the cross-sectional regression of PV on each of the firm characteristics, and then, decile portfolios are constructed by sorting stocks based on the residuals. We build both the value-weighted (VW) portfolios and equal-weighted (EW) portfolios and calculate monthly returns on each portfolio in month t+2.The out-of-sample returns begin in January 1980 and end in December 2020. Column P01 presents the results for the portfolio at the bottom 10% of the residual of PV. Column P10 provides the results for the portfolio at the top 10% of the residual of PV. DP10 is the zero-cost portfolio buying P10 and selling P01. Alphas of Fama-French five-factor (FF5) and six-factor (FF6) are reported. The figures in brackets are t-values. ** and * report significance at 1% and 5%.

	VW						EW					
	FF5			FF6			FF5			FF6		
	P01	P10	DP10	P01	P10	DP10	P01	P10	DP10	P01	P10	DP10
CRASHP	0.95**	1.54**	0.58**	0.98**	1.58**	0.60**	0.91**	1.50**	0.59**	0.95**	1.55**	0.60**
	(3.25)	(4.70)	(3.17)	(3.34)	(4.81)	(3.21)	(3.25)	(4.83)	(3.28)	(3.11)	(4.95)	(3.31)
JACKP	0.82*	1.37**	0.55*	0.88*	1.39**	0.51*	0.78*	1.37**	0.60*	0.84*	1.40**	0.56*
	(2.31)	(6.70)	(2.48)	(2.46)	(6.76)	(2.30)	(2.17)	(6.73)	(2.75)	(2.33)	(6.81)	(2.55)
TVOL	0.85*	1.61**	0.76**	0.89*	1.65**	0.76**	0.80*	1.58**	0.78**	0.85*	1.63**	0.78**
	(2.58)	(5.38)	(4.40)	(2.68)	(5.48)	(4.36)	(2.35)	(5.54)	(4.46)	(2.47)	(5.65)	(4.40)
SKEW	0.86**	1.52**	0.66**	0.91**	1.55**	0.64**	0.79*	1.50**	0.71**	0.85**	1.53**	0.69**
	(3.06)	(4.61)	(3.00)	(3.21)	(4.65)	(2.87)	(2.75)	(4.75)	(3.33)	(2.92)	(4.81)	(3.20)
MAX	0.82*	1.60**	0.78**	0.87**	1.63**	0.76**	0.76*	1.57**	0.81**	0.81*	1.61**	0.08**
	(2.69)	(5.01)	(4.24)	(2.84)	(5.07)	(4.12)	(2.43)	(5.13)	(4.47)	(2.59)	(5.21)	(4.33)
MIN	0.86**	1.56**	0.70**	0.91**	1.59**	0.68**	0.81*	1.53**	0.72**	0.86**	1.57**	0.70**
	(2.86)	(4.76)	(3.65)	(2.99)	(4.83)	(3.55)	(2.60)	(4.89)	(3.83)	(2.77)	(4.98)	(3.70)
PRC	0.93**	1.54**	0.60*	0.98**	1.57**	0.59*	0.86**	1.51**	0.65**	0.92**	1.55**	0.63**
	(3.16*)	(4.68)	(2.70)	(3.30)	(4.75)	(2.60)	(2.84)	(4.81)	(3.02)	(3.00)	(4.88)	(2.90)
SIZE	0.81*	1.54**	0.73**	0.88**	1.57**	0.69**	0.75*	1.59**	0.84**	0.82*	1.63**	0.80***
	(2.54)	(4.84)	(3.11)	(2.76)	(4.89)	(2.90)	(2.37)	(4.95)	(3.71)	(2.61)	(5.02)	(3.51)
BM	0.85**	1.59**	0.74**	0.90**	1.63**	0.73**	0.80*	1.58**	0.78**	0.85**	1.62**	0.77**
	(2.98)	(4.66)	(3.32)	(3.12)	(4.72)	(3.22)	(2.76)	(4.76)	(3.67)	(2.92)	(4.83)	(3.57)
DTURN	0.89**	1.58**	0.69**	0.94**	1.62**	0.67**	0.83**	1.56**	0.73**	0.88**	1.59**	0.71**
	(3.17)	(4.72)	(3.00)	(3.33)	(4.78)	(2.90)	(2.88)	(4.85)	(3.31)	(3.05)	(4.92)	(3.20)
ILLIQ	0.86**	1.60**	0.74**	0.91**	1.63**	0.72**	0.80*	1.58**	0.79**	0.85**	1.62**	0.77**
	(3.02)	(4.75)	(3.29)	(3.17)	(4.79)	(3.17)	(2.75)	(4.86)	(3.64)	(2.92)	(4.93)	(3.51)
IO	0.83**	1.59**	0.76**	0.88**	1.63**	0.75**	0.76*	1.59**	0.82**	0.82**	1.63**	0.81**
	(2.96)	(4.61)	(3.55)	(3.11)	(4.67)	(3.47)	(2.66)	(4.72)	(3.93)	(2.83)	(4.80)	(3.83)

Table 6

Effects across diffident sub-periods.

