Safety First, Loss Probability, and the Cross Section of Expected Stock Returns

Ji Cao[*], Marc Oliver Rieger[†], Lei Zhao[‡]

May 4, 2019

Abstract

Recent studies show that loss probability (LP) is a decisive factor when people evaluate risk of assets in laboratory experiments, suggesting a positive relationship between LP and expected stock returns. This corresponds to the classical "Safety-First" principle. We find empirical support for this prediction in the U.S. stock market. During our sample period, average risk-adjusted return differences between stocks in the two extreme LP deciles exceed 0.73% per month. The positive LP effect, characterized by the intention of some investors to pay low prices for high LP stocks, remains significant after controlling for microcaps as in Hou et al. (2019).

Keywords: Loss Probability, Stock Returns, Mental Accounting, Safety-First, Risk Attitudes

JEL classification: G11, G12, G14

[*]School of Development Studies, Yunnan University, Cuhui North Road 2, 650091 Kunming, China. Email: ji.cao@ynu.edu.cn

[†]Faculty IV, University of Trier, Universitätsring 15, 54296 Trier, Germany. Email: mrieger@uni-trier.de

[‡]Finance Department, ESCP Europe, Paris Campus, 79, avenue de la République, 75543 Paris Cedex 11, France, and Labex ReFi, France. Email: lzhao@escpeurope.eu

Safety First, Loss Probability, and the Cross Section of Expected Stock Returns

Abstract

Recent studies show that loss probability (LP) is a decisive factor when people evaluate risk of assets in laboratory experiments, suggesting a positive relationship between LP and expected stock returns. This corresponds to the classical "Safety-First" principle. We find empirical support for this prediction in the U.S. stock market. During our sample period, average risk-adjusted return differences between stocks in the two extreme LP deciles exceed 0.73% per month. The positive LP effect, characterized by the intention of some investors to pay low prices for high LP stocks, remains significant after controlling for microcaps as in Hou et al. (2019).

Keywords: Loss Probability, Stock Returns, Mental Accounting, Safety-First, Risk Attitudes

JEL classification: G11, G12, G14

1 Introduction

Since the seminal work of Sharpe (1964), Lintner (1965), and Mossin (1966), many theoretical and empirical studies in the asset pricing field have been relating the return on an asset to its risk, with risk being modeled by the variance of the asset, or, popularly, by the covariance between the return of the asset and the return of the market portfolio or other variables (e.g., aggregate consumption).[1] In predicting expected stock returns, the focus on the joint distribution of individual stocks and market portfolio is motivated by the idea that investors can create well-diversified portfolios without incurring (substantial) costs, and therefore firm-specific risk is not compensated by the market. The joint distribution is usually captured by beta, as specified in the classic capital asset pricing model (CAPM). However, the assumption that all investors, especially individual investors, can and do hold diversified portfolios is not supported by empirical evidence. Specifically, the phenomenon of individual investors holding under-diversified portfolios is presented in a very early study by Blume and Friend (1975). This phenomenon still exists; refer to the more recent studies of Calvet et al. (2007), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008).[2] The main implication is that the total risk of an individual stock, rather than just its co-movement with the market, holds significance in explaining its future returns.[3]

Although return variance is an intuitively appealing measure of stock risk, empirically, the evidence of a positive relationship between stock variance (and idiosyncratic volatility) and stock return, as postulated by various asset pricing models, is at best weak, if not non-existent (see, for example, Baillie and Degennaro, 1990; Bali et al., 2005; Bali and Cakici, 2008). The ambiguous empirical results have called into question the use of variance or standard deviation as the only measure to model risk and suggest that investors may regard

[1]For example, refer to Black et al. (1972), Fama and MacBeth (1973), Black and Scholes (1974), Pindyck (1984), Chen et al. (1986), and Breeden et al. (2012).

[2]One plausible explanation for the lack of diversification, as argued in Merton (1987), is that a given investor only has information about certain securities; this may be attributed to the fact that the collection and analyses of information are costly (see Van Nieuwerburgh and Veldkamp, 2010).

[3]Levy (1978) and Merton (1987) exert restrictions on the number of risky assets that an investor holds and develop models predicting that, in equilibrium, firm-specific risk is priced.

risk measures other than variance to be more important. Alternative risk indicators have been investigated in the literature. Specifically, lower partial moments are theoretically shown to be superior to variance (Hogan and Warren, 1974; Price et al., 1982), and skewness measures have received significant empirical support (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Mitton and Vorkink, 2007).

The aforementioned risk measures are based on the expected utility framework and are largely driven by the magnitudes of possible return outcomes. Other studies, however, argue that investors' portfolio choices are probability-based. This idea dates back to the 1950s, in particular to the path-breaking work of Roy (1952). He observes that individuals consider investment outcomes below a certain threshold a "disaster" and they associate risk with the probability of falling below this threshold. Roy (1952)'s idea that investors aim to minimize the probability of reaching the "disaster zone" when making investment decisions is broadly referred to as "Safety First."[4] Later studies further develop the "Safety First" framework and confirm the significant role it plays in decision-making (For example, refer to Arzac and Bawa, 1977; Fishburn, 1997; Stutzer, 2003; Levy and Levy, 2009). However, there has been surprisingly no explicit empirical confirmation of the theory with stock market data. Our study attempts to fill this void. An important question that arises in applying the "Safety First" idea to the context of investment is: do investors pay attention to the safety of individual stocks or do they make investment decisions at the portfolio level? From a normative point of view, investors should indeed only care about the portfolio level, but it is by now common knowledge that financial decision-making does not always follow normative views. Indeed we find strong evdence that investors apply the "Safety First" principle to individual stocks (narrow framing).

The idea is consistent with the concept of mental accounting (MA) proposed by Thaler (1980) and the behavioral portfolio theory (BPT) coined by Shefrin and Statman (2000).

[4] The point of "Safety First" can best be illustrated in Roy's words as follows: "[Maneuvering in a hostile jungle], decisions taken in practice are less concerned with whether a little more of this or of that will yield the largest net increase in satisfaction than with avoiding known rocks of uncertain position or with deploying forces so that, if there is an ambush round the next corner, total disaster is avoided."

MA refers to the process by which people think about, categorize, and evaluate their financial activities. Specifically, the theory suggests that people intend to have multiple mental accounts, with each account representing a particular goal associated with spending decisions. The examples of mental accounts include a retirement account and a college education account for individual investors and an account for paying promised benefits to beneficiaries for institutional investors. Building on MA, the BPT further suggests that each mental account of an investor has a threshold level of return, reflecting the unique goal of the account (e.g., the threshold level of a retirement mental account could either be zero or the risk-free rate). Instead of considering their portfolios as a whole, investors consider different MA sub-portfolios separately, and they aim to achieve the best trade-off between expected return and risk for each sub-portfolio. Importantly, deviating from expected utility theory, risk is measured by the probability of failing to reach the threshold level of return (refer to Das et al., 2010). The theory immediately points out the relevance and significance of investigating probability-based measures of risk, such as the loss probability (LP) examined in this study. Interestingly, the BPT also predicts that even institutional investors, that are arguably more sophisticated than individual investors, may exhibit preference against high LP stocks.

Consistent with the idea of avoiding non-preferred outcomes (e.g., suffering a loss), results of recent research, as documented in Klos et al. (2005) and Koonce et al. (2005), show that LP is perceived by investors as a significant determinant of risk.[5] With a series of experiments conducted with (mostly economics) university students, Anzoni and Zeisberger (2016) conclude that investors explicitly focus on loss probabilities, irrespective of loss magnitudes, which are neither captured by the expected utility theory nor classical behavioral decision models like cumulative prospect theory. Huber et al. (2017) further provide experimental evidence that investors' aversion to loss probability affects asset prices in trading. However, there is ambiguity concerning whether decision preferences of student subjects in

[5]Apparently, the minimization of LP can be interpreted as a special case of the "Safety First" framework, with suffering a loss being the "disaster" event.

experiments have any connection with the real-life behavior of investors trading in financial markets. There is a likelihood that students' behavior may differ from that of usual retail investors; professional investors may behave very differently and have a much more important impact on prices; and people, generally, behave very differently from laboratory experiments when their money is at stake. Therefore, it is an open question whether loss probability aversion has any significant effect on investing on stock markets.

In this study, we document empirical evidence of a strong LP effect on stock return. Specifically, we sort stocks by their LP during the previous month and investigate the monthly returns of the resulting portfolios over the period from July 1963 to December 2016. Our main empirical prediction is that stocks with a high (low) LP will have high (low) subsequent returns because of investors' desire to avoid high LP stocks. This prediction is confirmed in our empirical analysis of the U.S. stock returns over the sample period. Specifically, the difference between monthly returns on the equal-weighted (value-weighted) decile portfolios with the highest and lowest LPs is 0.88% (0.66%). The t-values ($t = 6.27$ for the equal-weighted portfolio and $t = 4.88$ for the value-weighted portfolio) are much larger than the multiple test hurdle of 2.78 recommended by Harvey et al. (2016). The corresponding Fama-French-Carhart's four-factor alpha of a zero-cost portfolio that is long high-LP stocks and short low-LP stocks (high-low LP portfolio) is 0.91% ($t = 7.43$) if equal-weighted and 0.75% ($t = 5.48$) if value-weighted. The differences in the return and the high-low LP portfolio alphas are significant at the 1% significance level. These results are robust across different sample periods and to alternative definitions of LP. The empirical finding is consistent with our hypothesis and suggests that investors are less (more) willing to hold stocks that exhibit a high (low) LP during the previous month, and thus these stocks are undervalued (overvalued) and earn higher (lower) subsequent returns.

The effect of various predictors on stock returns has been studied in a large number of articles over the past decades. While some of these articles are indeed motivated from behavioral models (similar to our study), many are not based on a sophisticated theory, but nonetheless show significant impact of their predictors, i.e., deviations from a classical model with efficient markets, often called anomalies. This "data mining" or "p-hacking"[6] as it is called has recently been increasingly criticized: if one only tries enough predictors, some will be significant, after all! Besides, in a large-scale effort, Hou et al. (2019) investigate 452 anomalies and find that most of these anomalies rely on microcaps (stocks smaller than the 20th percentile of the market equity for NYSE stocks), i.e., these return predictors only impact stocks of very small companies. An anomaly, however, that only works for microcaps, does not tell us much about the efficiency of the market as a whole and is of course entirely useless for constructing profitable trading strategies (that usually rely on a sufficiently high liquidity, which does not exist for microcaps).

Since our work is based on a solid (and already experimentally verified) behavioral model, we are less concerned about accusations of "p-hacking", but we nevertheless take these concerns very seriously. First, following Harvey et al. (2016), we have a close eye on the size of t-values in our results and evaluate the significance of the LP effect with much higher and more conservative hurdles (compared with the traditional single test hurdle of $t = 1.96$). It turns out that our LP-related t-values are in nearly all settings much larger than the cutoffs recommended by Harvey et al. (2016).[7] Second and more important, we deal in particular with the overly large impact of microcap stocks and address this issue by applying the Hou et al. (2019) methods (via portfolio sorts with NYSE breakpoints and value-weighted returns; and via dropping the microcaps from the sample) to re-do our analyses. Fortunately, the LP effect remains strong and significant after isolating the impact of microcaps, indicating that we have found a predictor that passes the high bar set by Hou et al. (2019).

The asset pricing literature has shown a strong effect of short-term reversal, characterized by the observation that previous stock return performance over short periods, such as a

[6] p-hacking refers to the engagement of researchers in searching model specifications, selecting samples and adjusting test procedures until insignificant results finally become significant.

[7] Specifically, to adjust for multiple testing, Harvey et al. (2016) propose two reliable t-cutoffs: 2.78 and 3.39, based on the Benjamini, Hochberg, and Yekutieli adjustment method at the 5% and 1% levels of the false discovery rate, respectively (Benjamini and Hochberg, 1995; Benjamini and Yekutieli, 2001).

month, tends to be negatively related to future performance, as first documented in Jegadeesh (1990) and Lehmann (1990). Not surprisingly, our measure of LP—the probability of a loss during the past month—is correlated with the short-term reversal variable by construction. Specifically, the stocks with the highest LP are likely to be the stocks with the lowest past-month return. Additionally, we also find that high-LP stocks tend to be small, illiquid securities with low returns over the prior 11 months. To ensure that the significant return differences discovered in this study are the result of investors' LP aversion, rather than merely being the result of a reversal effect or being driven by other firm characteristics, we perform a battery of bivariate-sort analyses. The positive return and alpha differences remain highly significant after we control for size, illiquidity, momentum, and short-term reversal. This conclusion is further corroborated by the results of single-sort analyses with the component of LP that is orthogonal to competing characteristics (characteristics that are correlated with LP) being the sorting variable and the results from the firm-level Fama-MacBeth regressions.

Does LP provide extra useful information when predicting stock returns in addition to other prevailing stock-level risk measures? A concern that has recently been discussed in the literature is that many predictors are actually just reincarnations of a few common variables (Kelly et al., 2019). There is a "zoo" of factors (Cochrane, 2011) where a "horse racing" between different factors might reveal that only a few of them actually matter in predicting stock returns. To account for such concerns, we conduct "horse racing" analyses as well to test the validity of LP as a predictor of stock market returns against a number of previously suggested "downside risk" variables. The results suggest that the probability-based risk measure represents a different and significant perspective of risk that is not captured by traditional magnitude-based risk measures. In addition, theoretical studies in behavioral finance and asset pricing suggest that prospect theory, which is proposed by Kahneman and Tversky (1979) and Tversky and Kahneman (1992), captures investors' attitudes toward risk in a more accurate manner when compared to the expected utility framework. On the empirical side, Barberis et al. (2016) provide international evidence that investors find stocks with a high prospect theory value appealing, which is reflected in the cross-section pricing of stocks. By including the prospect theory variable, as computed in Barberis et al. (2016), we explicitly test, with a cross-sectional regression analysis, whether LP continues to be a powerful predictor of stock returns in the presence of the prospect theory variable. Our results confirm that the LP effect is not subsumed even after controlling for the much more complicated and presumably comprehensive measure of risk attitudes.

