

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

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JEL classification: G11, G12, G14

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Abstract

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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 as the only measure to model risk and suggest that investors may regard risk measures other

¹For 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).

²One 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).

³Levy (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.

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 evidence 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).

⁴The 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. 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 the cumulative prospect theory. Huber et al. (2020) further provide experimental evidence that investors' aversion to loss probability affects asset prices in trading. More recently, Holzmeister et al. (2020) find, in a large-scale survey experiment, strong evidence that the probability of suffering a loss is the main driver for both the perception of financial

risk and investment propensity among financial professionals and lay people. However, there is ambiguity concerning whether decision preferences of subjects in experiments have any connection with the real-life behavior of investors trading in financial markets. There is a likelihood that students' and professionals' behavior may differ from that of usual retail investors; institutional investors may behave very differently from individual investors 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 revealed in experiments has any significant implication on investing in 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 0.92% (0.72%). The t -values ($t = 6.49$ for the equal-weighted portfolio and $t = 5.17$ for the value-weighted portfolio) are much larger than the multiple test hurdle of 2.78 recommended by Harvey et al. (2016). The corresponding q -factor alpha of a zero-cost portfolio that is long high-LP stocks and short low-LP stocks (high-low LP portfolio) is 1.10% ($t = 4.56$) if equal-weighted and 0.77% ($t = 4.32$) if value-weighted. The differences in 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”⁵ 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 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).⁶ 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. The LP effect remains strong and significant after isolating the impact of microcaps, indicating that

⁵ p -hacking refers to the engagement of researchers in searching model specifications, selecting samples and adjusting test procedures until insignificant results finally become significant.

⁶Specifically, 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).

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 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 find that high-LP stocks tend to be small. 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, momentum, short-term reversal, idiosyncratic volatility, skewness, and Max. 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 confirmed by 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 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, and illiquid stocks) 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 “mispricing” 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 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

It does not require any theoretical model to intuitively predict a positive relation between a stock's LP and its subsequent return. Nevertheless, following Barberis et al. (2016) we present in this section a simple one-period model to formalize our prediction.

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:

$$w = w_{Tan} + kw_{LP}, \quad (1)$$

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 i th element

$$w_{LP}^i = \overline{LP} - LP_i, \quad (2)$$

where LP_i is the loss probability of stock i , as can be defined in Equation (7); 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:

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

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

Rearranging the equation above, we obtain:

$$w_{Tan} = w_M - \phi w_{LP}. \quad (4)$$

As detailed in Barberis et al. (2016), in our assumed economy it can be shown:

$$\begin{aligned} \frac{\mu_i - r_f}{\mu_M - r_f} &= \beta_i - \frac{\phi w_{LP}^i \sigma_{\epsilon_i}^2}{\sigma_M^2 (1 - \phi \beta_{LP})} \\ &= \beta_i - \frac{\phi (\overline{LP} - LP_i) \sigma_{\epsilon_i}^2}{\sigma_M^2 (1 - \phi \beta_{LP})}, \end{aligned} \quad (5)$$

where μ_i and μ_M are the mean return of asset i and the market portfolio, respectively. r_f is the risk-free rate. β_{LP} is the market beta of the portfolio whose asset weights are given by w_{LP} . σ_M^2 is the variance of the market portfolio and $\sigma_{\epsilon_i}^2$ is the variance of the residuals in the single index model:

$$r_i = \alpha_i + \beta_i r_M + \epsilon_i, \quad (6)$$

where r_i and r_M are asset i 's return and the market portfolio's return, respectively.

The second term on the right-hand side of Equation (5), $-\frac{\phi(\overline{LP}-LP_i)\sigma_{\epsilon_i}^2}{\sigma_M^2(1-\phi\beta_{LP})}$, 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.⁷

⁷Note that, by definition, ϕ , $\sigma_{\epsilon_i}^2$, and σ_M^2 are positive. β_{LP} is the market beta of a zero-cost portfolio ($\sum_{i=1}^N w_{LP}^i = 0$) 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 V).