This table reports the average risk-adjusted returns on value-weighted (VW) and equal-weighted (EW) portfolios of DP10 in different sub-periods, and sub-periods are divided by several binary indexes. Column P01 presents the results for the portfolio at the bottom 10% of values based on prospect theory (PV). Column P10 provides the results for the portfolio at the top 10% of PV. Column DP10 shows the results for the zero-cost portfolio buying the highest 10% and selling the lowest 10% of PV. At the end of month t, decile portfolios are constructed by grouping stocks based on PV, and the monthly value-weighted and equal-weighted returns are calculated in month t+2. The out-of-sample returns are from January 2006 to December 2020. The means of excess return relative to the Fama-French five-factor model (FF5) and six-factor model (FF6) are reported. The excess returns following sub-periods are the estimates of α_1 and α_2 in the regression $R_t - r_f = \alpha_1 D_{1,t-1} + \alpha_2 D_{2,t-1} + \sum \beta_i f_{i,t} + \varepsilon_t$, where $D_{1,t-1}$ and $D_{2,t-1}$ are dummy variables indicating each of states at month t-1, and $f_{i,t}$ are factors of FF (or Carhart) at month t. High- and low- sentiment periods are classified by the median value of the sentiment index of Baker and Wurgler (2006). Up- and down- market periods classified based on the sign of the RM24. Expansion and recession periods are classified by the NBER recession indicator. High- and low- liquidity periods are classified by the sign of the liquidity innovation introduced by Pastor and Stambaugh (2003). The sample period is from January 1972 to December 2020.The figures in brackets are t-values. ** and * report significance at 1% and 5%.

	VW						EW					
	FF5			FF6			FF5			FF6		
	P01	P10	DP10	P01	P10	DP10	P01	P10	DP10	P01	P10	DP10
Panel A: High-vs. low-sentiment												
High	-0.35**	0.49*	0.84**	-0.26*	0.43	0.69*	-0.82**	0.71**	1.53**	-0.58**	0.66**	1.24**
	(-2.90)	(2.26)	(3.09)	(-2.19)	(1.95)	(2.53)	(-5.30)	(4.76)	(6.23)	(-3.99)	(4.38)	(5.19)
Low	-0.18	0.39	0.57*	-0.15	0.37	0.51	-0.70**	0.43**	1.13**	-0.60**	0.41**	1.00**
	(-1.55)	(1.84)	(2.16)	(-1.26)	(1.71)	(1.94)	(-4.62)	(2.92)	(4.67)	(-4.26)	(2.78)	(4.34)
Diff.	-0.17	0.10	0.27	-0.11	0.06	0.18	-0.12	0.28	0.40	0.02	0.25	0.24
	(-1.00)	(0.34)	(0.71)	(-0.71)	(0.21)	(0.48)	(-0.57)	(1.38)	(1.20)	(0.10)	(1.24)	(0.72)
Panel B: Up-vs. down-market												
Up	-0.21*	0.47*	0.68**	-0.16	0.43*	0.59*	-0.65**	0.70**	1.35**	-0.51**	0.67**	1.18**
	(-1.97)	(2.36)	(2.76)	(-1.52)	(2.16)	(2.41)	(-4.64)	(5.14)	(6.02)	(-3.91)	(4.89)	(5.46)
Down	-0.33*	0.40	0.74*	-0.26*	0.35	0.60*	-0.91**	0.37*	1.29**	-0.70**	0.32	1.03**
	(-2.53)	(1.68)	(2.46)	(-1.97)	(1.44)	(2.02)	(-5.38)	(2.26)	(4.74)	(-4.44)	(1.96)	(3.93)
Diff.	0.12	0.07	-0.06	0.10	0.08	-0.01	0.26	0.33	0.06	0.19	0.35	0.15
	(0.71)	(0.21)	(-0.14)	(0.57)	(0.27)	(-0.03)	(1.22)	(1.56)	(0.18)	(0.97)	(1.63)	(0.45)
Panel C: Expansion vs. recession												
Exp.	-0.23*	0.36*	0.59**	-0.15	0.30	0.45*	-0.75**	0.51**	1.26**	-0.55**	0.46**	1.01**
	(-2.53)	(2.19)	(2.87)	(-1.70)	(1.80)	(2.20)	(-6.47)	(4.48)	(6.78)	(-5.01)	(4.01)	(5.58)
Rec.	-0.50*	1.04*	1.54**	-0.53*	1.06*	1.59**	-0.77*	1.01**	1.78**	-0.85**	1.03**	1.88**
	(-2.15)	(2.44)	(2.91)	(-2.30)	(2.50)	(3.03)	(-2.55)	(3.45)	(3.70)	(-3.05)	(3.52)	(4.08)
Diff	0.27	-0.68	-0.95	0.38	-0.76	-1.14*	0.02	-0.50	-0.52	0.30	-0.57	-0.87
	(1.10)	(-1.51)	(-1.70)	(1.54)	(-1.69)	(-2.04)	(0.06)	(-1.62)	(-1.02)	(1.02)	(-1.83)	(-1.78)
Panel D: High-vs. low-liquidity												
High	-0.37**	0.66**	1.03**	-0.29**	0.60**	0.90**	-0.90**	0.83**	1.72**	-0.68**	0.78**	1.47**
	(-3.31)	(3.24)	(4.06)	(-2.64)	(2.94)	(3.54)	(-6.21)	(5.94)	(7.52)	(-5.06)	(5.57)	(6.60)
Low	-0.13	0.17	0.29	-0.09	0.14	0.22	-0.58**	0.24	0.82**	-0.47**	0.22	0.68**
	(-1.01)	(0.74)	(1.04)	(-0.69)	(0.61)	(0.80)	(-3.61)	(1.54)	(3.21)	(-3.13)	(1.39)	(2.79)
Diff.	-0.24	0.49	0.74*	-0.20	0.46	0.68	-0.32	0.59**	0.90**	-0.21	0.56**	0.79*
	(-1.49)	(1.65)	(1.98)	(-1.29)	(1.56)	(1.83)	(-1.48)	(2.88)	(2.68)	(-1.10)	(2.78)	(2.43)