Further analysis lends additional support to our hypothesis that investors associate risk with LP, and their avoidance of high-risk stocks results in those stocks being undervalued. Specifically, we show that the predictive power of LP for subsequent stock returns is stronger among stocks that are less subject to arbitrage activities (e.g., small stocks, illiquid stocks, and stocks with high idiosyncratic volatility) and among stocks better known to investors (e.g., stocks with high analyst coverage). In addition, consistent with the findings in Jang and Kang (2019), we find evidence that institutional ownership does not mitigate the "mis-pricing" caused by LP-averse investors.

The rest of this paper is organized as follows. Section 2 presents a simple theoretical model and its predictions about the LP effect on stock returns. Section 3 introduces variable definitions and the data. Section 4 provides the univariate portfolio-level analyses, bivariate analyses, and firm-level Fama-MacBeth regressions that thoroughly examine the LP effect on stock returns. Section 5 focuses on the impact of the forces of arbitrage, investor attention, and ownership structure on the predictive power of loss probability. Section 6 concludes the study.

2 The model

To guide and motivate the empirical tests, we present a simple one-period model, similar to the one adopted in Barberis et al. (2016), that relates LP to stock prices, formalizing our main prediction: that LP of a stock will have a positive impact on the stock's subsequent return.

In our model, there is a risk-free asset and N risky assets that investors can trade and hold in their portfolio. There are two types of investors in the economy. Type 1 investors are traditional mean-variance investors who hold the tangency portfolio (P_{Tan}) that, among all combinations of risky assets, has the highest Sharpe ratio. Type 2 investors are LP-averse investors who construct their portfolio in the following way. They start with the tangency portfolio P_{Tan} and adjust it, tilting toward stocks with low LP and tilting against stocks with high LP. Formally, they hold a final portfolio P whose risky asset weights (w, an $N \times 1$ vector) are given by:

$$w = w_{Tan} + kw_{LP}, \tag{1}$$

for some $k > 0$, and where w_{Tan} is the $N \times 1$ vector of the weights of P_{Tan}; w_{LP} is an $N \times 1$ vector, with the ith element

$$w^i_{LP} = \overline{LP} - LP_i, \tag{2}$$

where LP_i is the loss probability of stock i, as can be defined in Equation (14); and $\overline{LP}$ is the average loss probability of all risky assets: $\overline{LP} = \frac{\sum_{i=1}^{N} LP_i}{N}$. Thus, LP-averse investors hold a risky portfolio that is different from the tangency portfolio, with higher weights on low-LP stocks and lower weights on high-LP stocks.

Assuming the fraction of mean-variance investors in the overall population is θ and the fraction of LP-averse investors is $1 - \theta$, the weights of the market portfolio (w_M, an $N \times 1$ vector) can be written as:

$$\begin{aligned} w_M = \theta w_{Tan} + (1-\theta)w &= \theta w_{Tan} + (1-\theta)(w_{Tan} + kw_{LP}) \\ &= w_{Tan} + \phi w_{LP}, \end{aligned} \tag{3}$$

where $\phi = (1 - \theta)k$.

Rearranging the equation above, we obtain:

$$w_{Tan} = w_M - \phi w_{LP}. \tag{4}$$

It is well known that the weights of the tangency portfolio w_{Tan} satisfy, for some γ, the following equation:

$$\mu - r_f \mathbf{1} = \gamma \Sigma w_{Tan}, \tag{5}$$

where μ is the $N \times 1$ vector of mean asset returns of the N risky assets; Σ is the $N \times N$ matrix of their return covariances; $\mathbf{1}$ is a $N \times 1$ vector of ones; and r_f is the risk-free rate.

Substitute Equation (4) into Equation (5):

$$\mu - r_f \mathbf{1} = \gamma(\Sigma w_M - \phi \Sigma w_{LP}). \tag{6}$$

Pre-multiply both sides of (6) by w_M:

$$\mu_M - r_f = \gamma \sigma_M^2 (1 - \phi \beta_{LP}), \tag{7}$$

where μ_M and σ_M^2 are the mean and the variance of the market portfolio return, respectively; β_{LP} is the market beta of the portfolio whose asset weights are given by w_{LP}.

Next, divide Equation (6) by Equation (7), we obtain for asset i:

$$\frac{\mu_i - r_f}{\mu_M - r_f} = \frac{\beta_i - \frac{\phi \sigma_{i,LP}}{\sigma_M^2}}{1 - \phi \beta_{LP}}, \tag{8}$$

where μ_i and β_i are the mean return and the market beta of asset i, respectively; $\sigma_{i,LP}$ is the covariance between asset i and the portfolio whose asset weights are given by w_{LP}.

To derive $\sigma_{i,LP}$, we further assume that the single-index model holds:

$$\begin{aligned} r_i &= r_f + \beta_i(r_M - r_f) + \epsilon_i, \\ r_{LP} &= r_f + \beta_{LP}(r_M - r_f) + \epsilon_{LP}, \end{aligned} \tag{9}$$

where r_i and r_M are asset i's return and the market portfolio's return, respectively; r_{LP} is the return of the portfolio whose asset weights are given by w_{LP}.

Then, $\sigma_{i,LP}$ can be expressed as:

$$\sigma_{i,LP} = \beta_i \beta_{LP} \sigma_M^2 + \text{cov}(\epsilon_i, \epsilon_{LP}). \tag{10}$$

One assumption of the single-index model is that $\text{cov}(\mu_i, \mu_j) = 0$ for distinct $i, j \in \{1, \ldots, N\}$. Under this assumption, we obtain:

$$\text{cov}(\epsilon_i, \epsilon_{LP}) = w_{LP}^i \sigma_{\epsilon_i}^2, \tag{11}$$

where $\sigma_{\epsilon_i}^2$ is the variance of the residuals ϵ_i.

Substitute Equation (11) into Equation (10), we have:

$$\sigma_{i,LP} = \beta_i \beta_{LP} \sigma_M^2 + w_{LP}^i \sigma_{\epsilon_i}^2. \tag{12}$$

Finally, substitute Equation (12) into Equation (8), we obtain:

$$\begin{aligned} \frac{\mu_i - r_f}{\mu_M - r_f} &= \beta_i - \frac{\phi w_{LP}^i \sigma_{\epsilon_i}^2}{\sigma_M^2(1 - \phi\beta_{LP})} \\ &= \beta_i - \frac{\phi(\overline{LP} - LP_i)\sigma_{\epsilon_i}^2}{\sigma_M^2(1 - \phi\beta_{LP})}. \end{aligned} \tag{13}$$

The second term on the right-hand side, $-\frac{\phi(\overline{LP} - LP_i)\sigma_{\epsilon_i}^2}{\sigma_M^2(1-\phi\beta_{LP})}$, is the CAPM alpha. It offers the main prediction we test in the following sections of this paper: that stocks with higher LP (than average) will have higher alphas.[8]

3 Variables and data

3.1 Variables

LP is the key variable of interest in our analyses. We measure a stock's LP in the given month t as the fraction of the total trading days in the month with a return below the risk-free rate.[9] Precisely, for each stock, its loss probability in month t is

$$LP = \frac{\sum_{d=1}^{D} \mathbb{1}_{R_d < R_{f,d}}}{D}, \tag{14}$$

where D is the number of trading days in the month, R_d and $R_{f,d}$ are the return of the stock and the risk-free rate on day d, respectively, and $\mathbb{1}_{R_d < R_{f,d}}$ is an indicator function equal to one if $R_d < R_{f,d}$ and zero otherwise. We focus on this definition of LP throughout the study, unless otherwise stated. A minimum of 15 daily return observations within the month t is required to calculate LP. We rely on daily stock returns to construct monthly LP. First, daily data have been intensively used in the asset pricing literature (see, for example, Harvey and Siddique, 2000, Ang et al., 2006b, Bali et al., 2014, and Cosemans and Frehen, 2017). Second and more important, most of our data are drawn from the information age beginning around 1970. During this period, facilitated by the development of computer technology, the digitization of information has had a profound impact on media businesses and on how investors receive and process market data. Not only have daily data become available at almost no cost (through major financial websites), but also they might have been preferred by investors (e.g. as high-frequency trading has become increasingly popular).

The main dependent variable that we intend to explain using LP is the month $t+1$

[8] Note that, by definition, ϕ, $\sigma^2_{\epsilon_i}$, and σ^2_M are positive. β_{LP} is the market beta of a zero-cost portfolio ($\sum_{i=1}^{N} w^i_{LP} = 0$) that is long in stocks with low LP and short in stocks with high LP. It should have a value close to zero because of the low correlation between LP and beta (see Table 5).

[9] For alternative definitions, refer to Section 4.1.

(1-month ahead) excess stock return, which is calculated as the monthly return of the stock minus the return of the risk-free asset.[10] The main contribution of this study is to show that, even after controlling for a large number of variables known in the literature to predict future stock returns, LP (computed as of month t) can forecast the cross-section of stock returns in the month $t+1$. Our control variables can be grouped into two categories. The first category contains firm characteristics, including market capitalization, book-to-market ratio, momentum, stock illiquidity, and previous-month return. The second category represents measures of risk, including market beta, idiosyncratic volatility, co-skewness, skewness, Max, expected loss, Min, semivariance, downside beta, and the prospect theory value. These variables are defined in detail in Appendix 1 and are discussed as they are used throughout the study.

3.2 Data

Our data are from standard sources. Daily and monthly stock data are collected from the Center for Research in Security Prices (CRSP). Balance sheet data used to calculate the book-to-market ratio are retrieved from Compustat. Daily and monthly market excess returns, size factor and value factor returns, and the U.S. 1-month treasury-bill-rates are collected from Kenneth French's data library. Monthly liquidity factor returns (Pastor and Stambaugh, 2003) are collected from Lubos Pastor's website. Monthly returns of the q-factors of Hou et al. (2015) are obtained from Lu Zhang.[11] Our sample includes all the U.S.-based common stocks (with a CRSP share code value of either 10 or 11) trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ). To avoid the impact of the smallest and most illiquid stocks, following An (2016) we exclude stocks whose price

[10] Although our variable of interest LP is measured at the daily frequency, following Cosemans and Frehen (2017), we predict monthly rather than daily returns to produce comparable results with those in the literature that predicts monthly returns. Results are similar when predicting the average daily return over the next month.

[11] We are grateful to Lu Zhang for providing the data.

is below $2 at the time of portfolio formation.[12] The primary sample used throughout this study covers 642 months, from July 1963 to December 2016.

4 Loss probability and expected stock returns

We start our empirical investigation on the hypothesis that stocks with a higher (lower) LP, on average, will subsequently earn higher (lower) returns, with a univariate analysis of decile sorts. In Section 4.2, we further examine the hypothesis by controlling for other potentially relevant variables in a bivariate analysis context. We devote Section 4.3 to differentiate the LP effect from the existing anomaly of short-term return reversal effect. In Section 4.4, we examine whether the predictive power of LP varies over time, following which we, in Section 4.5, conduct a Fama-MacBeth regression analysis, controlling for multiple effects simultaneously. Lastly, in Section 4.6, we perform a "horse racing" analysis between LP and some alternative risk measures.

4.1 Univariate portfolio-level analysis

We implement the univariate decile-sort analysis as follows. In each month t, starting in July 1963 and ending in November 2016, we sort stocks into deciles based on their LP. Next, we calculate the average return of each LP-decile portfolio over the next month, both equal- and value-weighted. Subsequently, the resulting time series of monthly portfolio returns for each LP decile are used to calculate the average excess return and various alphas of each decile portfolio over the entire sample period. Results are presented in Table 1, wherein we report, for decile portfolios and the high-low LP portfolio, the average month $t+1$ portfolio excess returns; the four-factor alphas (FFC4 α), following Fama and French (1993) and Carhart (1997); the five-factor alphas obtained from the FFC4 model augmented with the Pastor and Stambaugh (2003) liquidity factor (FFC4+PS α); and the q-factor alphas (HXZ α),

[12] Using a $5 price threshold to filter out illiquid stocks does not qualitatively change our results.

estimated using the state-of-the-art q-factor model proposed by Hou et al. (2015).[13]

[Table 1 about here]

Portfolio 1 (low LP) contains stocks with the lowest LP during month t, and, on the other hand, Portfolio 10 (high LP) is the portfolio of stocks with the highest LP. It is noteworthy that, as we move from the low LP to the high LP portfolios, the excess returns and alphas increase monotonically, with the value-weighted excess return being the only exception, which climbs in a near-monotonic fashion. Further, the last column of Table 1 shows that the equal-weighted (value-weighted) average excess return difference between decile 10 and decile 1 portfolios is 0.88% (0.66%) per month with a corresponding Newey and West (1987) t-statistic of 6.27 (4.88). The positive and strong LP effect is further confirmed by the significant values of the alphas (FFC4 α, FFC4+PS α, and HXZ α) of the difference portfolio, suggesting that the stock return effect of LP is not driven by the most popular risk factors used in the finance literature. It is also worth mentioning that the economic magnitudes of the alphas are sizable, ranging from 0.73% to 0.95% per month. Another interesting observation from Table 1 is that the difference in average excess returns (alphas) is larger for equal-weighted than for value-weighted portfolios. This finding is consistent with our prediction as we expect that the LP effect is stronger for small-cap stocks, where it is costlier for expected utility investors to engage in arbitrage activities as those stocks are less liquid.

An examination of the predictive power of LP on future returns within each decile of LP indicates that the LP effect is detected among both low- and high-LP stocks, since the various alphas are significant for portfolios with extreme LPs (either lowest or highest). However, the portfolios with moderate LP, which stand in the middle of the 10 sorted LP deciles, generate abnormal returns that are statistically indistinguishable from zero. As expected, the alphas of low-LP portfolios are negative, and the alphas of high-LP portfolios are positive.

[13] The new five-factor model of Fama and French (2015) (FF5) augments the three-factor model by adding profitability and investment factors. Because the q-factor model also includes these two factors, to save space we do not report FF5 alphas. Our results remain qualitatively unchanged when using the FF5 asset pricing model.