3 Variables and data

3.1 Variables

LP is the key variable of interest in our analyses. We measure a stock’s LP in a given month t as the fraction of the total trading days in the month with a negative return.⁸ Precisely, for each stock, its loss probability in month t is

$$LP = \frac{\sum_{d=1}^D \mathbb{1}_{R_d < 0}}{D}, \quad (7)$$

where D is the number of trading days in the month, R_d is the return of the stock on day d , and $\mathbb{1}_{R_d < 0}$ is an indicator function equal to one if $R_d < 0$ and zero otherwise. We focus on this definition of LP throughout the study, unless otherwise stated. When calculating LP, we exclude zero-return observations.⁹ First, a zero return is neither a gain nor a loss for a typical investor. Second, zero returns are quite frequent (as much as 14.2% of all non-missing returns of our sample stocks are zero during the sample period), which are likely the result of illiquidity. Marginal investors will not trade a stock, causing a zero return, if for example the value of the new information signal is insufficient to cover the costs of trading. 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

⁸For alternative definitions, refer to Section 4.1.

⁹Including zero returns when calculating LP does not qualitatively change our results.

trading has become increasingly popular).

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

¹⁰Although our variable of interest LP is measured with daily data, 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.

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

of the smallest and most illiquid stocks, following An (2016) we exclude stocks whose price 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 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 factors 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 I, 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

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

and Stambaugh (2003) liquidity factor (FFC4+PS α); and the q -factor alphas (HXZ α), estimated using the state-of-the-art q -factor model proposed by Hou et al. (2015).¹³

[Table I 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 in a near-monotonic fashion. Further, the last column of Table I shows that the equal-weighted (value-weighted) average excess return difference between decile 10 and decile 1 portfolios is 0.92% (0.72%) per month with a corresponding Newey and West (1987) t -statistic of 6.49 (5.17). 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 0.75% to 1.10% per month. Another interesting observation from Table I 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 LP (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

¹³The new five-factor model of Fama and French (2015) (FF5) augments their 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.

are positive, suggesting that investors chase low-LP stocks and avoid high-LP stocks.

Although regarding negative returns (stocks being “in the red”) as losses 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 the risk-free and market returns, respectively. Specifically, we consider two alternative measures of LP. The first is constructed as the probability of having a return that is below the risk-free rate, 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). We report the difference between alphas (FFC4+PS α and HXZ α) of the two extreme decile portfolios (the highest versus the lowest LP decile portfolios) in Table II. The results show that alpha differences for both equal- and value-weighted portfolios are economically and statistically significant, confirming the previous results obtained when loss is defined as negative returns.

[Table II about here]

Our benchmark estimate of LP is based on daily returns over the past 1 month. Alternative estimates of LP could be computed over longer past periods. The second panel of Table II shows that if we instead use daily returns over the previous 2 or 3 months to calculate LP, we will still obtain expected results. However, the magnitude and the significance of alpha decrease 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 II confirm that our main conclusion holds in both sub-periods, but the LP effect

¹⁴One 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.

obtained from the first sub-period is stronger.

As a further robustness test, in each month 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 all sample firms, and the other that consists of large firms—firms with a market value that is larger than the median market value of all sample firms. The fourth panel of Table II shows a significant LP effect for both small and large firms, suggesting 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 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 II, revealing a significant LP effect.¹⁶

¹⁵Refer to Appendix 2 for the details of the parametric LP estimation. The average correlation between Normal LP (Skewed t LP) and the benchmark LP is 0.615 (0.664) during the sample period.

¹⁶Because parametric LP under the normal distribution assumption is a function of the mean return and the standard deviation measured in month t , one might suspect that its return predictive power comes from

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 III 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 III Panel B strongly suggest that the LP effect survives this test.

[Table III 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 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? 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 IV 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

the volatility effect and the short-term reversal effect. However, (unreported and available upon request) results from regression analysis show that after simultaneously controlling for volatility, short-term reversal, and their interaction term, the LP effect remains significant, suggesting that LP itself is a unique return predictor.

¹⁷In 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).

of interest, showing a positive and significant coefficient.

[Table IV about here]

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 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 IV, 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. It is worth mentioning that the low autocorrelation of 0.01, despite statistically significant, and the low adjusted R^2 of 0.36%, shown in the first row of Table IV, suggest that although investors are not wrong by looking at historical LP, the predictive power of lagged LP is economically weak. Further, it seems that other characteristics, such as market beta and idiosyncratic volatility, might be better predictors of future LP. However, for most investors, lagged LP is likely to be the most intuitive and accessible variable they can rely on to form the expectation of future LP.