Table 7
Limits to arbitrage.

This table presents returns on the zero-cost portfolios sorted by values based on prospect theory (PV) for subgroups divided by arbitrage restrictions. Four arbitrage limit variables are selected, including company size (SIZE), residual of price (RPRC), residual of liquidity (RILLIQ), and residual of institutional ownership (RIO). Last three variables are obtained from the cross-sectional regressions of each of the log price per share, the log of illiquidity and the logit of institutional ownership on SIZE and squared in each month t. At the end of month t, stocks are sorted based on arbitrage constraints. Stocks contained in the lowest SIZE (RPRC, RILLIQ, or RIO) decile are classified as small size, low price, illiquid, and low institutional ownership group. Stocks contained in the highest SIZE (RPRC, RILLIQ, or RIO) decile are classified as the big size, high price, liquid, and high institutional ownership group. Then, within each of the eight groups, decile portfolios are constructed by classifying stocks based on PV, and the monthly value-weighted (VW) and equal-weighted (EW) returns are calculated in month t+2. The out-sample returns begin in January 1972 and end in December 2020. The mean excess returns, Fama-French five-factor (FF5) model and six-factor (FF6) model alphas of the zero-cost portfolio are reported. T-statistics are reported within brackets below the estimates. ** and * report significance at 1% and 5%.