It appears, however, that the LP effect is stronger among high-LP stocks, suggesting that investors' avoidance of high-LP stocks plays a larger role in driving the positive abnormal returns obtained by the difference portfolio (P10–P1).

Although using the risk-free rate to define the loss is both intuitive and appealing, investors may have a differing minimum return target in mind when making investment decisions. In order to provide alternatives, we also define the loss on the basis of zero and market returns, respectively. Specifically, we consider two alternative measures of LP. The first is constructed as the probability of having a negative return (stocks being "in the red"), and the second as the probability of having a return that is below the return of the market portfolio (stocks being beaten by the market). As before, we report the difference between alphas (FFC4 α and HXZ α) of the two extreme decile portfolios (the highest versus the lowest LP decile portfolios) in Table 2. The results show that alpha differences for both equal- and value-weighted portfolios are economically and statistically significant, confirming the previous results obtained using the risk-free rate to define loss.

It is worth noting that the average daily risk-free rate (0.001%) is almost identical to zero in magnitude during our sample period. However, the alphas shown in the first row of Table 2 where loss is defined using zero return are noticeably different from those of the benchmark analysis shown in Table 1, where loss is defined using the risk-free rate. This seemingly surprising difference is caused by stocks that have a bunch of 0% returns, which are likely to be the result of illiquidity. The benchmark LP measure treats those 0% returns as losses, whereas the alternative 0%-based LP measure doesn't. To show that this is the case, we remove exactly 0% stock returns from the sample and redo the sorting analysis using 0%-based LP. The results, as expected, become close to those obtained using risk-free-rate-based LP (See the second row of Table 2).

[Table 2 about here]

Our benchmark estimate of LP is based on daily returns over the past 1 month. Another alternative measure of LP is to compute LP over longer past periods. The second panel of

Table 2 shows that if we instead use daily returns over the previous 2 or 3 months, then we will still obtain expected and significant results. However, the magnitude of alpha decreases as the LP estimation window increases from 1 month to 3 months. Unreported results show that the significant LP effect disappears when LP is estimated over a period longer than 3 months. This suggests that average investors might only look at recent stock returns to have a sense of loss probability.[14]

The third robustness test we conduct is to check whether our results are sensitive to the sample period. Specifically, we split the full sample period into two sub-periods—one that starts in July 1963 and ends in December 1989, and the other that starts in January 1990 and ends in December 2016. The significant and positive alphas shown in the third panel of Table 2 confirm that our main conclusion holds in both sub-periods, but the LP effect obtained from the first sub-period is stronger.

As a further robustness test, we split the sample into two sub-samples according to a firm's market value as follows: one that consists of small firms—firms with a market value that is smaller than the median market value of the whole sample, and the other that consists of large firms—firms with a market value that is larger than the median market value of the whole sample. The fourth panel of Table 2 shows a significant LP effect for both small and large firms, confirming that our main results are not confined solely to small-cap stocks.

Our next robustness test is conducted on how we predict the LP. Throughout the study we use, as a benchmark, the loss frequency observed in the month t to proxy the expected LP in the month $t + 1$. In addition to the obvious advantage of simplicity, using the past loss frequency to forecast LP is intuitively appealing, which might be exactly how investors, especially unsophisticated investors, formulate LP. However, relying solely on the loss frequency ignores other valuable information embedded in observed return distribution, such as volatility and mean, which could be used to better predict LP. For example, there are two stocks with the same loss frequency and the same mean return in the month t, but one stock

[14] One might alternatively assume that the LP effect is driven by the well-known short-term reversal (Jegadeesh, 1990, and Lehmann, 1990). We will see in Section 4.3 that this is not the case.

is twice as volatile as the other. Although investors may reasonably predict a higher LP for the more volatile stock, our benchmark measure of nonparametric LP fails to distinguish the two stocks from each other. To consider the fact that some investors may consciously (or unconsciously) predict a stock's LP using the distribution of its past returns, we estimate parametric LP by assuming that stock returns follow a certain distribution, and we investigate the corresponding LP effect on stock returns. Precisely, we parametrically estimate LP on the basis of the normal distribution and the skewed t distribution of Hansen (1994), respectively.[15] The results obtained with the parametric LP are reported in the last panel of Table 2, revealing a significant LP effect.[16]

Finally, responding to the critics of Hou et al. (2019) that most (65%) anomalies they study are driven by microcaps, we re-estimate the LP effect, controlling for microcaps in exactly the same way they do.[17] Specifically, we conduct two further tests. First, instead of sorting stocks using NYSE-AMEX-NASDAQ breakpoints as in our baseline analysis, which may assign disproportionately more microcaps into extreme deciles (Decile 1 and Decile 10), we sort stocks using NYSE breakpoints, which assign a fair number of small and big stocks into extreme deciles, as a robustness check. Table 3 Panel A contains the sorting results, which clearly show a reduced but still strong and significant LP effect. Second, we drop microcaps from the sample and then repeat the sorting analysis. Again, the results shown in Table 3 Panel B strongly suggest that the LP effect survives this test.

[Table 3 about here]

We have shown that our main result of a positive LP effect in predicting future stock returns is strong and robust. However, it is worth noting that the LP-averse investors, as defined in this study, would have reached the same investment decisions as the expected utility investors if stock returns were normally distributed in the forecasting month (see Roy,

[15] Refer to Appendix 2 for the details of the parametric LP estimation.

[16] The average correlation between Normal LP (Skewed t LP) and the benchmark LP is 0.615 (0.664) during the sample period.

[17] In a previous test, we split our sample into small firms and large firms and still find robust LP effect in large firms. This finding already alleviates the concern that our results are mainly driven by microcaps. Nevertheless, we further address the microcaps issue following the methods articulated in Hou et al. (2019).

1952). Hence, we expect that the LP effect will be stronger among stocks with a distribution that is farther away from normality. We explicitly test this idea by a double-sort analysis, with the Jarque-Bera (JB) statistic measured at month $t+1$ as the first-sorting (control) variable.[18] The larger the JB statistic, the farther away would be the distribution from normality.[19] The sorting results are presented in Table 4 Panel A. As one would expect, the LP effect is the strongest among stocks with the highest JB statistics.

[Table 4 about here]

It is also important to point out that the LP measure that we use as a risk proxy is calculated in the portfolio formation month, not in the subsequent month over which we measure average returns. Investors pay low prices for stocks with a high historical LP because they expect that those high LP stocks will also tend to have high LP in the future. Are their expectations accurate or rational? If not, then the investors should learn from their mistakes; and consequently, the LP, as measured in this study, should eventually become an insignificant return predictor. Although our univariate-sort analyses suggest that this is not the case, we explicitly investigate the persistence of LP by looking at the firm-level cross-sectional regressions of LP on lagged LP and other lagged control variables. Specifically, we conduct the Fama-MacBeth regression analysis examining the relationship between LP measured in the month $t+1$ and LP measured in the month t. Table 4 Panel B reports the average cross-sectional coefficients over the sample period and the Newey and West (1987) adjusted t-statistics. Results from the univariate regression of LP on lagged LP provide immediate evidence of the persistence of the variable of interest, showing a positive and extremely significant coefficient.

To address the concern that the predictive power of lagged LP is spurious, resulting from model misspecifications (e.g., the omitted variable bias), we include seven lagged control variables, which are defined in Appendix 1 and discussed in detail later. These variables are

[18] Refer to Section 4.2 for a detailed description of the double-sort procedure.

[19] The JB statistic is calculated as $JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right)$, wherein n is the sample size, s is the sample skewness, and k is the sample kurtosis. The non-negative JB statistic measures whether sample data have the skewness and kurtosis matching a normal distribution, with $JB = 0$ indicating a normal distribution.

as follows: the market beta (Market beta), the natural logarithm of market capitalization (Size), the book-to-market ratio (BM), intermediate-term momentum (Mom), the short-term reversals (Rev), a measure of illiquidity (Illiq), and the idiosyncratic volatility (Ivol). As shown in Table 4 Panel B, after including these seven control variables, the coefficient of lagged LP remains positive and significant. This reassures that stocks with a high LP in one month also tend to exhibit a high LP in the following month and vice versa.

Having demonstrated the persistence of our risk measure LP, and thus justified the idea that investors make decisions based on LP in the past, we now focus on the composition of different LP decile portfolios. Table 5 reports summary statistics for the stocks in the deciles. Specifically, the table reports the average across the months in the sample of the mean values within each month t of various firm characteristics and risk measures for the stocks in each LP decile. It also reports the average of month $t+1$ (1-month ahead) loss probability (LP_{t+1}) in each month-t LP decile. The monotonically increasing pattern of LP_{t+1} confirms the previous finding that LP is persistent. Turning to firm characteristics and other risk measures, not surprisingly, the stocks with the highest (or lowest) LP are not representative of the average equity in the U.S. As the average LP of stocks increases across deciles from 40.49% (decile 1) to 74.57% (decile 10), the average firm size (MktCap) decreases monotonically, with the mean size of the decile 1 stocks being more than double of that of the decile 10 stocks. This indicates that the high LP portfolios are dominated by smaller firms. While this pattern is not surprising, to the extent that firm size (negatively) predicts the cross-section of expected returns, it indicates that the results shown previously may be driven by the size effect. The fact that the various difference portfolio alphas we investigate, which control for the size factor (SMB), are all significant (see Table 1) alleviates this concern to a large extent, but it is worth further investigating because it is possible that the SMB factor of Fama and French does not fully capture the size effect.

[Table 5 about here]

Looking at the Momentum variable (Mom), we observe that as LP increases across the 10 sorted portfolios, Mom decreases dramatically. However, this pattern works against finding a positive effect of LP on raw excess returns in Table 1; this is because the concentration of stocks with low momentum in the high LP deciles would suggest that these portfolios should have lower, rather than higher, expected returns. This phenomenon may partially explain why the FFC4 alpha difference is larger than the difference in raw return in magnitude, as shown in Table 1.

Consistent with the fact that the high LP deciles contain smaller stocks, we also find that illiquidity (Illiq) increases monotonically from LP decile 1 to LP decile 10. This pattern raises concerns regarding the raw return differences, as shown in Table 1, because the finding that high LP stocks earn significantly higher future returns may result from the fact that illiquid stocks require a return premium. Again, this concern is allayed by the fact that the FFC4+PS alpha differences are positive and significant, which explicitly control for the PS liquidity factor.

In Table 5, we also observe a clearly decreasing pattern across the LP deciles for short-term reversal (Rev). This observation is expected because, by construction, LP is negatively correlated with the return over the same time period. In other words, it is not surprising that stocks with a high probability of incurring daily losses during a month also have a low monthly return for the same month. This relationship between LP and Rev questions the conclusion of a positive expected return effect of LP, drawn from the raw return differences shown in Table 1. The factor models (the FFC4 factor model, FFC4+PS model, and HXZ model) do not help to address the issue because they do not control for the effects of short-term reversal.[20] To address the issue, we rely on the bivariate-sort analyses and the cross-sectional regressions that conducted later in the study.

Other firm characteristics and risk measures studied in the study (e.g., Market beta, BM ratio, Ivol, Skew, Coskew, and Max) are similar across the different LP portfolios, suggesting

[20]We also calculate the alpha from a five-factor model including the Fama-French-Carhart's four factors and a short-term reversal factor (STR) obtained from Kenneth French's data library. This FFC4+STR alpha for the difference portfolio is 0.57, with a t-statistic 4.92 if equal-weighted and 0.34 with a t-statistic 3.31 if value-weighted, both significant at the 1% level.

that they are not likely to confound the true LP effect on expected stock returns.

Given the fact that high LP stocks exhibit other characteristics that also predict stock returns (e.g., low MktCap, low Mom, high Illiq, and low Rev), and to the extent that the three types of alpha we examine may not be adequate to capture the true difference in expected returns across the LP-sorted portfolios, further investigations are warranted. Consequently, we dedicate the following two subsections to deal with the potential interaction of LP with other competing variables (firm characteristics that are correlated with LP, e.g., firm size, illiquidity, and past returns).

4.2 Bivariate portfolio-level analysis

In this section, we examine the relationship between LP and future stock returns after controlling for market capitalization, momentum, short-term reversal, and liquidity. Specifically, we adopt the following double-sort procedure. Suppose that we want to know whether the predictive power of LP is subsumed by the control variable X (e.g., market capitalization). At the end of each month t, we sort stocks into deciles based on X. Within each decile, we again sort stocks into deciles, but this time based on LP. The returns over the next month (month $t + 1$) of the 10 LP-decile portfolios are then averaged across different deciles of the control variable X. Mathematically, let $r_{i,j}$ denote the return in the month $t + 1$ of the portfolio of stocks in the i'th decile of X and the j'th decile of LP, we compute, for $j = 1, \dots, 10$,

$$\bar{r}_j = \frac{1}{10} \sum_{i=1}^{10} r_{i,j}. \tag{15}$$

Subsequently, we compute $\bar{r}_{10} - \bar{r}_1$ as a measure of the return of the high-low LP portfolio, controlling for variable X. The results of this double sort analysis are reported in Table 6. Each column corresponds to a specific control variable. Within each column, we report the excess returns, FFC4 alphas, and HXZ alphas of the difference portfolios on both an equal- and value-weighted bases. All excess returns and alphas are significant and have the expected sign, as shown in Table 6,[21] meaning that LP retains significant predictive power for future returns even after controlling for the correlated predictors of returns.[22] In other words, firm characteristics and risk measures that are correlated with LP, as shown in Table 5, do not explain the high (low) returns earned by high (low) LP stocks. However, we notice that after controlling for Rev, the positive difference portfolio returns decrease; for example, the equal-weighted high-low LP portfolio's HXZ alpha decreases from 0.95 to 0.36, but remains highly significant with a t-statistic of 3.52.