We now focus on the composition of different LP decile portfolios. Table V 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. 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 32.88% (decile 1) to 67.95% (decile 10), the average firm size (MktCap) decreases monotonically, with the mean size of the decile 1 stocks being nearly 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 I) 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 V about here]

As expected, we observe a clearly decreasing pattern across the LP deciles for short-term reversal (Rev). 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 I. The factor models (the FFC4 factor model, FFC4+PS model, and HXZ model) do not help to allay the concern because they do not control for the effects of short-term reversal. To address the issue, we rely on the bivariate-sort analyses and the cross-sectional regressions that conducted later in the study.

In Table V, we also observe that as LP increases, Mom and Max tend to decrease, whereas Ivol and Skew tend to increase. We are not much concerned by this observation because of the weak correlation between LP and these variables. Other firm characteristics and risk measures studied in the study (e.g., Market beta, BM ratio, Illiq, and Coskew) are similar across the different LP portfolios, suggesting 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, 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, 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, idiosyncratic volatility, skewness, and Max. 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 $j = 1, \dots, 10$,

$$\bar{r}_j = \frac{1}{10} \sum_{i=1}^{10} r_{i,j}. \quad (8)$$

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 VI. Each column corresponds to a specific control variable. Within each column, we report the excess returns, FFC4+PS 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 VI,¹⁸ meaning that LP retains significant predictive power for future returns even after controlling for the correlated predictors of returns.¹⁹ In other words, firm characteristics and risk measures that are correlated with LP, as shown in Table V, do not explain the high (low) returns earned by high (low) LP stocks. However, we notice

¹⁸Not suprisingly, after controlling for size, the value-weighted and equal-weighted portfolio alphas are similar in magnitude.

¹⁹In 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.”

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 1.10% to 0.44%, but remains highly significant with a t -statistic of 5.89.

[Table VI about here]

4.3 Loss probability and short-term reversal

The results in Tables V and VI 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 VI. 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 $LP_{\perp Rev}$, 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 $LP_{\perp Rev}$. Since, by construction, $LP_{\perp Rev}$ is completely (linearly) independent of Rev, significant return differences from this single sort exercise, if observed, would further confirm the evidence shown in Table VI that the LP effect is not solely caused by short-term reversals. The sorting results are displayed in Table VII, which unanimously support our hypothesis that LP itself is a significant return predictor.

[Table VII about here]

Further, the reversal phenomenon is often attributed to liquidity and micro-structure effects. Specifically, the stock returns are calculated using the traded prices, which can be either the bid prices or the ask prices. Thus, the recorded prices contain a measurement error to the extent of the bid-ask spread. A stock tends to have a lower return at day d if

the closing price is the bid price, which is below its true fundamental value. The same stock will tend to rise in price the next day, correcting the error and leading to a higher day $d + 1$ return (consistent with the short-term reversal effect). Similar argument may apply to the LP effect studied in this paper. To eliminate the potential mechanical bias induced by the bid-ask spread, we re-calculate month $t + 1$ return (R_{t+1}), excluding the first trading day of the month $t + 1$. As shown in Table VIII Panel A, the LP effect largely remains unchanged. The high-low LP portfolio alphas when predicting month $t + 1$ returns, excluding the first trading day, are between 0.76% and 1.11%, which are in line with those reported in Table I. As an added precaution, we skip the first three trading days to re-calculate R_{t+1} and the LP effect persists (see Panel B of Table VIII).

[Table VIII 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. Specifically, 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).

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 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 IX 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). Interestingly, as shown in column (4), the coefficient of Rev is insignificant. 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 IX 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.²⁰ 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 X suggest that including alternative downside risk measures as controls does not take away the significant predictive power of LP. Importantly, in specification (5) in Table X, 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 originally specified in Barberis et al. (2016), the prospect theory value (TK) is calculated using the past 60 monthly returns, whereas our LP is calculated using the daily returns of the past month. To make a more comparable investigation, we calculate the prospect theory value using the daily returns of the past month, denoted as TK1M. The regression results with TK1M being used as the measure of the prospect theory value are reported in column (6). LP still obtains a positive and significant coefficient.

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 IX and X. As shown in Appendix 3, the smallest t -value of the coefficient of LP across

²⁰Downside beta is introduced by Bawa and Lindenberg (1977) and intensively examined in Ang et al. (2006a).

different model specifications is 4.95. Some other variables, however, become insignificant, in particular expected loss (EL) and prospect theory value (TK).