		Firm size			Price			Liquidity			Institutional ownership		
		Small	Big	Diff.	Low	High	Diff.	Illiquid	Liquid	Diff.	Low	High	Diff.
VW	Excess Return	1.34**	1.14**	0.20	1.18**	0.24	0.94	1.20**	-0.21	1.41**	0.69	0.03	0.66
		(3.79)	(4.18)	(0.55)	(3.14)	(0.56)	(1.96)	(3.14)	(-0.46)	(2.62)	(1.80)	(0.08)	(1.40)
	FF five-factor	1.49**	0.73**	0.77*	1.28**	0.44	0.84	1.65**	-0.15	1.81**	0.93**	0.43	0.51
		(4.16)	(4.46)	(2.11)	(3.36)	(1.11)	(1.68)	(4.46)	(-0.33)	(3.22)	(2.62)	(1.17)	(1.01)
	FF six-factor	1.39**	0.66**	0.73*	1.21**	0.32	0.89	1.60**	-0.29	1.89**	0.77*	0.46	0.31
		(3.86)	(4.09)	(1.98)	(3.16)	(0.80)	(1.77)	(4.29)	(-0.63)	(3.35)	(2.17)	(1.27)	(0.61)
EW	Excess Return	1.47**	0.20	1.28**	0.65*	1.20**	-0.55	1.27**	0.08	1.19**	1.42**	0.44	0.97**
		(4.60)	(0.79)	(3.51)	(2.12)	(3.83)	(-1.48)	(4.15)	(0.26)	(3.30)	(4.66)	(1.69)	(2.93)
	FF five-factor	1.77**	0.61*	1.16**	0.82**	1.58**	-0.76*	1.98**	0.35	1.63**	1.73**	0.87**	0.86*
		(5.43)	(2.46)	(3.08)	(2.62)	(5.04)	(-1.98)	(6.93)	(1.11)	(4.45)	(5.79)	(3.35)	(2.47)
	FF six-factor	1.68**	0.44	1.24**	0.67*	1.43**	-0.76	1.85**	0.08	1.77**	1.55**	0.80**	0.74*
		(5.14)	(1.82)	(3.28)	(2.17)	(4.60)	(-1.96)	(6.51)	(0.26)	(4.84)	(5.28)	(3.09)	(2.14)

Table 8

Alpha on sorted portfolios under different liquidity

This table exhibits excess returns and alphas on equal-weighted (EW) portfolios sorted by the ex-ante values based on prospect theory (PV) and residual of illiquidity (RILLIQ). At the end of month t, we sort decile portfolios based on RILLIQ. Stocks contained in the lowest 10% RILLIQ decile are classified as the highest liquid group. Stocks contained in the highest 10% RILLIQ decile are classified as the lowest liquid group. Then, within each of the ten groups, decile portfolios are constructed by classifying stocks based on PV, and the monthly returns of EW portfolios are calculated in month t+2. Column Low presents the results for the portfolio at the bottom 10% of PV sorted by liquidity. Column High provides the results for the portfolio at the top 10% of PV sorted by liquidity. Column High-Low presents the results for the long-short portfolio that long the highest 10% PV stocks and short the lowest 10% PV stocks sorted by liquidity. Column All represents decile portfolios sorted by liquidity. Row Low presents the results for the portfolio at the highest 10% RILLIQ. Row High provides the results for the portfolio at the lowest 10% RILLIQ. The out-of-sample returns begin in March 1980 and end in December 2020. The average excess return (mean) relative to the risk-free rate and alphas of Fama-French six-factor (FF6) are reported. Our inference is based on t-statistics. ** and * report significance at 1% and 5%.

PV		Low	2	3	4	5	6	7	8	9	High	High-Low	All
Panel A: Excess return													
liquidity	Low	0.03	0.45	0.52*	0.78**	0.97**	0.95**	1.06**	1.13**	1.19**	1.29**	1.27**	0.84**
	2	-0.01	0.45	0.58*	0.65*	0.82**	0.91**	0.95**	0.99**	0.95**	1.23**	1.24**	0.75**
	3	-0.09	0.62*	0.79**	0.53*	0.76**	0.97**	0.91**	1.23**	0.91**	1.33**	1.42**	0.80**
	4	0.25	0.71*	0.66*	0.74**	0.82**	0.74**	1.02**	0.92**	1.08**	1.16**	0.92**	0.81**
	5	0.24	0.59*	0.73**	0.84**	0.89**	0.80**	0.94**	0.96**	1.27**	1.40**	1.15**	0.87**
	6	0.72*	0.76**	1.13**	0.98**	0.92**	0.94**	0.98**	1.06**	1.05**	1.31**	0.59*	0.99**
	7	0.41	1.03**	0.89**	1.07**	0.95**	1.00**	1.11**	1.22**	1.29**	1.27**	0.86**	1.02**
	8	0.39	0.82*	1.01**	1.17**	1.01**	1.16**	1.07**	1.09**	1.28**	1.25**	0.86**	1.03**
	9	0.90*	0.92**	1.13**	1.05**	1.22**	1.05**	1.05**	1.22**	1.11**	1.15**	0.25	1.08**
	High	1.00*	1.14**	1.14**	0.99**	1.25**	1.23**	1.27**	1.21**	0.82*	1.08**	0.08	1.12**
Panel B: Alpha of FF6													
liquidity	Low	-0.78**	-0.45**	-0.31**	-0.02	0.15	0.27	0.43**	0.61**	0.86**	1.07**	1.85**	0.18*
	2	-0.79**	-0.49**	-0.33**	-0.34**	-0.02	0.12	0.23	0.28	0.41**	0.75**	1.53**	-0.02
	3	-0.89**	-0.29*	-0.17	-0.34**	-0.10	0.07	0.10	-0.58**	0.27	0.86**	1.75**	0.01
	4	-0.59**	-0.23	-0.28*	-0.17	-0.07	-0.20	0.15	0.24	0.54**	0.73**	1.32**	0.01
	5	-0.60**	-0.27*	-0.19	-0.01	0.02	-0.08	01.0	0.13	0.53**	0.89**	1.49**	0.05
	6	-0.13	-0.20	0.21	0.08	-0.02	0.04	0.18	0.21	0.38*	0.83**	0.96**	0.16**
	7	-0.40*	0.10	-0.06	0.17	0.14	0.11	0.25	0.49**	0.69**	0.77*	1.15**	0.23**
	8	-0.40*	-0.16	0.01	0.25	0.07	0.29*	0.23	0.31*	0.57**	0.73**	1.13**	0.19**
	9	0.13	-0.026	0.24	0.11	0.38**	0.26	0.23	0.44**	0.44**	0.68**	0.55	0.29**
	High	0.34	0.25	0.18	0.15	0.39**	0.35*	0.51**	0.56**	0.23	0.42	0.08	0.34**