[Table 6 about here]

4.3 Loss probability and short-term reversal

The results in Tables 5 and 6 suggest a close connection between LP and Rev. Does our LP measure simply pick up the short-term reversal effect? The double-sort technique we implement in Section 4.2 is meant to isolate the effect of the first sorting variable (the control variable) and "dig out" the pure effect of the second sorting variable (the variable of interest)—LP in this study. However, there might still be some control variable (e.g. Rev) heterogeneity left across stocks within each sorted portfolio, which could contaminate the results related to Rev in Table 6. To address the issue that the double-sort technique may not sufficiently control for short-term reversals, we perform a further investigation. Specifically, we first extract the portion of LP that is orthogonal to Rev, denoted as $\mathrm{LP}_{\perp \mathrm{Rev}}$, by regressing LP on Rev and taking the sum of the intercept and the residual from the cross-sectional regression. Subsequently, we sort stocks in our sample by $\mathrm{LP}_{\perp \mathrm{Rev}}$. Since, by construction, $\mathrm{LP}_{\perp \mathrm{Rev}}$ is completely (linearly) independent of Rev, significant return differences from this single sort exercise, if observed, would further confirm the evidence shown in Table 6 that the LP effect is not solely caused by short-term reversals. The sorting results are displayed

[21]Not suprisingly, after controlling for size or variables that are correlated with size, the value-weighted and equal-weighted portfolio alphas are similar in magnitude.

[22]In unreported results (available upon request), we show the robustness of the findings in this section, using an alternative proxy for illiquidity: the fraction of total trading days in a month with zero returns. This alternative proxy, as stated in Lesmond et al. (1999), "is inversely related to firm size, and directly related to both the quoted bid-ask spread and Roll's measure of the effective spread."

in Table 7, which unanimously support our hypothesis that LP itself is a significant return predictor.

[Table 7 about here]

4.4 The dynamics of the LP effect

So far, the significant and positive results are obtained from the whole sample period. A follow-up question is how the LP effect evolves over time. To answer this question, we examine the dynamics of the LP effect. Specifically, we repeat the single-sort procedure described in Section 4.1. This time, instead of applying the procedure to the whole sample period, we use a rolling 10-year estimation window to ensure that we obtain time-varying alphas. Since Rev has been shown to have a significant impact on the LP effect, we calculate alpha from factor models augmented with the short-term reversal factor retrieved from Kenneth French's data library. Precisely, we estimate time-varying five-factor alpha from the augmented Carhart (1997)'s four-factor model (FFC4+STR α), and alpha from the augmented Hou et al. (2015)'s q-factor model (HXZ+STR α), respectively. Figure 1 presents the evolution of the alphas over a period of time on a value-weighted basis. The figure depicts a consistently positive LP effect over our sample period.[23]

4.5 Firm-level regression analysis

Relying on both single-sort and double-sort analyses, we illustrated the significance of LP as a determinant of future stock returns at the portfolio level. This portfolio-level methodology is popular in the asset pricing literature because it is nonparametric in the sense that no functional form of the relationship between the variable of interest and future returns is imposed. However, one critical disadvantage of such analysis is that it is difficult to control for multiple factors simultaneously. Consequently, we test the relationship between LP and

[23]In the entire sample period, the estimated alphas associated with LP are almost always significantly positive. This finding also indicates that LP is unlikely to be a "useless" factor (refer to Kan and Zhang, 2010).

expected stock returns by using the Fama-MacBeth methodology. We implement the Fama-MacBeth technique in the conventional manner. In each month t, starting in July 1963 and ending in November 2016, we run a cross-sectional regression of stock returns in the month $t + 1$ on LP and on variables that are already known to predict returns as controls. All explanatory variables are measured in the month t.

Table 8 reports the time-series averages of the coefficients on the independent variables. The four numbered columns in the table correspond to four different regression specifications. The univariate regression results in the specification (1) confirm a positive and highly significant LP effect. In columns (2) through (4), we introduce controls, including the four most common return predictors (Market beta, Size, BM, and Mom), an illiquidity measure (Illiq), idiosyncratic volatility (Ivol), two measures of skewness (Coskew and Skew), a proxy for the lottery demand (Max), and a measure of the short-term reversal (Rev). The coefficient of the LP variable remains statistically significant for all specifications—(2) through (4). As expected and explained in the decile-sort analyses, controlling for Rev in column (4) significantly reduces the economic magnitude of the LP effect. Nevertheless, the coefficient of LP is still significant at all conventional levels, with a t-statistic above 4.8 in magnitude. In a nutshell, the cross-sectional regressions clearly offer corroborating evidence for an economically and statistically strong positive relation between LP and future returns, echoing the results obtained from the previous univariate- and bivariate-sort analyses.

[Table 8 about here]

4.6 Loss probability and alternative risk measures

To further understand LP as a risk-related return predictor and its relationship with other risk measures that also solely look at the left side of the return distribution, we introduce four additional control variables: expected loss (EL), Min, semivariance (Semivar), and Downside beta.[24] [25] These four risk measures are similar to LP in the sense that they all focus on the "bad news," disregarding positive deviations from the target return. However, they are also very different from LP in the sense that they are all magnitude-driven, whereas LP is probability-based, which is completely magnitude-irrelevant. Regression results contained in columns (1) through (4) of Table 9 suggest that including alternative downside risk measures as controls does not take away the significant predictive power of LP. Importantly, in the last specification in Table 9, we include, as a control variable, the prospect theory value (TK) of a stock, which is considered in the literature to be a comprehensive measure of risk, considering investors' risk attitudes such as loss aversion, risk aversion in gain, risk-seekingness in loss, and probability weighting. The coefficient of LP, however, remains positive and significant as shown in column (5).[26]

[Table 9 about here]

To complement the results obtained from the linear regressions, we further conduct double-sort analyses as described in Section 4.2, with the five alternative risk measures (four downside risk measures and TK) being control variables, respectively. As shown in Table 10, the sorting results reassure us that LP is not just a variation of existing popular risk measures.

[Table 10 about here]

[24]Downside beta is introduced by Bawa and Lindenberg (1977) and intensively examined in Ang et al. (2006a).

[25]These control variables are defined in detail in Appendix 1.

[26]As advocated by Hou et al. (2019), to mitigate the (potentially) disproportionately large impact of microcaps (which is the case for many of the published anomalies), we re-perform all cross-sectional regressions with weighted least squares with the market equity as the weights. The results are qualitatively the same as the OLS regression results contained in Tables 8 and 9. As shown in Appendix 3, the smallest adjusted t-value of the coefficient of LP across different model specifications is 3.86. Some other variables, however, become insignificant, in particular expected loss (EL) and prospect theory value (TK).

5 Roles of limits to arbitrage, investor attention, and institutional holdings

We expect the predictive power of LP to be stronger for stocks with limits to arbitrage because, for stocks that are more subject to the forces of arbitrage, trading activities of "rational investors" (e.g., expected utility investors) will quickly balance out the price impact of the "irrational" trading preference from LP-sensitive investors and thus weaken the LP effect.

In this section, we test this hypothesis. Specifically, we consider stocks that are less subject to the forces of arbitrage to be stocks with low market capitalization, illiquid stocks, and stocks with high idiosyncratic volatility. Table 11 presents the results of Fama-MacBeth regressions in specifications (1) through (3). The three specifications are the same as the regression Model (4) of Table 8, except that they include three new independent interaction terms as follows: LP interacted with Size, LP interacted with Illiq, and LP interacted with Ivol. The coefficients on the interaction terms are of interest, all of which are significant and have expected signs (e.g., negative for LP*Size and positive for both LP*Illiq and LP*Ivol). This is consistent with our prediction and confirms that the predictive power of LP is greater for stocks that are less subject to arbitrage activities.

[Table 11 about here]

We also expect that the LP effect is stronger among stocks that receive more investors' attention; this is because investors should be able to identify high (low)-LP stocks before they can trade to exercise their LP-based risk attitudes. Using analyst coverage (Analyst) as a proxy for investor attention (refer to Bali et al., 2014), we examine this hypothesis.[27] Again, we focus on the newly added interaction term in the fourth column of Table 11—LP interacted with Analyst. Consistent with the idea that analyst coverage grabs investors' attention, and therefore helps them to identify high (low)-LP stocks, the positive and signif-

[27] Data on analyst coverage are from the I/B/E/S Historical Summary File and are available on a monthly basis beginning in 1976.

icant coefficient of the interaction term suggests that the predictive power of LP is stronger among stocks better known to investors.

Finally, we investigate the strength of the LP effect among stocks with differing levels of institutional ownership. The standard theories on limited arbitrage predict that the LP effect is inversely related to institutional ownership because sophisticated investors always trade against "mispricing" unless their arbitrage ability is limited by, for example, noise trader risk or short-sell constraints. However, as suggested by the BPT, even sophisticated institutional investors might be LP-averse because, like individual investors, they may aim to achieve certain return targets, e.g., avoiding losses for pension funds. Further, recent studies document evidence that institutional investors may not always trade against "mispricing" (see Edelen et al., 2016 for various possible explanations and Jang and Kang, 2019 for a rational speculation argument). Therefore, it is an empirical question whether on average institutional investors behave differently from individual investors when it comes to avoiding high LP stocks and seeking low LP stocks. The insignificant coefficient of the interaction term (LP*IO), as shown in the last column of Table 11, suggests that institutional ownership (IO) does not play a significant role on the LP effect documented in this paper.[28] Although reasoning along the line of theories on agency-induced preferences and rational speculation can help to understand this empirical finding (see, for example, Edelen et al., 2016 and Jang and Kang, 2019), we do not intend to explore further with this paper all possible explanations of why the LP effect is not weakened among stocks with greater ownership of sophisticated institutions.

6 Conclusion

How do investors evaluate risk? This question has been the focus of all the asset pricing models. Numerous academic studies in finance are dedicated to answering the question.

[28] We define a stock's IO at month t as the fraction of its total shares outstanding that are owned by institutional investors as of the end of the last fiscal quarter during or prior to month t. Institutional holdings data are available from January 1980 through December 2016 in Thompson-Reuters' 13F database.

Most of the existing risk models are based on the expected utility framework, which has advanced our understanding of risk and has been successful in explaining certain patterns of the relationship between risk and expected stock returns. Nevertheless, an emerging body of research shows that, at least in laboratory settings, investors' risk attitudes can depart significantly from predictions of the expected utility theory. In this study, we empirically test the idea that, when thinking about risk, some investors consider LP. This idea predicts that, in the cross-section, the LP of a stock will be positively related to the stock's subsequent return. Using data from the U.S. stock market, we find strong support for this prediction.

Our finding that there exists an economically and statistically significant relationship between LP and future returns is robust to controls for traditional risk measures. This suggests that LP captures a unique aspect of the risk that is not incorporated in other potential risk measures examined in this study. Our results remain strong when using different sample periods and empirical approaches.

The reader may have the following question in mind: why is the effect, as reported in this study, not traded away by other investors (e.g., expected utility investors) who do not regard LP as the priced-risk? We provide an explanation from the perspective of limits to arbitrage. Specifically, we find that stocks with a high LP are, on average, small and illiquid, which are usually relatively difficult to trade and are associated with high transaction costs. This, in turn, impedes expected utility investors from taking advantage of the "underpricing" of the high LP stocks. Particularly, consistent with our explanation, we find evidence that the loss probability effect is indeed stronger for stocks that are less subject to the forces of arbitrage. This does not mean, however, that LP only plays a role for microcaps (following the concerns of Hou et al., 2019): we also find a smaller, but still very robust effect for stocks of larger companies.

Using a simple and model-free risk measure—LP—we offer empirical and statistical support for the Safety-First framework and the behavioral portfolio theory. Our results show that the probability-based risk measure offers additional information that can improve our understanding of stock returns, which are not reflected by the risk measures based on the alternative expected utility theory or prospect theory.

It is interesting to notice that the framework we adopt in this study can be used empirically to test decision theoretical models, which surpasses the usual tests in surveys or experiments. Given the magnitude and robustness of the results, this study also presents a potentially fruitful avenue of further research. For example, can the combination of probability-based and expected utility-based risk measures improve our ability to predict future stock returns? Is the LP effect state-dependent, reflecting the state-dependent feature of risk preferences? Finally, it would also be of interest in future research to investigate the determinants of a stock's LP.

References

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

An, L. (2016). Asset pricing when traders sell extreme winners and losers. *Review of Financial Studies*, 29(3):hhv060.

Ang, A., Chen, J., and Xing, Y. (2006a). Downside Risk. *The Review of Financial Studies*, 19(4):1191–1239.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006b). The cross-section of volatility and expected returns. *Journal of Finance*, 61(1):259–299.

Anzoni, L. and Zeisberger, S. (2016). What is risk? How investors perceive risk in return distributions. *SSRN Working Paper*.

Arzac, E. R. and Bawa, V. S. (1977). Portfolio choice and equilibrium in capital markets with safety-first investors. *Journal of Financial Economics*, 4(3):277–288.

Baillie, R. T. and Degennaro, R. P. (1990). Stock returns and volatility. *Journal of Financial & Quantitative Analysis*, 25(2):203–214.

Bali, T. G., Brown, S. J., Murray, S., and Yi, T. (2017). A lottery-demand-based explanation of the beta anomaly. *Journal of Financial & Quantitative Analysis*, 52(6):2369–2397.

Bali, T. G. and Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial & Quantitative Analysis*, 43(1):29–58.

Bali, T. G., Cakici, N., and Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2):427–446.

Bali, T. G., Cakici, N., Yan, X., and Zhang, Z. (2005). Does idiosyncratic risk really matter? *Journal of Finance*, 60(2):905–929.

Bali, T. G., Demirtas, K. O., and Levy, H. (2009). Is there an intertemporal relation between downside risk and expected returns? *Journal of Financial & Quantitative Analysis*, 44(4):883–909.

Bali, T. G., Engle, R. F., and Murray, S. (2016). *Empirical Asset Pricing: The Cross Section of Stock Returns*. Wiley.

Bali, T. G., Peng, L., Shen, Y., and Tang, Y. (2014). Liquidity shocks and stock market reactions. *Review of Financial Studies*, 27(5):1434–1485.