[Table X 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 six alternative risk measures (four downside risk measures, TK and TK1M) being control variables, respectively. As shown in Table XI, the sorting results reassure us that LP is not just a variation of existing popular risk measures.

[Table XI about here]

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 XII 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 IX, 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 have expected signs (e.g., negative for LP*Size and positive for both LP*Illiq and LP*Ivol), with the coefficient of LP*Ivol being insignificant though. 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 XII 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.²¹ Again, we focus on the newly added interaction term in the fourth column of Table XII—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 significant (at the 10% level) 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 XII, suggests that institutional ownership (IO) does not play a significant role on the LP effect documented in this paper.²² Although

²¹Data on analyst coverage are from the I/B/E/S Historical Summary File and are available on a monthly basis beginning in 1976.

²²We 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

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. 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,

holdings data are available from January 1980 through December 2016 in Thompson-Reuters' 13F database.

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 find a smaller, yet very significant and 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 other decision models, which surpasses the usual tests in surveys or experiments.

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	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
LP	32.884	39.865	43.711	46.667	49.380	51.912	54.518	57.489	61.213	67.953	
Excess return	EW	0.254 (1.200)	0.434 (1.962)	0.578 (2.528)	0.620 (2.589)	0.677 (2.710)	0.730 (2.981)	0.784 (3.109)	0.851 (3.307)	0.954 (3.650)	0.920 (6.494)
	VW	0.144 (0.824)	0.342 (1.830)	0.484 (2.477)	0.601 (2.814)	0.599 (2.915)	0.609 (2.985)	0.564 (2.748)	0.635 (3.054)	0.710 (3.388)	0.723 (5.172)
FFC4 alpha	EW	-0.485 (-6.070)	-0.301 (-5.191)	-0.147 (-2.624)	-0.114 (-2.405)	-0.038 (-0.842)	0.037 (0.797)	0.090 (1.746)	0.184 (2.913)	0.300 (4.346)	1.049 (6.962)
	VW	-0.410 (-5.795)	-0.196 (-3.519)	-0.068 (-1.329)	0.065 (1.305)	0.127 (2.545)	0.084 (1.867)	0.061 (1.180)	0.171 (2.583)	0.275 (3.376)	0.764 (5.082)
FFC4+PS alpha	EW	-0.467 (-5.540)	-0.292 (-4.758)	-0.139 (-2.358)	-0.107 (-2.127)	-0.024 (-0.515)	0.040 (0.832)	0.083 (1.567)	0.186 (2.775)	0.304 (4.213)	1.036 (6.568)
	VW	-0.405 (-5.380)	-0.213 (-3.629)	-0.065 (-1.191)	0.077 (1.465)	0.160 (3.205)	0.089 (1.830)	0.055 (1.063)	0.165 (2.317)	0.257 (3.015)	0.749 (4.927)
HXZ alpha	EW	-0.448 (-4.853)	-0.287 (-4.969)	-0.123 (-2.099)	-0.120 (-2.464)	-0.006 (-0.093)	0.092 (1.163)	0.146 (1.421)	0.247 (2.034)	0.390 (2.978)	1.097 (4.561)
	VW	-0.361 (-4.133)	-0.180 (-2.221)	-0.049 (-0.671)	0.078 (1.142)	0.156 (2.743)	0.052 (1.022)	-0.001 (-0.010)	0.172 (1.909)	0.413 (1.819)	0.774 (4.323)

Table I: 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+PS α	VW FFC4+PS α	EW HXZ α	VW HXZ α
Definition for loss				
Return < Risk-free rate	1.036 (6.533)	0.753 (4.962)	1.095 (4.548)	0.777 (4.339)
Return < Market return	0.780 (5.511)	0.545 (3.590)	0.781 (4.296)	0.422 (2.473)
Window for calculating LP				
Two months	0.562 (3.832)	0.696 (4.511)	0.719 (2.671)	0.698 (2.866)
Three months	0.116 (0.741)	0.465 (2.673)	0.235 (0.785)	0.395 (1.358)
Subperiods				
Jul 1963 - Dec 1989	1.717 (8.673)	1.235 (5.817)	1.709 (7.491)	1.243 (4.948)
Jan 1990 - Dec 2016	0.504 (2.543)	0.444 (2.285)	0.576 (1.793)	0.483 (2.003)
Firm size				
MktCap > Median	0.834 (5.491)	0.807 (5.769)	0.896 (3.690)	0.803 (4.576)
MktCap \leq Median	1.356 (6.431)	1.014 (4.856)	1.393 (5.826)	1.093 (4.535)
Parametric LP				
Normal distribution	1.552 (9.020)	0.916 (5.847)	1.513 (5.383)	0.800 (3.461)
Skewed t distribution	1.280 (8.355)	0.946 (5.796)	1.334 (5.236)	0.935 (3.965)