Table 9

Parameter estimates for the different liquidity groups

This table shows the regression coefficients of prospect theory values (PV) on change in institutional ownership for the liquidity and illiquidity groups. The regression (1) is $DIO_t = \alpha + \beta_0 PV_t + \varepsilon_t$, where *DIO* is a cross-sectional average of the change in IO between the end of quarter t and the end of quarter t-6. The regression (2) is $DIO_t = \alpha + \beta_0 RPV_t + \sum \beta_i CV_{i,t} + \varepsilon_t$, where CV is the control variable including SIZE, AGE, DTURN, SKEW, TVOL, EXRET, SALE, and TANG; RPV is the residual of cross-sectional regressions of PV on SIZE, AGE, DTURN, SKEW, TVOL, EXRET, SALE, and TANG in each month t. T-statistics are reported within brackets below the estimates. ** and * report significance at 1% and 5%.

	Illiquid		Liquid	
	(1)	(2)	(1)	(2)
Intercept	0.022**	0.018**	0.031**	0.034**
	(4.478)	(3.600)	(8.272)	(9.491)
PV	0.003		0.007**	
	(1.728)		(5.423)	
RPV		0.004		0.004**
		(1.608)		(2.732)

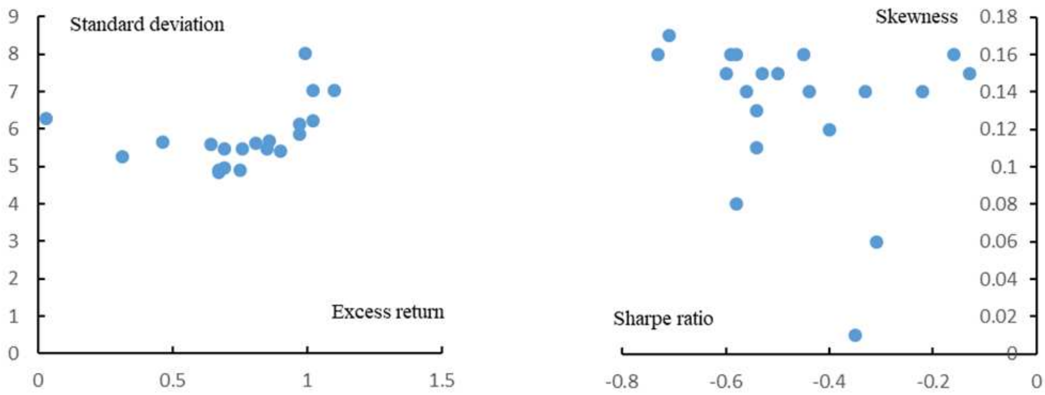


Figure 1. Descriptive of portfolios classified by PV. The Figure plots scatter graphs of VW and EW portfolios classified by ex-ante PV. The sample period is from January 1972 to December 2020.