Barberis, N., Mukherjee, A., and Wang, B. (2016). Prospect theory and stock returns: An empirical test. *Review of Financial Studies*, 29(11):3068–3107.

Bawa, V. S. and Lindenberg, E. B. (1977). Capital market equilibrium in a mean-lower partial moment framework. *Journal of Financial Economics*, 12(4):635–635.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society*, 57(1):289–300.

Benjamini, Y. and Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of Statistics*, 29(4):1165–1188.

Black, F., Jensen, M. C., and Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests. In *Studies in the Theory of Capital Markets*. Praeger, New York.

Black, F. and Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of Financial Economics*, 1(1):1–22.

Blume, M. E. and Friend, I. (1975). The asset structure of individual portfolios and some implications for utility functions. *Journal of Finance*, 30(2):585–603.

Breeden, D. T., Gibbons, M. R., and Litzenberger, R. H. (2012). Empirical tests of the consumption-oriented capm. *Journal of Finance*, 44(2):231–262.

Calvet, L. E., Campbell, J., and Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, 115(5):707–747.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82.

Chen, N. F., Roll, R., and Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 59(3):383–403.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance*, 66(4):1047–1108.

Cosemans, M. and Frehen, R. (2017). Salience theory and stock prices: Empirical evidence. *SSRN Working Paper*.

Das, S., Markowitz, H., Scheid, J., and Statman, M. (2010). Portfolio optimization with mental accounts. *Journal of Financial & Quantitative Analysis*, 45(2):311–334.

Edelen, R. M., Ince, O. S., and Kadlec, G. B. (2016). Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119(3):472–488.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock return. *Journal of Finance*, 47(2):427–65.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Some empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fishburn, P. (1997). Mean-risk analysis with risk associated with below-target returns. *American Economic Review*, 67(1):116–126.

Gao, X. and Ritter, J. R. (2010). The marketing of seasoned equity offerings. *Journal of Financial Economics*, 97(1):33–52.

Goetzmann, W. N. and Kumar, A. (2008). Equity portfolio diversification. *Review of Finance*, 12:433–463.

Green, J., Hand, J. R. M., and Zhang, X. F. (2017). The characteristics that provide independent information about average u.s. monthly stock returns. *Review of Financial Studies*, 30(12):4389–4436.

Hansen, B. E. (1994). Autoregressive conditional density estimation. *International Economic Review*, 35(3):705–730.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *Journal of Finance*, 55(3):1263–1295.

Hogan, W. W. and Warren, J. M. (1974). Toward the development of an equilibrium capital-market model based on semivariance. *Journal of Financial & Quantitative Analysis*, 9(1):1–11.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

Hou, K., Xue, C., and Zhang, L. (2019). Replicating anomalies. *Review of Financial Studies*, Forthcoming.

Huber, J., Palan, S., and Zeisberger, S. (2017). Does investor risk perception drive asset prices in markets? Experimental evidence. *SSRN Working Paper*.

Jang, J. and Kang, J. (2019). Probability of price crashes, rational speculative bubbles, and the cross-section of stock returns. *Journal of Financial Economics*, 132(1):222 – 247.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance*, 45(3):881–898.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48(1):65–91.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(4):263–291.

Kan, R. and Zhang, C. (2010). Two-pass tests of asset pricing models with useless factors. *Journal of Finance*, 54(1):203–235.

Kelly, B. T., Pruitt, S., and Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, Forthcoming.

Klos, A., Weber, E. U., and Weber, M. (2005). Investment decisions and time horizon: Risk perception and risk behavior in repeated gambles. *Management Science*, 51(12):1777–1790.

Koonce, L., Mcanally, M. L., and Mercer, M. (2005). How do investors judge the risk of financial items? *Accounting Review*, 80(1):221–241.

Kraus, A. and Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *Journal of Finance*, 31(4):1085–1100.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics*, 105(1):1–28.

Lesmond, D. A., Ogden, J. P., and Trzcinka, C. A. (1999). A new estimate of transaction costs. *Review of Financial Studies*, 12(5):1113–1141.

Levy, H. (1978). Equilibrium in an imperfect market: A constraint on the number of securities in a portfolio. *American Economic Review*, 68:643–659.

Levy, H. and Levy, M. (2009). The safety first expected utility model: Experimental evidence and economic implications. *Journal of Banking & Finance*, 33(8):1494–1506.

Linnainmaa, J. T. and Roberts, M. R. (2018). The history of the cross-section of stock returns. *Review of Financial Studies*, 31(7):2606–2649.

Lintner, J. (1965). The valuation of risky assets and the selection of risky portfolio in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47:13–37.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *Journal of Finance*, 42(3):483–510.

Mitton, T. and Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies*, 20(4):1255–1288.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica*, 34(4):768–783.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

Pastor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111:642–685.

Pindyck, R. S. (1984). Risk, inflation, and the stock market. *American Economic Review*, 74(3):335–351.

Price, K., Price, B., and Nantell, T. J. (1982). Variance and lower partial moment measures of systematic risk: Some analytical and empirical results. *Journal of Finance*, 37(3):843–855.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica*, 20(3):431–449.

Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3):425–442.

Shefrin, H. and Statman, M. (2000). Behavioral portfolio theory. *Journal of Financial & Quantitative Analysis*, 35(2):127–151.

Stutzer, M. (2003). Portfolio choice with endogenous utility: A large deviations approach. *Journal of Econometrics*, 116(1):365–386.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1(1):39–60.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk & Uncertainty*, 5(4):297–323.

Van Nieuwerburgh, S. and Veldkamp, L. (2010). Information acquisition and underdiversification. *Review of Economic Studies*, 77(2):779–805.

		P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
LP		40.490	47.029	50.814	53.973	56.847	59.376	62.190	65.245	68.632	74.571	
Excess return	EW	0.360	0.461	0.522	**0.573**	**0.730**	**0.717**	**0.841**	**0.848**	**1.064**	**1.243**	**0.883**
		(1.357)	(1.638)	(1.751)	(2.107)	(2.342)	(2.468)	(2.650)	(2.853)	(3.223)	(3.788)	(6.271)
	VW	0.296	**0.436**	**0.508**	**0.517**	**0.631**	**0.647**	**0.740**	**0.723**	**0.813**	**0.952**	**0.656**
		(1.232)	(2.107)	(2.281)	(2.609)	(3.024)	(3.379)	(3.572)	(3.725)	(3.903)	(4.165)	(4.875)
FFC4 α	EW	**-0.376**	**-0.282**	**-0.222**	**-0.096**	-0.007	0.051	**0.123**	**0.203**	**0.336**	**0.529**	**0.906**
		(-5.741)	(-5.748)	(-4.688)	(-2.439)	(-0.178)	(1.004)	(2.074)	(3.180)	(4.665)	(6.356)	(7.431)
	VW	**-0.274**	-0.079	-0.005	0.071	**0.135**	**0.214**	**0.281**	**0.331**	**0.396**	**0.478**	**0.752**
		(-4.377)	(-1.823)	(-0.127)	(1.862)	(3.225)	(4.407)	(4.007)	(4.040)	(4.686)	(4.605)	(5.477)
FFC4+PS α	EW	**-0.360**	**-0.272**	**-0.214**	**-0.096**	-0.009	0.049	0.116	**0.192**	**0.325**	**0.525**	**0.885**
		(-5.234)	(-5.268)	(-4.295)	(-2.372)	(-0.214)	(0.987)	(1.930)	(2.902)	(4.252)	(5.770)	(6.825)
	VW	**-0.294**	**-0.091**	0.009	0.076	**0.132**	**0.214**	**0.282**	**0.331**	**0.385**	**0.479**	**0.773**
		(-4.455)	(-2.033)	(0.223)	(1.911)	(2.949)	(4.177)	(3.854)	(3.998)	(4.546)	(4.449)	(5.430)
HXZ α	EW	**-0.326**	**-0.236**	**-0.169**	-0.035	0.068	0.132	0.201	**0.283**	**0.422**	**0.624**	**0.950**
		(-3.755)	(-4.069)	(-3.089)	(-0.545)	(0.872)	(1.216)	(1.551)	(2.044)	(2.778)	(3.722)	(4.106)
	VW	**-0.232**	-0.083	0.005	**0.084**	**0.133**	**0.196**	**0.263**	**0.330**	**0.437**	**0.497**	**0.730**
		(-2.656)	(-1.323)	(0.123)	(1.965)	(2.548)	(2.730)	(2.410)	(2.759)	(4.143)	(4.087)	(4.052)

Table 1: *Returns and alphas on portfolios of stocks sorted by loss probability (LP). At the end of each month t, all stocks are sorted into ascending LP-decile portfolios. The table presents for each decile the average across the months in the sample of the month-t LP, the month-$(t+1)$ equal-weighted (EW) and value-weighted (VW) excess returns, Carhart (1997)'s four-factor alphas (FFC4 α), alphas of the four-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor (FFC4+PS α), and Hou et al. (2015)'s four-factor alphas (HXZ α). The last column presents the differences in monthly returns and the differences in alphas between portfolios P10 and P1 and the corresponding t-statistics. Average excess, risk-adjusted returns, and LP are given in percentage terms. The sample runs from July 1963 to December 2016, except in the cases of the FFC4+PS α and the HXZ α, where it starts in January 1968 for FFC4+PS α and in January 1967 for HXZ α, due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

		EW FFC4 α	VW FFC4 α	EW HXZ α	VW HXZ α
Definition for loss	Return < 0	**0.716**	**0.972**	**0.781**	**0.915**
		(4.214)	(6.785)	(3.724)	(4.867)
	Return < 0 (excl. 0 returns)	**1.049**	**0.764**	**1.097**	**0.774**
		(6.962)	(5.082)	(4.561)	(4.323)
	Return < Market return	**0.780**	**0.545**	**0.781**	**0.422**
		(5.511)	(3.590)	(4.296)	(2.473)
Window for calculating LP	Two months	**0.645**	**0.747**	**0.749**	**0.878**
		(5.230)	(4.875)	(2.992)	(3.087)
	Three months	**0.328**	**0.431**	0.416	0.515
		(2.507)	(2.727)	(1.572)	(1.870)
Subperiods	Jul 1963 - Dec 1989	**1.347**	**0.986**	**1.628**	**1.168**
		(8.129)	(4.731)	(7.851)	(4.368)
	Jan 1990 - Dec 2016	**0.474**	**0.650**	0.477	**0.554**
		(3.127)	(3.445)	(1.717)	(2.193)
Firm size	MktCap > Median	**0.637**	**0.701**	**0.521**	**0.646**
		(5.167)	(5.438)	(2.487)	(3.727)
	MktCap $\leq$ Median	**1.210**	**0.856**	**1.236**	**0.925**
		(9.024)	(6.051)	(6.583)	(5.102)
Parametric LP	Normal distribution	**1.552**	**0.916**	**1.513**	**0.800**
		(9.020)	(5.847)	(5.383)	(3.461)
	Skewed t distribution	**1.280**	**0.946**	**1.334**	**0.935**
		(8.355)	(5.796)	(5.236)	(3.965)

Table 2: *Robustness. The table presents the results of five robustness checks. The right columns reports the equal-weighted (EW) and value-weighted (VW) Carhart (1997)'s four-factor alphas (FFC4 α) and Hou et al. (2015)'s four-factor alphas (HXZ α) of a long-short portfolio that, each month, buys (shorts) stocks with LP values in the highest (lowest) decile (P10 - P1). In the first panel, we compute LP by defining loss as negative raw returns (including and excluding 0 returns respectively in the computation), and returns below the market return, respectively. In the second panel, we use two, and three months of daily returns to compute LP. The third panel presents results for two subperiods. In the fourth panel, we divide the sample according to the median of market capitalizations in each month. In the fifth panel, we estimate LP with one month of daily returns under the assumption that returns follow normal distributions, and skewed t distributions (Hansen, 1994), respectively. The full sample period runs from July 1963 to December 2016, except in the case of the HXZ α, where it starts in January 1967 due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

Panel A. Single sort - NYSE breakpoints

		P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
Excess return	EW	0.332	0.513	0.455	0.524	0.699	0.619	0.691	**0.866**	**1.013**	**1.197**	**0.865**
		(1.106)	(1.556)	(1.365)	(1.486)	(1.677)	(1.742)	(1.878)	(2.025)	(2.325)	(2.781)	(6.148)
	VW	0.251	**0.450**	0.504	**0.604**	**0.555**	**0.573**	**0.669**	**0.751**	**0.812**	**0.887**	**0.637**
		(1.246)	(2.095)	1.882	(2.270)	(2.378)	(2.444)	(2.702)	(2.740)	(2.585)	(2.758)	(4.947)
FFC4 α	EW	**-0.316**	-0.154	**-0.196**	**-0.132**	-0.052	-0.027	0.021	0.097	**0.217**	**0.385**	**0.701**
		(-3.456)	(-1.774)	(-3.531)	(-2.843)	(-1.177)	(-0.629)	(0.429)	(1.606)	(2.967)	(4.238)	(4.749)
	VW	**-0.310**	-0.036	-0.021	**0.097**	**0.111**	**0.133**	**0.204**	**0.236**	**0.252**	**0.311**	**0.621**
		(-4.078)	(-0.531)	(-0.400)	(2.022)	(2.289)	(2.444)	(2.778)	(3.177)	(2.761)	(2.759)	(3.853)
HXZ α	EW	**-0.212**	-0.118	**-0.174**	**-0.122**	-0.045	-0.038	0.010	0.058	0.165	**0.344**	**0.556**
		(-2.064)	(-1.369)	(-2.975)	(-1.993)	(-0.677)	(-0.432)	(0.100)	(0.487)	(1.146)	(1.963)	(2.175)
	VW	**-0.218**	-0.013	0.018	**0.108**	0.080	0.074	0.105	0.157	**0.226**	0.236	**0.455**
		(-2.245)	(-0.157)	(0.296)	(2.103)	(1.471)	(1.055)	(1.142)	(1.553)	(2.258)	(1.929)	(2.363)