Table II: Robustness. The table presents the results of five robustness checks. The right columns report the equal-weighted (EW) and value-weighted (VW) alphas of Carhart (1997)'s 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) 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 returns below the risk-free rate and below the market return of the month, 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 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.

Panel A. Single sort - NYSE breakpoints

	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
Excess return	0.250 (1.172)	0.433 (1.895)	0.590 (2.476)	0.593 (2.531)	0.639 (2.529)	0.731 (2.802)	0.797 (3.062)	0.928 (3.330)	0.943 (3.515)	1.165 (4.238)	0.915 (6.430)
VW	0.136 (0.992)	0.347 (1.995)	0.501 (2.577)	0.564 (2.638)	0.585 (2.759)	0.609 (2.759)	0.589 (2.918)	0.629 (2.960)	0.719 (3.412)	0.864 (3.748)	0.727 (5.144)
FFC4+PS alpha	-0.470 (-5.262)	-0.289 (-4.507)	-0.140 (-2.482)	-0.109 (-2.181)	-0.065 (-1.290)	-0.003 (-0.076)	0.060 (1.182)	0.188 (3.285)	0.266 (3.499)	0.525 (5.577)	0.995 (6.284)
VW	-0.415 (-4.935)	-0.224 (-3.530)	-0.061 (-1.091)	0.078 (1.649)	0.132 (2.535)	0.031 (0.610)	0.043 (0.685)	0.132 (1.941)	0.260 (2.969)	0.380 (3.605)	0.795 (4.762)
EW	-0.431 (-4.809)	-0.277 (-4.845)	-0.136 (-2.413)	-0.130 (-2.454)	-0.082 (-1.537)	0.035 (0.544)	0.078 (1.019)	0.179 (2.069)	0.269 (2.573)	0.508 (3.803)	0.939 (4.657)
HXZ alpha	-0.339 (-3.980)	-0.157 (-1.838)	-0.029 (-0.337)	0.049 (0.987)	0.101 (1.884)	0.019 (0.321)	-0.054 (-0.680)	0.099 (1.262)	0.178 (1.863)	0.396 (3.809)	0.735 (4.643)

Panel B. Single sort - excluding microcaps

	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
Excess return	0.296 (1.464)	0.511 (2.513)	0.587 (2.814)	0.668 (3.012)	0.692 (3.093)	0.739 (3.295)	0.746 (3.352)	0.819 (3.404)	0.854 (3.583)	1.015 (4.049)	0.719 (5.213)
VW	0.135 (0.553)	0.301 (1.501)	0.427 (2.097)	0.510 (2.399)	0.587 (2.829)	0.584 (2.811)	0.549 (2.657)	0.589 (2.963)	0.689 (3.277)	0.878 (3.929)	0.743 (5.376)
FFC4+PS alpha	-0.390 (-4.741)	-0.170 (-2.644)	-0.097 (-1.780)	-0.040 (-0.794)	0.005 (0.114)	0.092 (1.979)	0.116 (2.255)	0.153 (2.533)	0.222 (3.103)	0.401 (4.228)	0.790 (5.170)
VW	-0.444 (-5.848)	-0.286 (-4.551)	-0.134 (-2.618)	0.007 (0.150)	0.147 (2.801)	0.091 (1.905)	0.045 (0.850)	0.097 (1.690)	0.232 (2.949)	0.423 (4.350)	0.866 (5.978)
EW	-0.384 (-3.685)	-0.189 (-2.695)	-0.092 (-1.540)	-0.050 (-1.073)	-0.001 (-0.023)	0.084 (1.566)	0.146 (1.910)	0.205 (2.109)	0.279 (2.275)	0.468 (3.106)	0.853 (3.532)
HXZ alpha	-0.417 (-4.613)	-0.252 (-2.884)	-0.146 (-1.825)	-0.010 (-0.171)	0.106 (1.962)	0.084 (1.634)	-0.018 (-0.280)	0.084 (1.156)	0.216 (2.064)	0.469 (3.977)	0.886 (4.783)

Table III: 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, alphas of Carhart (1997)'s 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, 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. 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.