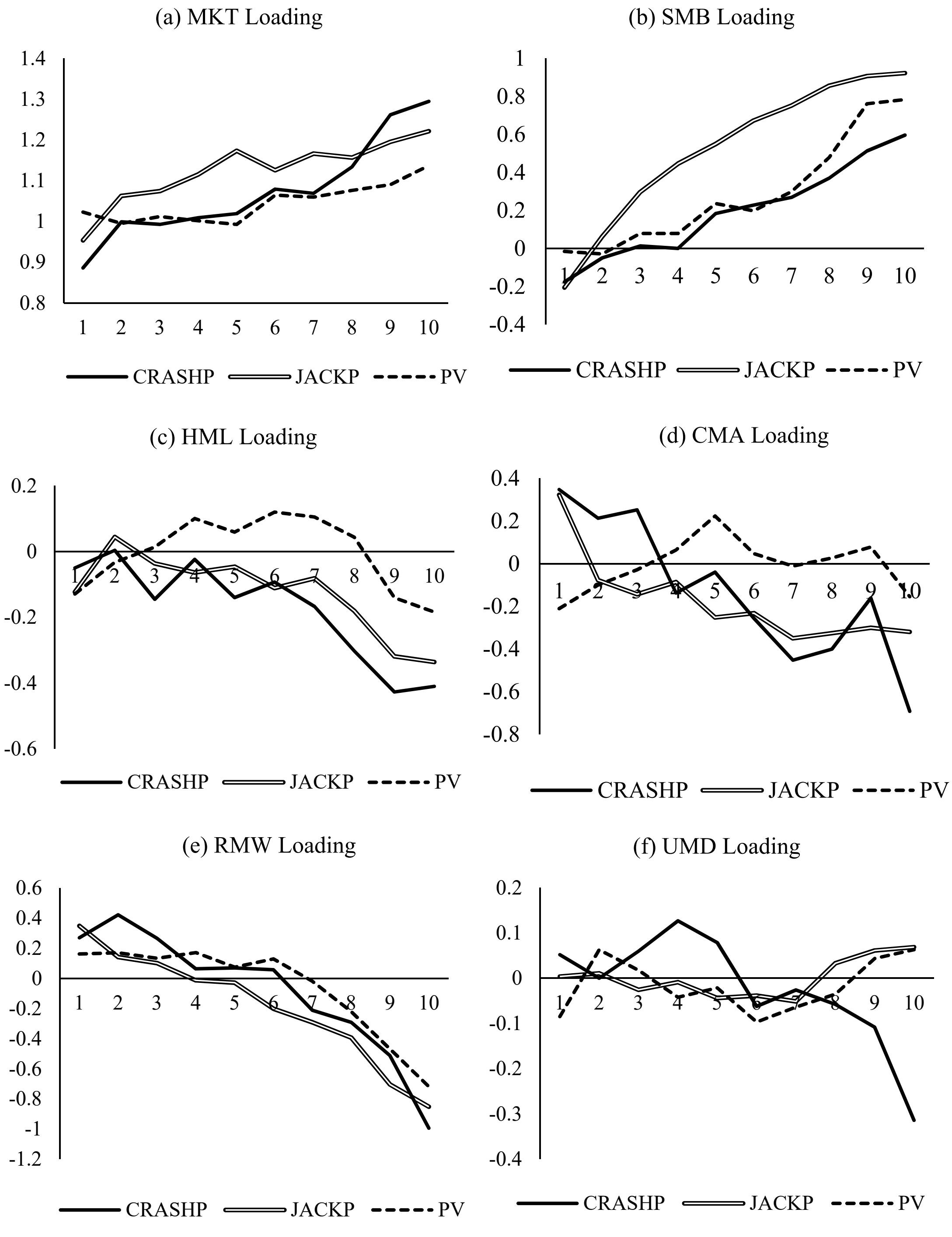


Figure 2. Factor loadings of sorted decile portfolios. The figure plots loadings of the Fama-French five-factor (FF5) and six-factor (FF6) on the excess market return (MKT), the size factor (SMB), the value factor (HML), the investment factor (CMA), the profit factor (RMW) and the momentum factor (UMD) for value-weighted portfolios from January 1972 to December 2020. The portfolios are sorted by the ex-ante probability of price crashes (CRASHP), ex-ante probability of price jackpots (JACKP), and Prospect theory values (PV).