Panel B. Single sort - excluding microcaps

		P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
Excess return	EW	0.378	**0.532**	**0.540**	**0.701**	**0.705**	**0.758**	**0.803**	**0.789**	**0.860**	**0.982**	**0.603**
		(1.956)	(2.722)	(2.699)	(3.052)	(3.329)	(3.489)	(3.570)	(3.717)	(3.728)	(4.001)	(4.711)
	VW	0.223	**0.423**	**0.461**	**0.636**	**0.598**	**0.577**	**0.614**	**0.676**	**0.724**	**0.819**	**0.596**
		(1.669)	(2.651)	(2.871)	(3.203)	(3.395)	(3.560)	(3.542)	(4.034)	(3.949)	(4.149)	(4.757)
FFC4 α	EW	**-0.316**	**-0.144**	**-0.127**	-0.042	0.043	**0.098**	**0.131**	**0.185**	**0.227**	**0.343**	**0.659**
		(-4.564)	(-2.500)	(-2.246)	(-0.968)	(1.082)	(2.574)	(3.338)	(3.602)	(4.013)	(4.684)	(5.608)
	VW	**-0.370**	**-0.122**	-0.055	0.031	**0.101**	**0.143**	**0.133**	**0.226**	0.285	**0.369**	**0.738**
		(-5.029)	(-2.566)	(-1.054)	(0.628)	(2.273)	(3.133)	(2.329)	(3.315)	(3.331)	(3.902)	(5.187)
HXZ α	EW	**-0.309**	**-0.164**	**-0.142**	-0.053	0.053	**0.128**	**0.179**	**0.245**	**0.299**	**0.438**	**0.747**
		(-3.418)	(-2.448)	(-2.562)	(-1.203)	(1.187)	(2.611)	(3.066)	(2.857)	(2.715)	(3.368)	(3.639)
	VW	**-0.280**	-0.098	-0.057	0.024	**0.096**	**0.123**	0.096	**0.186**	**0.265**	**0.398**	**0.678**
		(-2.966)	(-1.171)	(-0.733)	(0.442)	(2.006)	(2.309)	(1.355)	(2.172)	(2.289)	(3.241)	(3.479)

Table 3: *Returns and alphas on portfolios of stocks sorted by loss probability (LP). Panel A sorts the full sample with NYSE breakpoints. Panel B sorts stocks from the full sample with market equity equal or above the 20th percentile of the NYSE stocks (excluding microcaps) in each month t. The table presents for each decile the month-$(t+1)$ equal-weighted (EW) and value-weighted (VW) excess returns, Carhart (1997)'s four-factor alphas (FFC4 α), and Hou et al. (2015)'s four-factor alphas (HXZ α). The last column presents the differences in monthly returns and the differences in alphas between portfolios P10 and P1 and the corresponding t-statistics. Average excess, and risk-adjusted returns are given in percentage terms. The sample runs from July 1963 to December 2016, except in the cases the HXZ α, where it starts in January 1967, due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

Panel A. Double sort - LP controlling for JB

		P1 (Low JB)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High JB)
FFC4 α	EW	-0.005	0.079	0.296	0.117	**0.541**	**0.432**	**1.087**	**1.238**	**1.675**	**2.436**
		(-0.041)	(0.595)	(1.896)	(0.799)	(3.585)	(2.653)	(6.972)	(7.343)	(8.355)	(9.008)
	VW	0.029	**0.393**	**0.537**	0.351	**0.740**	**0.465**	**1.291**	**1.185**	**1.484**	**1.062**
		(0.169)	(1.990)	(2.180)	(1.887)	(3.767)	(2.476)	(6.055)	(5.467)	(5.343)	(2.928)
HXZ α	EW	0.146	0.082	0.380	0.256	**0.593**	0.516	**1.155**	**1.180**	**1.548**	**2.473**
		(0.866)	(0.428)	(1.759)	(1.154)	(2.468)	(1.832)	(5.195)	(4.292)	(5.179)	(7.303)
	VW	0.008	0.280	0.519	0.241	**0.658**	0.535	**1.356**	**1.222**	**1.568**	**1.024**
		(0.043)	(0.861)	(1.766)	(1.197)	(2.667)	(1.935)	(4.956)	(3.513)	(5.131)	(2.365)

Panel B. Persistence of LP

LP	Market beta	Size	BM	Mom	Rev	Illiq	Ivol	Adjusted R^2
0.159								3.329%
(20.991)								
0.090	**-0.284**	**-1.136**	**0.325**	**-0.018**	**0.041**	**0.064**	**0.402**	12.029%
(18.147)	(-2.862)	(-20.510)	(5.289)	(-13.121)	(10.139)	(3.847)	(12.261)	

Table 4: *Normal distribution and persistence of LP.* *Panel A:* *Each month, stocks are sorted into deciles based on Jarque-Bera statistic (JB). Then, within each JB-decile, stocks are further sorted into deciles based on LP. We report Carhart (1997)'s four-factor alphas (FFC4 α), and Hou et al. (2015)'s four-factor alphas (HXZ α), on both an equal-weighted (EW) basis and a value-weighted (VW) basis, of the high-LP minus low-LP long-short portfolio within each JB-decile. The sample period runs from July 1963 to December 2016, except in the case of the HXZ α, where it starts in January 1967 due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

Panel B: *Each month from July 1963 to December 2016 we run a firm-level cross-sectional regression of the loss probability (LP) in that month (month $t+1$) on subsets of lagged predictor variables including LP in the previous month (month t) and seven control variables: Market beta is the beta coefficient calculated with daily returns over the past twelve months (from the start of month $t-11$ to the end of month t), following Fama and French (1992). Size is the logarithm of market capitalization. BM is the logarithm of book-to-market ratio. Mom is the cumulative return from the start of month $t-11$ to the end of month $t-1$. Rev is the return of month t. Illiq is Amihud (2002)'s measure of illiquidity. Ivol is the idiosyncratic volatility in percentage over month t, as in Ang et al. (2006b). The table reports the time-series averages of the cross-sectional regression coefficients, their associated Newey and West (1987) adjusted t-statistics (in parentheses), and the regression adjusted R-squareds. Bold typeface indicates a coefficient significant at the 5% level.*

Decile	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)
LP	40.490	47.029	50.814	53.973	56.847	59.376	62.190	65.245	68.632	74.571
LP_{t+1}	55.393	56.164	56.649	57.153	57.596	58.120	58.578	59.215	59.703	60.878
					Firm characteristics					
MktCap	2539.859	2252.949	2088.335	1931.103	1766.402	1630.386	1505.604	1370.729	1256.017	1023.250
BM ratio	0.757	0.781	0.800	0.823	0.838	0.851	0.875	0.896	0.920	0.962
Mom	24.800	22.130	20.331	18.812	17.248	16.252	14.940	14.172	12.948	11.289
Illiq	0.575	0.861	1.104	1.340	1.593	1.774	1.972	2.149	2.248	2.315
Rev	12.592	8.195	5.728	3.717	1.901	0.406	-1.267	-3.032	-4.932	-7.972
					Risk measures					
Market beta	0.955	0.947	0.935	0.922	0.910	0.896	0.882	0.866	0.850	0.809
Ivol	2.139	2.229	2.299	2.348	2.402	2.442	2.475	2.503	2.515	2.478
Skew	0.393	0.408	0.423	0.437	0.452	0.470	0.489	0.515	0.543	0.592
Coskew	-4.453	-4.408	-4.371	-4.392	-4.420	-4.552	-4.574	-4.752	-4.757	-4.833
Max	3.703	3.685	3.697	3.687	3.691	3.681	3.654	3.604	3.513	3.162

Table 5: *Characteristics for decile portfolios of stocks sorted by loss probability (LP). At the end of each month t, all stocks are sorted into ascending LP-decile portfolios. Portfolio P1 (P10) is the portfolio of stocks with the lowest (highest) LP over the month. The table reports for each decile the average across the months in the sample of the mean values within each month of various characteristics for the stocks: LP is the loss probability in percentage. LP_{t+1} is the one-month ahead loss probability. MktCap is the market capitalization in millions of dollars. BM ratio is the book-to-market ratio. Mom is the cumulative return in percentage from the start of month $t-11$ to the end of month $t-1$. Illiq is Amihud (2002)'s measure of illiquidity. Rev is the return in percentage in month t. Market beta is the beta coefficient calculated with daily returns over the past twelve months, following Fama and French (1992). Ivol is the idiosyncratic volatility in percentage over the month, as in Ang et al. (2006b). Skew is the total skewness of daily returns over the past twelve months. Coskew is the co-skewness computed as in Harvey and Siddique (2000) using daily returns over the past twelve months. Max is the average of the five largest returns in percentage in month t, as in Bali et al. (2017). The sample runs from July 1963 to November 2016.*

Control variable	MktCap		Mom		Rev		Illiq	
	EW	VW	EW	VW	EW	VW	EW	VW
Excess return	**0.725**	**0.700**	**1.188**	**1.017**	**0.307**	**0.396**	**0.749**	**0.781**
	(6.168)	(6.178)	(9.251)	(7.976)	(2.998)	(3.977)	(5.913)	(6.872)
FFC4 α	**0.815**	**0.792**	**1.139**	**0.979**	**0.296**	**0.393**	**0.836**	**0.845**
	(7.452)	(7.391)	(10.619)	(8.596)	(3.619)	(5.478)	(6.902)	(7.838)
HXZ α	**0.823**	**0.802**	**1.205**	**1.023**	**0.360**	**0.397**	**0.869**	**0.865**
	(4.492)	(4.528)	(7.140)	(6.948)	(3.523)	(3.825)	(4.298)	(4.804)

Table 6: *Returns and alphas on difference portfolios in double sort. Each month, stocks are sorted into deciles based on a control variable (one of MktCap, Mom, Rev or Illiq). Then, within each decile, stocks are further sorted into deciles based on LP. The returns of the ten LP-portfolios over the next month are averaged across the ten control variable deciles. We report the excess return, Carhart (1997)'s four-factor alphas (FFC4 α), and Hou et al. (2015)'s four-factor alphas (HXZ α), on both an equal-weighted (EW) basis and a value-weighted (VW) basis, of the high-LP minus low-LP long-short portfolio (P10 - P1). The sample period runs from July 1963 to December 2016, except in the case of the HXZ α, where it starts in January 1967 due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

	Excess return		FFC4 α		FFC4+PS α		HXZ α	
	EW	VW	EW	VW	EW	VW	EW	VW
P1 (Low $LP_{\perp Rev}$)	0.430	0.234	-0.261	-0.318	-0.241	-0.319	-0.253	-0.275
P2	0.538	0.471	-0.168	-0.062	-0.166	-0.071	-0.138	-0.071
P3	0.613	0.504	-0.072	-0.005	-0.083	0.009	-0.043	0.008
P4	0.695	0.567	0.012	0.065	0.016	0.056	0.076	0.049
P5	0.808	0.705	0.137	0.226	0.131	0.213	0.189	0.190
P6	0.766	0.676	0.064	0.207	0.054	0.195	0.132	0.207
P7	0.873	0.718	0.171	0.225	0.168	0.241	0.258	0.186
P8	0.920	0.656	0.223	0.179	0.214	0.168	0.312	0.160
P9	0.919	0.792	0.231	0.287	0.215	0.299	0.291	0.337
P10 (High $LP_{\perp Rev}$)	0.835	0.867	0.127	0.346	0.089	0.386	0.119	0.336
P10 - P1	**0.405**	**0.634**	**0.388**	**0.664**	**0.330**	**0.705**	**0.452**	**0.612**
t-statistic	(3.074)	(4.806)	(3.637)	(5.666)	(2.941)	(5.677)	(3.154)	(4.300)

Table 7: *Returns and alphas on portfolios of stocks sorted by $LP_{\perp Rev}$. At the end of each month t, all stocks are sorted into ascending decile portfolios, based on the portion of LP orthogonal to Rev ($LP_{\perp Rev}$). The table presents for each decile the average across the months in the sample of the month-$(t+1)$ equal-weighted (EW) and value-weighted (VW) excess returns, Carhart (1997)'s four-factor alphas (FFC4 α), alphas of the four-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor (FFC4+PS α), and Hou et al. (2015)'s four-factor alphas (HXZ α). The last two rows present the differences in monthly returns and the differences in alphas between portfolios P10 and P1 and the corresponding t-statistics. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses. Bold typeface indicates a coefficient significant at the 5% level. Average excess and risk-adjusted returns are given in percentage terms. The sample runs from July 1963 to December 2016, except in the cases of the FFC4+PS α and the HXZ α, where it starts in January 1968 for FFC4+PS α and in January 1967 for HXZ α, due to the availability constraint of the factors.*

	(1)	(2)	(3)	(4)
LP	**2.384**	**2.959**	**1.851**	**1.047**
	(5.785)	(8.975)	(6.952)	(4.845)
Market beta		-0.103	0.237	0.132
		(-0.685)	(1.677)	(0.994)
Size		-0.009	**-0.145**	**-0.155**
		(-0.197)	(-3.880)	(-4.188)
BM		**0.241**	**0.206**	**0.222**
		(4.145)	(3.691)	(3.945)
Mom		**0.008**	**0.008**	**0.007**
		(6.082)	(5.538)	(5.365)
Illiq			**0.031**	**0.031**
			(2.183)	(2.132)
Ivol			**0.126**	-0.087
			(2.440)	(-1.603)
Coskew			-0.001	-0.002
			(-0.337)	(-0.585)
Skew			**-0.072**	**-0.051**
			(-3.652)	(-2.620)
Max			**-0.337**	**-0.164**
			(-8.668)	(-3.686)
Rev				**-0.022**
				(-4.169)
Intercept	**-0.616**	**-0.905**	**1.016**	**1.567**
	(-2.238)	(-2.447)	(3.520)	(5.184)
Adjusted R^2	0.666%	5.680%	6.844%	7.120%
n	3246	2604	2526	2525