LP	Market beta	Size	BM	Mom	Rev	Illiq	Ivol	Adjusted R^2
0.014 (4.866)								0.359%
0.009 (3.975)	0.878 (10.306)	-0.254 (-8.384)	-0.080 (-1.270)	-0.009 (-9.212)	0.016 (5.103)	-0.098 (-6.633)	0.621 (14.685)	4.668%

Table IV: *Persistence of LP. 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	32.884	39.865	43.711	46.667	49.380	51.912	54.518	57.489	61.213	67.953
	Firm characteristics									
MktCap	2209.794	2179.169	2106.671	2089.774	2012.700	1958.301	1832.213	1738.064	1620.770	1408.552
BM ratio	0.809	0.803	0.807	0.803	0.803	0.802	0.797	0.803	0.796	0.787
Mom	21.513	20.388	19.793	19.683	19.168	19.230	18.741	18.480	18.779	18.887
Illiq	0.843	1.087	1.214	1.291	1.357	1.386	1.429	1.395	1.280	1.013
Rev	14.845	9.599	6.699	4.502	2.524	0.661	-1.231	-3.389	-5.958	-10.408
	Risk measures									
Market beta	0.861	0.907	0.925	0.938	0.948	0.963	0.963	0.969	0.978	0.971
Ivol	2.130	2.239	2.289	2.327	2.365	2.394	2.418	2.438	2.448	2.416
Skew	0.420	0.412	0.418	0.420	0.427	0.435	0.445	0.468	0.481	0.502
Coskew	-4.637	-4.599	-4.496	-4.419	-4.397	-4.404	-4.368	-4.443	-4.505	-4.494
Max	3.714	3.719	3.706	3.697	3.681	3.665	3.629	3.571	3.469	3.122

Table V: 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. 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		Ivol		Skew		Max	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Excess return	0.776 (6.082)	0.757 (6.139)	1.106 (8.923)	0.990 (7.433)	0.314 (4.205)	0.477 (5.284)	0.945 (7.976)	0.594 (4.117)	0.954 (7.182)	0.763 (5.786)	0.797 (5.867)	0.456 (2.988)
FFC4+PS α	0.873 (5.937)	0.857 (5.978)	1.195 (9.443)	1.033 (7.597)	0.358 (5.340)	0.527 (5.930)	1.026 (8.002)	0.668 (4.552)	1.064 (7.396)	0.805 (5.689)	0.844 (6.125)	0.479 (3.298)
HXZ α	0.920 (4.365)	0.903 (4.424)	1.207 (6.449)	1.051 (6.634)	0.443 (5.889)	0.532 (5.762)	1.017 (5.926)	0.554 (2.870)	1.098 (4.887)	0.798 (4.309)	0.934 (5.269)	0.455 (2.652)

Table VI: 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 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.

	Excess return		FFC4+PS α		HXZ α	
	EW	VW	EW	VW	EW	VW
P1 (Low $LP_{\perp Rev}$)	0.372	0.121	-0.314	-0.440	-0.376	-0.429
P2	0.546	0.349	-0.132	-0.209	-0.115	-0.155
P3	0.604	0.464	-0.109	-0.074	-0.063	-0.048
P4	0.715	0.609	0.012	0.112	0.045	0.130
P5	0.727	0.590	0.044	0.119	0.075	0.102
P6	0.741	0.564	0.054	0.051	0.100	0.013
P7	0.805	0.590	0.134	0.084	0.194	-0.010
P8	0.809	0.678	0.152	0.236	0.202	0.246
P9	0.877	0.702	0.224	0.244	0.310	0.229
P10 (High $LP_{\perp Rev}$)	0.794	0.781	0.144	0.324	0.222	0.296
P10 - P1	0.422	0.661	0.458	0.764	0.598	0.725
<i>t</i> -statistic	(4.129)	(5.537)	(5.058)	(6.327)	(5.384)	(6.108)

Table VII: *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, alphas of Carhart (1997)'s 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.*