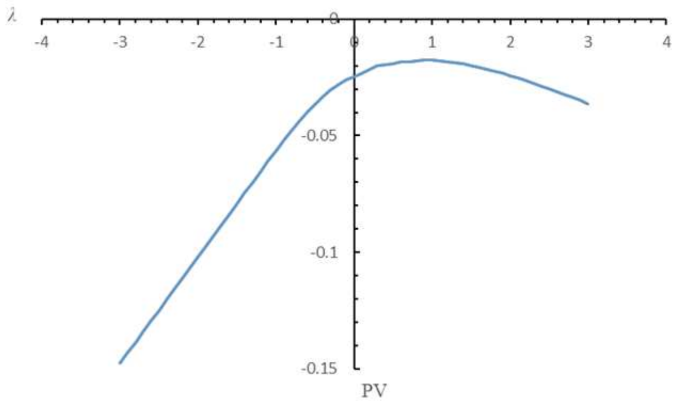
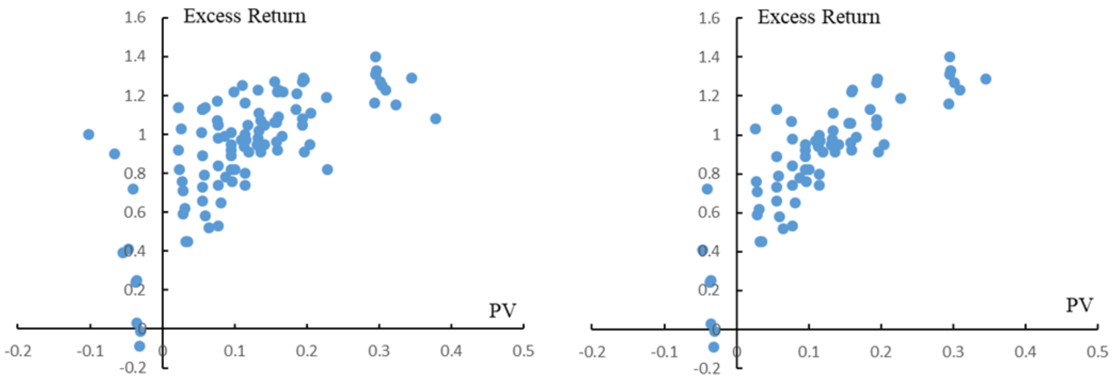


Figure 3. Ex-post PV of portfolios. The figure plots the ex-post PV of portfolios constructed by the market portfolio and the EW long-short portfolio of DP10. We allocate 100% of the weight in the market portfolio and $\lambda \times 100\%$ of the weight in the EW long-short portfolio of DP10.



(a) 10×10 EW portfolios (b) 8×10 EW portfolios

Figure 4. Excess return and ex-ante PV. The scatter charts plot the average excess return (mean) relative to the risk-free rate and ex-ante PV of equal-weighted (EW) portfolios sorted by the ex-ante values based on prospect theory (PV) and residual of illiquidity (RILLIQ). At the end of month t, we sort decile portfolios based on RILLIQ. Stocks contained in the lowest 10% RILLIQ decile are classified as the highest liquid group. Stocks contained in the highest 10% RILLIQ decile are classified as the lowest liquid group. Then, within each of the ten groups, decile portfolios are constructed by classifying stocks based on PV, and the monthly returns of EW portfolios are calculated in month t+2. Part (a) is for all 10×10 EW portfolios, and part (b) is for 8×10 EW portfolios excluding the lowest 20% RILLIQ portfolios. The sample is from March 1980 to December 2020.