Table 8: *Firm-level Fama-MacBeth regressions. The table reports the results of Fama and MacBeth (1973) regression analyses of the relation between loss probability (LP) and future stock returns. In each month t, we run a cross-sectional regression of month-$(t+1)$ stock excess returns (in percentage) on LP and combinations of the firm characteristics, and risk measures. Size is the logarithm of market capitalization. BM is the logarithm of book-to-market ratio.The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags are shown in parentheses. The average adjusted R-squared of the cross-sectional regressions is presented in the row labeled Adjusted R^2. The row labeled n presents the average number of observations used in the monthly cross-sectional regressions. The sample period runs from July 1963 to December 2016. Bold typeface indicates a coefficient significant at the 5% level.*

	(1)	(2)	(3)	(4)	(5)
LP	**1.468**	**0.597**	**0.531**	**1.028**	**0.792**
	(5.897)	(2.661)	(2.288)	(4.842)	(3.556)
Market beta	0.126	0.163	0.130	0.276	0.017
	(0.972)	(1.230)	(0.979)	(1.700)	(0.134)
Size	**-0.149**	**-0.164**	**-0.147**	**-0.155**	**-0.108**
	(-4.115)	(-4.436)	(-3.998)	(-4.177)	(-3.161)
BM	**0.223**	**0.219**	**0.225**	**0.223**	**0.210**
	(3.971)	(3.875)	(3.999)	(3.956)	(3.544)
Mom	**0.007**	**0.008**	**0.007**	**0.007**	**0.007**
	(5.465)	(5.562)	(5.471)	(5.419)	(5.643)
Illiq	**0.032**	**0.030**	**0.034**	**0.031**	0.023
	(2.210)	(2.088)	(2.413)	(2.088)	(1.780)
Ivol	**-0.141**	0.107	0.007	-0.087	-0.092
	(-2.679)	(1.878)	(1.450)	(-1.596)	(-1.791)
Coskew	-0.002	-0.002	-0.002	-0.006	0.000
	(-0.614)	(-0.503)	(-0.523)	(-1.168)	(-0.014)
Skew	**-0.046**	**-0.077**	**-0.073**	**-0.049**	-0.038
	(-2.293)	(-3.943)	(-3.676)	(-2.512)	(-1.776)
Max	**-0.261**	**-0.196**	**-0.161**	**-0.162**	**-0.168**
	(-4.323)	(-4.388)	(-3.629)	(-3.679)	(-3.974)
Rev	-0.002	**-0.031**	**-0.035**	**-0.023**	**-0.025**
	(-0.176)	(-5.803)	(-5.770)	(-4.227)	(-4.520)
EL	**0.525**				
	(2.493)				
Min		**0.079**			
		(7.710)			
Semivar			**-4.827**		
			(-5.252)		
Downside beta				-0.148	
				(-1.895)	
TK					**-0.041**
					(-2.906)
Intercept	**1.230**	**1.912**	**1.652**	**1.577**	**1.306**
	(3.996)	(6.290)	(5.449)	(5.233)	(4.331)
Adjusted R^2	7.285%	7.197%	7.255%	7.211%	6.968%
n	2525	2525	2525	2525	2500

Table 9: *Fama-MacBeth regressions with alternative risk measures. The table reports the results of Fama and MacBeth (1973) regression analyses of the relation between loss probability (LP) and future stock returns. In each month t, we run a cross-sectional regression of month-$(t+1)$ stock excess returns (in percentage) on LP and combinations of the firm characteristics, and risk measures. EL (Semivar) is the expected loss (semivariance) defined as in Equation (19) (Equation (25)) in the Appendix, calculated with daily return in month t. Min is a stock's minimum one-day return in month t, as in Bali et al. (2011). Downside beta is calculated with daily returns over the past twelve months (from the start of month $t-11$ to the end of month t), following Ang et al. (2006a). TK is the prospect theory value calculated with monthly returns over the past five years (from the start of month $t-59$ to the end of month t), following Barberis et al. (2016). The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags are shown in parentheses. The average adjusted R-squared of the cross-sectional regressions is presented in the row labeled Adjusted R^2. The row labeled n presents the average number of observations used in the monthly cross-sectional regressions. The sample period runs from July 1963 to December 2016. Bold typeface indicates a coefficient significant at the 5% level.*

Control variable	EL		Min		Semivar		Downside beta		TK	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Excess return	**0.950**	**0.888**	**0.955**	**0.868**	**0.952**	**0.895**	**0.955**	**0.785**	**0.938**	**0.721**
	(7.940)	(6.441)	(8.084)	(6.018)	(8.425)	(6.652)	(6.930)	(6.158)	(7.779)	(5.703)
FFC4 α	**1.024**	**0.940**	**0.985**	**0.881**	**1.005**	**0.916**	**0.967**	**0.807**	**0.972**	**0.732**
	(9.571)	(7.840)	(9.455)	(6.613)	(9.812)	(7.936)	(8.427)	(7.567)	(8.890)	(5.475)
HXZ α	**0.967**	**0.794**	**1.009**	**0.854**	**1.001**	**0.823**	**1.015**	**0.777**	**0.983**	**0.741**
	(5.363)	(4.295)	(5.884)	(4.501)	(5.828)	(4.432)	(5.580)	(5.712)	(5.538)	(4.163)

Table 10: *Double sort with alternative risk measures. Each month, stocks are sorted into deciles based on a control variable (one of EL, Min, Semivar, Downside beta, or TK). Then, within each decile, stocks are further sorted into deciles based on LP. The returns of the ten LP-portfolios over the next month are averaged across the ten control variable deciles. We report the excess return, Carhart (1997)'s four-factor alphas (FFC4 α), and Hou et al. (2015)'s four-factor alphas (HXZ α), on both an equal-weighted (EW) basis and a value-weighted (VW) basis, of the high-LP minus low-LP long-short portfolio (P10 - P1). The sample period runs from July 1963 to December 2016, except in the case of the HXZ α, where it starts in January 1967 due to the availability constraint of the factors. Newey and West (1987) adjusted t-statistics with six lags are reported in parentheses, and bold typeface indicates a coefficient significant at the 5% level.*

	(1)	(2)	(3)	(4)	(5)
LP	**2.322**	**0.866**	0.434	0.124	-0.178
	(3.900)	(3.855)	(1.449)	(0.353)	(-0.566)
LP*Size	**-0.265**				
	(-2.701)				
LP*Illiq		**0.253**			
		(2.322)			
LP*Ivol			**0.345**		
			(2.603)		
LP*Analyst				**0.468**	
				(2.904)	
LP*IO					2.685
					(1.492)
Market beta	0.133	0.130	0.138	0.178	0.108
	(1.002)	(0.983)	(1.040)	(1.207)	(0.649)
Size	-0.004	**-0.158**	**-0.159**	**-0.115**	**-0.146**
	(-0.061)	(-4.265)	(-4.322)	(-2.498)	(-3.583)
BM	**0.223**	**0.222**	**0.221**	**0.238**	**0.237**
	(3.959)	(3.944)	(3.927)	(4.105)	(3.932)
Mom	**0.007**	**0.007**	**0.007**	**0.006**	**0.006**
	(5.389)	(5.373)	(5.420)	(4.532)	(3.998)
Illiq	**0.028**	**-0.133**	**0.031**	0.013	0.017
	(2.035)	(-2.172)	(2.152)	(1.398)	(1.593)
Ivol	-0.081	-0.082	**-0.295**	**-0.116**	-0.074
	(-1.497)	(-1.512)	(-3.052)	(-2.093)	-1.310
Coskew	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.622)	(-0.581)	(-0.584)	(-0.376)	(-0.420)
Skew	**-0.052**	**-0.051**	**-0.056**	**-0.054**	**-0.049**
	(-2.713)	(-2.611)	(-2.897)	(-2.644)	(-2.230)
Max	**-0.173**	**-0.169**	**-0.171**	**-0.155**	**-0.178**
	(-3.900)	(-3.785)	(-3.873)	(-3.246)	(-3.639)
Rev	**-0.021**	**-0.022**	**-0.021**	**-0.015**	-0.010
	(-3.922)	(-4.067)	(-3.791)	(-2.850)	(-1.845)
Analyst				**-0.344**	
				(-3.780)	
IO					-0.238
					(-0.207)
Intercept	0.840	**1.696**	**1.979**	**2.161**	**2.155**
	(1.771)	(5.593)	(6.494)	(5.373)	(5.239)
Adjusted R^2	7.200%	7.216%	7.212%	6.049%	5.841%
n	2525	2525	2525	2878	2994

Table 11: *Fama-MacBeth regressions with limits to arbitrage, investor attention, and institutional holdings. The table reports the results of Fama and MacBeth (1973) regression analyses of the relation between future stock returns and LP interacted with each of the four variables: Size, the natural logarithm of market capitalization; Illiq, Amihud (2002)'s measure of illiquidity; Ivol, the idiosyncratic volatility in percentage over the month, as in Ang et al. (2006b); Analyst, the logarithm of one plus the number of analysts following the stock in a given month according to I/B/E/S; IO, the logarithm of one plus the fraction of shares outstanding held by investors filing Form 13F. The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags are shown in parentheses. The sample period runs from July 1963 to December 2016, except in the cases of the Analyst regression and the IO regression. The Analyst regression starts in January 1976 and the IO regression in January 1980, due to the availability constraint of the data. Bold typeface indicates a coefficient significant at the 5% level.*

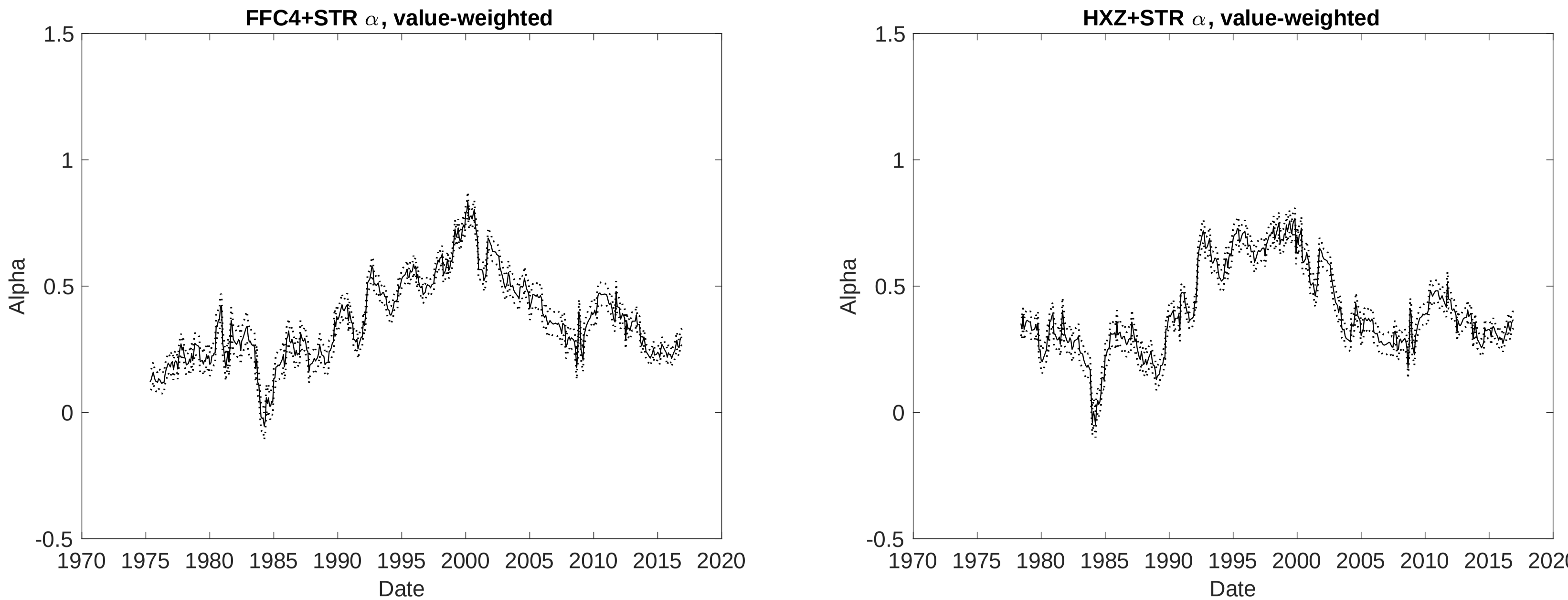

Figure 1: *Ten-year trailing alpha of the difference portfolio. Each month, stocks are sorted into deciles based on LP. The figure presents alpha from Carhart (1997)'s four-factor model augmented with the short-term reversal factor (FFC4+STR α, left panel), and alpha from Hou et al. (2015)'s four-factor model augmented with the short-term reversal factor (HXZ+STR α, right panel) of the high-LP minus low-LP long-short portfolio (P10 - P1), both on a value-weighted basis, estimated with the past 120 months' data. Dotted lines indicate the 95% confidence interval, calculated using Newey and West (1987) adjusted standard errors with six lags.*

Appendix 1. Variable definitions

This section describes the calculation of the variables used in the paper. For variables calculated using one year's daily data (Market beta, Downside beta, Coskew, Skew), we require a minimum of 200 valid daily return observations during the given year. For variables calculated using one month's daily data (LP, Max, Ivol, Illiq, EL, Semivar), we require 15 valid daily return observations during the given month. For variables calculated using five years' monthly data (TK), we require a minimum of 24 valid monthly return observations during the five-year measurement period. If the data requirements for calculating the value of a variable for a stock i in a month t are not satisfied, the given stock-month observation is set to be missing. Variables that are measured on a return scale (Max, Mom, Ivol, Min, TK, EL, Semivar) are recorded as percentages.

Market Beta We calculate market beta using a one-factor market model regression specification applied to one year of daily observations. Specially, we use the following model,

$$r_d = a + b_1 MKT_d + \epsilon_d, \tag{16}$$

where r_d is the excess return of the stock on day d; MKT_d is the excess return of the market portfolio (the market factor) on day d. Market beta is taken to be the estimated value of the regression coefficient b_1. To calculate a stock's month-t value of beta, the regression is fitted using daily return data covering the 12-months up to and including the month for which beta is being calculated (months $t-11$ through t, inclusive). Daily market excess return and risk-free security return data are taken from Kenneth French's data library at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. The stock excess return is calculated as the stock return minus the return on the risk-free security.