Panel A. Single sort - month $t + 1$ return without the first trading day

	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
EW	0.239 (1.134)	0.426 (1.926)	0.576 (2.520)	0.618 (2.578)	0.671 (2.685)	0.722 (2.953)	0.772 (3.061)	0.844 (3.269)	0.945 (3.627)	1.170 (4.336)	0.930 (6.533)
VW	0.140 (0.737)	0.327 (1.713)	0.481 (2.414)	0.582 (2.684)	0.594 (2.859)	0.608 (2.928)	0.559 (2.634)	0.597 (2.877)	0.694 (3.301)	0.863 (3.707)	0.724 (5.134)
EW	-0.484 (-5.685)	-0.301 (-4.877)	-0.143 (-2.397)	-0.112 (-2.175)	-0.030 (-0.652)	0.036 (0.756)	0.071 (1.354)	0.174 (2.613)	0.297 (4.105)	0.562 (5.731)	1.046 (6.591)
VW	-0.418 (-5.515)	-0.234 (-4.041)	-0.070 (-1.271)	0.072 (1.363)	0.151 (2.993)	0.083 (1.735)	0.041 (0.811)	0.157 (2.087)	0.249 (2.922)	0.346 (3.371)	0.764 (4.998)
EW	-0.463 (-4.965)	-0.298 (-5.098)	-0.128 (-2.168)	-0.124 (-2.516)	-0.011 (-0.163)	0.089 (1.131)	0.138 (1.341)	0.237 (1.958)	0.383 (2.927)	0.643 (3.796)	1.107 (4.587)
VW	-0.375 (-4.247)	-0.202 (-2.502)	-0.060 (-0.812)	0.079 (1.190)	0.151 (2.630)	0.054 (1.043)	-0.020 (-0.325)	0.168 (1.743)	0.197 (1.747)	0.419 (3.748)	0.794 (4.400)

Panel B. Single sort - month $t + 1$ return without the first three trading days

	P1 (Low LP)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High LP)	P10 - P1
EW	0.221 (1.098)	0.338 (1.635)	0.433 (2.037)	0.432 (1.964)	0.444 (1.938)	0.472 (2.098)	0.488 (2.097)	0.498 (2.092)	0.551 (2.299)	0.638 (2.589)	0.418 (3.335)
VW	0.021 (0.127)	0.156 (0.903)	0.262 (1.436)	0.340 (1.740)	0.356 (1.925)	0.354 (1.923)	0.299 (1.543)	0.296 (1.570)	0.369 (1.951)	0.492 (2.354)	0.472 (3.817)
EW	-0.457 (-5.046)	-0.333 (-4.162)	-0.227 (-2.681)	-0.230 (-2.797)	-0.194 (-2.358)	-0.152 (-1.698)	-0.159 (-1.700)	-0.113 (-1.084)	-0.049 (-0.460)	0.083 (0.663)	0.540 (3.728)
VW	-0.490 (-5.643)	-0.354 (-4.545)	-0.231 (-3.060)	-0.105 (-1.324)	-0.030 (-0.339)	-0.098 (-1.201)	-0.138 (-1.692)	-0.069 (-0.655)	-0.003 (-0.026)	0.070 (0.580)	0.559 (3.900)
EW	-0.434 (-4.256)	-0.333 (-3.969)	-0.222 (-2.423)	-0.256 (-2.989)	-0.190 (-2.033)	-0.134 (-1.244)	-0.131 (-1.062)	-0.086 (-0.625)	-0.008 (-0.052)	0.103 (0.592)	0.537 (2.518)
VW	-0.469 (-4.858)	-0.349 (-3.786)	-0.246 (-2.797)	-0.129 (-1.418)	-0.070 (-0.785)	-0.168 (-2.155)	-0.222 (-2.684)	-0.116 (-1.063)	-0.109 (-0.890)	0.058 (0.496)	0.528 (3.539)

Table VIII: Returns and alphas on portfolios of stocks sorted by loss probability (LP). Month $t + 1$ returns are calculated without the first trading day in Panel A, and without the first three trading days in Panel B. The table presents for each decile the month- $(t + 1)$ equal-weighted (EW) and value-weighted (VW) excess returns, alphas of Carhart (1997)'s four-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor (FFC4+PS α), and Hou et al. (2015)'s four-factor model augmented 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 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.