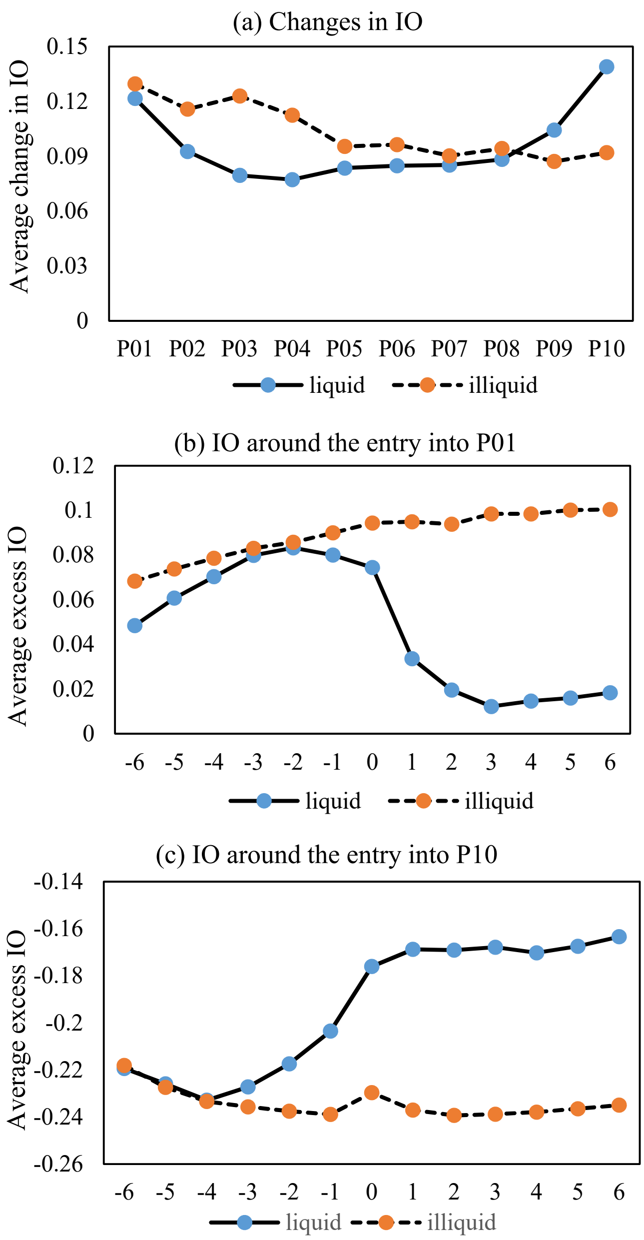
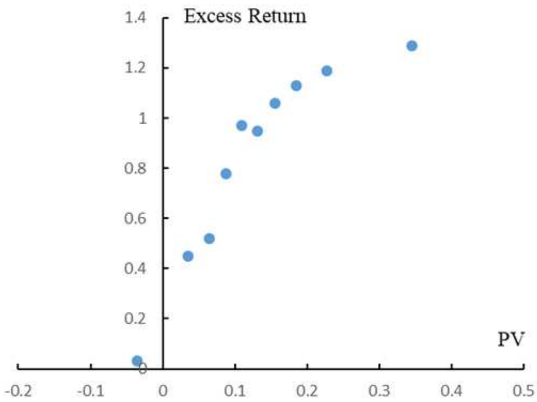
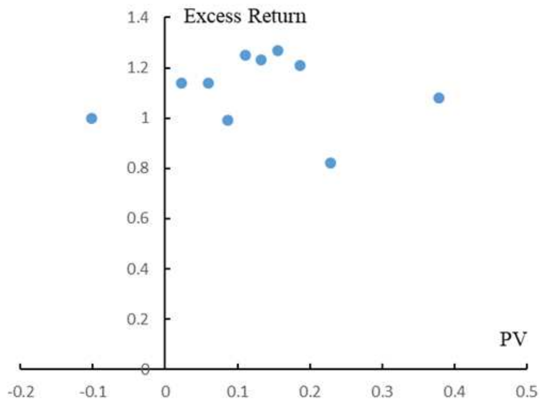


Figure 5. Changes in institutional holdings under different liquidity. This figure shows changes in institutional ownership (IO) for decile portfolios (P01-P10) sorted by values based on prospect theory (PV) in the illiquid and liquid groups. At the end of each quarter t, stocks are sorted based on the residual of liquidity (RILLIQ). Stocks contained in the lowest RILLIQ decile are classified as the illiquid group. Stocks contained in the highest RILLIQ decile are classified as the liquid group. Then, in both groups, decile portfolios are constructed by grouping stocks based on PV. P01 represents the portfolio at the bottom 10% of PV, and P10 is the portfolio at the top 10% of PV. In part (a), we plot the time-series and cross-sectional average of the change in IO between the end of quarter t and the end of quarter t-6 for each decile. Parts (b) and (c) display changes in IO around the entry into stocks of the bottom 10% and top 10% of values based on PV, respectively. For the stocks that enter into P01 (or P10) at the end of quarter t, we present the average number of IO of the stocks in excess of the mean of each measure for all stocks in the same quarter, for six quarters before and after the entry into P01 (or P10). The sample is from the fourth quarter of 1980 to the first quarter of 2020.



(a) Excess return and PV of the illiquidity group



(b) Excess return and PV of the liquidity group

Figure 6. Excess return and ex-ante PV. The scatter charts plot the average excess return (mean) relative to the risk-free rate and ex-ante PV of equal-weighted (EW) portfolios sorted by the ex-ante values based on prospect theory (PV) and residual of illiquidity (RILLIQ). At the end of month t, we sort decile portfolios based on RILLIQ. Stocks contained in the lowest 10% RILLIQ decile are classified as the liquid group. Stocks contained in the highest 10% RILLIQ decile are classified as the illiquid group. Then, within each of the two groups, decile portfolios are constructed by classifying stocks based on PV, and the monthly average excess returns and PV of EW portfolios are calculated in month t+2. Part (a) is for decile portfolios of the illiquidity group, and part (b) is for decile portfolios of the liquidity group. The sample is from March 1980 to December 2020.