Downside Beta We follow Ang et al. (2006a) to define downside beta of the month t as

$$Downside\ beta = \frac{\text{cov}(r_d, MKT_d | MKT_d < \mu_{MKT})}{\text{var}(MKT_d | MKT_d < \mu_{MKT})}, \tag{17}$$

where r_d is the excess return of the stock on day d; MKT_d is the excess return of the market portfolio on day d. μ_{MKT} is the average market excess return. We calculate downside beta for the month t using daily return data covering the 12-months up to and including the month for which downside beta is being calculated (months $t-11$ through t, inclusive).

Book-to-Market Ratio (BM ratio and BM): Following Bali et al. (2016), we define the book-to-market ratio for the months t from June of year y through May of year $y+1$ to be the book value of equity of the stock, calculated using balance sheet data from Compustat for the fiscal year ending in calendar year $y-1$, divided by the market capitalization of the stock at the end of calendar year $y-1$. The book value of equity is defined as stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock. For observations where the book value is negative, we deem the book-to-market ratio to be missing. In regressions, we use the natural logarithm of the book-to-market ratio and denote it with BM. We denote the raw book-to-market ratio with BM ratio.

Illiquidity (Illiq): We calculate the month t illiquidity (Illiq) for a stock following Amihud (2002) as the average of the absolute value of the stock's return (taken as a decimal) divided by the dollar volume traded in the stock (in millions of dollars), calculated using daily data from month t, taken from CRSP. We adjust for institutional features of the way that volume on the NASDAQ is reported (see Gao and Ritter, 2010). Specifically, for stocks that trade on the NASDAQ, we divide the volume reported in CRSP by 2.0, 1.8, 1.6, and 1 for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and during or subsequent to January 2004, respectively. For a given month, a stock's Illiq is defined as

$$Illiq = \frac{1}{D} \sum_{d=1}^{D} \frac{|R_d|}{VOLD_d}, \tag{18}$$

where D is the number of trading days in the month; R_d is the return of the stock on day d of the month, measured as a decimal; $VOLD_d$ is the dollar volume of the stock traded on day d, calculated as the closing price of the stock times the number of shares traded, both on day d, measured in millions of dollars.

Expected Loss (EL): The expected loss of a stock in month t is calculated as

$$EL = \frac{1}{D} \sum_{d=1}^{D} \mathbb{1}_{R_d < R_{f,d}} |R_d - R_{f,d}|, \tag{19}$$

where D is the number of trading days in the month; R_d and $R_{f,d}$ are the return of the stock and the risk-free rate on day d of the month, respectively; $\mathbb{1}_{R_d < R_{f,d}}$ is an indicator function equal one if $R_d < R_{f,d}$ and zero otherwise.

Loss Probability (LP): The loss probability of a stock in month t is calculated as

$$LP = \frac{\sum_{d=1}^{D} \mathbb{1}_{R_d < R_{f,d}}}{D}, \tag{20}$$

where D is the number of trading days in the month; R_d and $R_{f,d}$ are the return of the stock and the risk-free rate on day d of the month, respectively; $\mathbb{1}_{R_{i,d} < R_{f,d}}$ is an indicator function equal to one if $R_{i,d} < R_{f,d}$ and zero otherwise.

Max The month t value of Max for any stock is calculated as the average of the five highest daily returns of the stock in the month.

Market Capitalization (MktCap and Size): We calculate the month t market capitalization (MktCap) of a stock as the month-end stock price times the number of shares outstanding, taken from CRSP and measured in millions of dollars. Since the distribution of MktCap is highly skewed, in regression analysis, we use the natural logarithm of MktCap, which we denote Size.

Min The month t value of Min for any stock is calculated as the lowest daily return of the stock in the month.

Momentum (Mom): To control for the medium-term momentum effect of Jegadeesh and Titman (1993), we define the month t momentum variable (Mom) to be the stock return during the 11-month period up to but not including the current month (months $t-11$ through $t-1$, inclusive). Mom is calculated using monthly return data from CRSP.

Co-Skewness (Coskew): Following Harvey and Siddique (2000), we define the co-skewness (Coskew) of a stock in any month t to be the estimated slope coefficient on the squared market excess return from a regression of the stock's excess return on the market's excess return and the squared market excess return using one year of daily data up to and including the given month t (months $t-11$ through t, inclusive). Specifically, Coskew is the estimated coefficient b_2 from the regression specification

$$r_d = a + b_1 MKT_d + b_2 MKT_d^2 + \epsilon_d. \tag{21}$$

Total Skewness (Skew): We define the total skewness (Skew) of a stock in month t to be the skewness of the stock's daily returns calculated using one year of data up to and including the given month t (months $t-11$ through t, inclusive).

Prospect Theory Value (TK): Following Barberis et al. (2016), we calculate the prospect theory value (TK) of a stock for month t with the stock's monthly returns over the past five years up to and including the given month t (months $t-59$ through t, inclusive), according to the formula,

$$TK = \sum_{j=-m}^{-1} v(r_j)\left[w^-\left(\frac{j+m+1}{N}\right) - w^-\left(\frac{j+m}{N}\right)\right] + \sum_{j=1}^{n} v(r_j)\left[w^+\left(\frac{n-j+1}{N}\right) - w^+\left(\frac{n-j}{N}\right)\right], \tag{22}$$

where N is the number of valid monthly returns in the five years' period; r_j is the stock's jth monthly excess return over the past five years, in ascending order from $(r_{-m}, r_{-m+1}, \ldots, r_{-1}, r_1, \ldots, r_{n-1}, r_n)$ with r_{-m} the lowerst monthly excess return, r_{-1} the largest negative monthly excess return, r_1 the smallest non-negative monthly excess return, and r_n the largest monthly excess return $(m+n=N)$; $v(\cdot)$, $w^+(\cdot)$, $w^-(\cdot)$ are given by

$$v(x) = \begin{cases} x^\alpha, & x \geq 0 \\ -\lambda(-x)^\alpha, & x < 0, \end{cases} \tag{23}$$

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}, \;\; w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{1/\delta}}, \tag{24}$$

and $\alpha = 0.88$ is the parameter for risk attitudes both in gain and in loss; $\lambda = 2.25$ is the parameter for loss aversion; $\gamma = 0.61$, $\delta = 0.69$ are parameters for probability weighting in gain and in loss, respectively.

Semivariance (Semivar): The semivariance of a stock in month t is calculated as

$$Semivar = \frac{1}{D}\sum_{d=1}^{D} \mathbb{1}_{R_d < R_{f,d}} (R_d - R_{f,d})^2, \tag{25}$$

where D is the number of trading days in the month; R_d and $R_{f,d}$ are the return of the stock and the risk-free rate on day d of the month, respectively; $\mathbb{1}_{R_d < R_{f,d}}$ is an indicator function equal to one if $R_d < R_{f,d}$ and zero otherwise.

Idiosyncratic Volatility (Ivol): We calculate a stock's idiosyncratic volatility (Ivol) in month t following Ang et al. (2006b) as the standard deviation of the residuals from a Fama-French three-factor regression of the stock's excess return on the market excess return (MKT), size (SMB), and book-to-market ratio (HML) factors using daily return data from month t. The regression specification is

$$r_d = a + b_1 MKT_d + b_2 SMB_d + b_3 HML_d + \epsilon_d, \tag{26}$$

where SMB_d and HML_d are the returns of the size and book-to-market factors of Fama and French (1993), respectively, on day d.

Appendix 2. Parametric LP estimation

Normal distribution We assume that in month $t+1$, daily excess return of a stock, r, is normally distributed, $r \sim \mathcal{N}(\mu, \sigma^2)$. We use the sample mean $\bar{r}$ and sample variance s^2 of daily excess return in month t as the estimates for μ, and σ^2, respectively,

$$\bar{r} = \frac{\sum_{d=1}^{D} r_d}{D}, \;\; s^2 = \frac{\sum_{d=1}^{D} (r_d - \bar{r})^2}{D-1}, \tag{27}$$

where D is the number of trading days in month t; r_d is the excess return of the stock on day d of the month. We require 15 valid daily return observations during the month. Then, the parametric loss probability of the stock in month $t+1$ is given by,

$$LP_p = \mathrm{P}[r < 0] = \frac{1}{\sqrt{2\pi}s} \int_{-\infty}^{0} \exp\left(-\frac{(x-\bar{r})^2}{2s^2}\right) dx. \tag{28}$$

Skewed t distribution We assume that in month $t+1$, daily excess return of a stock, r, follows the skewed t (ST) distribution. Substantial empirical evidences show that the distribution of financial return is usually skewed, is peaked around the mean (leptokurtic), and has fat tails, i.e., is not normally distributed. To account for the nonnormality of returns, Hansen (1994) introduces a generalization of the Student t-distribution.

The ST probability distribution function (PDF) that provides a flexible tool for modeling the emprical distribution of stock returns exhibiting skewness and leptokurtosis is given by,

$$f_{ST}(z;\nu,\lambda) = \begin{cases} bc\left(1+\frac{1}{\nu-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-\frac{\nu+1}{2}} & \text{if } z < -\frac{a}{b} \\ bc\left(1+\frac{1}{\nu-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-\frac{\nu+1}{2}} & \text{if } z \geq -\frac{a}{b} \end{cases}, \tag{29}$$

where $z = (r-\mu)/\sigma$ is the standardized excess stock return, and the constants a, b, and c are given by,

$$\begin{gathered} a = 4\lambda c\left(\frac{\nu-2}{\nu-1}\right), \quad b^2 = 1+3\lambda^2-a^2, \\ c = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi(\nu-2)}\Gamma\left(\frac{\nu}{2}\right)}, \end{gathered} \tag{30}$$

where $\Gamma(\cdot)$ is the gamma function.

Parameters of the ST PDF are estimated by maximizing the log-likelihood function,[29] with daily excess returns in month t. We require 15 valid daily return observations during the month. Then, the parametric loss probability of the stock in month $t+1$ is given by,

$$LP_p = \mathrm{P}[r<0] = \mathrm{P}[z<-\mu/\sigma] = \int_{-\infty}^{-\mu/\sigma} f_{ST}(x;\nu,\lambda)dx. \tag{31}$$

[29]See Hansen (1994) and Bali et al. (2009) for more details

Appendix 3. Additional firm-level regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LP	**1.687**	**2.306**	**2.176**	**1.708**	**1.769**	**1.428**	**1.159**	**1.702**	**1.585**
	(4.485)	(7.682)	(7.795)	(5.696)	(5.690)	(4.701)	(3.862)	(5.732)	(5.146)
Market beta		-0.117	0.047	-0.001	0.021	0.036	0.014	0.275	-0.060
		(-0.639)	(0.263)	(-0.008)	(0.134)	(0.214)	(0.085)	(1.006)	(-0.358)
Size		-0.033	**-0.074**	**-0.084**	**-0.086**	**-0.084**	**-0.078**	**-0.084**	**-0.062**
		(-1.033)	(-2.480)	(-2.811)	(-2.861)	(-2.798)	(-2.608)	(-2.855)	(-1.996)
BM		0.058	0.043	0.059	0.062	0.059	0.064	0.059	0.096
		(0.902)	(0.671)	(0.893)	(0.949)	(0.901)	(0.975)	(0.901)	(1.420)
Mom		**0.007**	**0.007**	**0.007**	**0.007**	**0.007**	**0.007**	**0.007**	**0.007**
		(3.682)	(3.998)	(3.972)	(4.076)	(4.130)	(4.083)	(4.008)	(4.066)
Illiq			0.009	0.004	0.001	0.004	0.024	0.004	-0.017
			(0.266)	(0.099)	(0.016)	(0.109)	(0.672)	(0.101)	(-0.588)
Ivol			-0.096	**-0.228**	**-0.210**	-0.070	-0.005	**-0.222**	**-0.241**
			(-1.339)	(-2.702)	(-2.414)	(-0.732)	(-0.058)	(-2.698)	(-3.061)
Coskew			0.007	0.005	0.004	0.006	0.005	-0.002	0.006
			(1.142)	(0.903)	(0.745)	(0.999)	(0.973)	(-0.230)	(1.041)
Skew			-0.024	-0.016	-0.016	-0.037	-0.037	-0.015	-0.027
			(-0.883)	(-0.565)	(-0.545)	(-1.315)	(-1.296)	(-0.526)	(-1.042)
Max			**-0.087**	0.026	0.020	0.020	0.077	0.021	0.029
			(-2.045)	(0.372)	(0.239)	(0.294)	(1.115)	(0.320)	(0.439)
Rev				**-0.016**	-0.015	**-0.026**	**-0.038**	**-0.017**	**-0.019**
				(-2.168)	(-1.173)	(-3.394)	(-4.599)	(-2.232)	(-2.457)
EL					-0.026				
					(-0.084)				
Min						**0.074**			
						(3.715)			
Semivar							**-12.925**		
							(-6.176)		
Downside beta								-0.262	
								(-1.395)	
TK									-0.033
									(-1.703)
Intercept	-0.349	-0.444	0.160	0.515	0.482	**0.676**	0.546	0.518	0.396
	(-1.421)	(-1.348)	(0.503)	(1.544)	(1.312)	(1.998)	(1.613)	(1.575)	(1.085)
Adjusted R^2	1.452%	12.688%	14.707%	15.303%	15.619%	15.587%	15.533%	15.702%	15.794%
n	3246	2604	2526	2525	2525	2525	2525	2525	2500

Table A1: *Firm-level Fama-MacBeth regressions (WLS). The table reports the results of Fama and MacBeth (1973) regression analyses of the relation between loss probability (LP) and future stock returns, using weighted leaset square estimation with the market equity as the weights. The table presents the time-series averages of the monthly cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags are shown in parentheses. The average adjusted R-squared of the cross-sectional regressions is presented in the row labeled Adjusted R^2. The row labeled n presents the average number of observations used in the monthly cross-sectional regressions. The sample period runs from July 1963 to December 2016. Bold typeface indicates a coefficient significant at the 5% level.*