	(1)	(2)	(3)	(4)
LP	2.554 (6.325)	3.214 (9.679)	2.608 (9.577)	2.317 (11.520)
Beta		-0.202 (-1.361)	0.157 (1.124)	0.130 (0.984)
Size		-0.021 (-0.471)	-0.169 (-4.381)	-0.172 (-4.544)
BM		0.254 (4.221)	0.210 (3.625)	0.209 (3.585)
MOM		0.007 (5.696)	0.007 (5.160)	0.007 (5.199)
Illiq			0.033 (1.989)	0.036 (2.104)
IVola			-0.047 (-0.894)	-0.092 (-1.566)
Coskew			-0.002 (-0.410)	-0.003 (-0.682)
Tskew			-0.051 (-2.562)	-0.044 (-2.172)
Max			-0.249 (-6.524)	-0.222 (-4.710)
Rev				-0.005 (-0.898)
Intercept	-0.566 (-2.156)	-0.667 (-1.862)	1.053 (3.488)	1.219 (3.980)
Adjusted R^2	0.563%	5.884%	7.080%	7.327%
n	2775	2243	2206	2206

Table IX: *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)	(6)
LP	2.493 (11.367)	1.909 (8.757)	1.779 (8.318)	2.302 (11.592)	2.158 (10.042)	2.314 (10.296)
Beta	0.124 (0.961)	0.158 (1.191)	0.131 (0.986)	0.279 (1.659)	0.019 (0.146)	0.144 (1.110)
Size	-0.173 (-4.663)	-0.175 (-4.612)	-0.160 (-4.240)	-0.173 (-4.530)	-0.122 (-3.458)	-0.178 (-4.786)
BM	0.211 (3.624)	0.205 (3.515)	0.212 (3.638)	0.209 (3.580)	0.205 (3.363)	0.207 (3.551)
MOM	0.007 (5.276)	0.007 (5.393)	0.007 (5.318)	0.007 (5.245)	0.007 (5.291)	0.007 (5.296)
Illiq	0.034 (2.060)	0.035 (2.053)	0.039 (2.294)	0.035 (2.030)	0.032 (1.993)	0.037 (2.165)
IVola	-0.143 (-2.480)	0.058 (0.941)	0.039 (0.687)	-0.090 (-1.538)	-0.084 (-1.520)	-0.091 (-1.550)
Coskew	-0.003 (-0.725)	-0.002 (-0.603)	-0.003 (-0.637)	-0.007 (-1.303)	0.000 (-0.064)	-0.003 (-0.680)
Tskew	-0.037 (-1.761)	-0.065 (-3.180)	-0.062 (-3.017)	-0.042 (-2.053)	-0.032 (-1.409)	-0.042 (-2.018)
Max	-0.290 (-4.612)	-0.246 (-5.199)	-0.211 (-4.520)	-0.221 (-4.756)	-0.227 (-5.056)	-0.224 (-4.755)
Rev	0.010 (1.159)	-0.012 (-2.166)	-0.016 (-2.630)	-0.005 (-0.911)	-0.007 (-1.370)	-0.005 (-0.731)
EL	0.394 (1.898)					
Min		0.059 (5.264)				
Semivar			-4.111 (-3.888)			
Downside beta				-0.153 (-1.771)		
TK					-0.038 (-2.666)	
TK1M						0.006 (0.152)
Intercept	1.107 (3.658)	1.458 (4.742)	1.265 (4.135)	1.228 (4.023)	0.911 (3.055)	1.264 (4.196)
Adjusted R^2	7.497%	7.412%	7.480%	7.430%	7.185%	7.453%
n	2206	2206	2206	2206	2187	2206

Table X: *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 (12) (Equation (18)) in Appendix 2, 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). TK1M is the prospect theory value calculated with daily returns in month t . 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		TK1M	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Excess return	1.020 (7.942)	0.764 (5.419)	0.994 (8.633)	0.749 (5.282)	1.022 (8.927)	0.785 (5.862)	1.049 (7.987)	0.731 (5.659)	1.077 (8.467)	0.864 (6.518)	0.800 (9.309)	0.764 (7.605)
FFC4+PS α	1.220 (10.543)	0.939 (7.043)	1.085 (8.732)	0.800 (5.339)	1.151 (9.707)	0.856 (6.390)	1.141 (8.198)	0.752 (5.553)	1.194 (8.703)	0.965 (6.550)	0.934 (10.654)	0.882 (8.391)
HXZ α	1.041 (6.109)	0.694 (3.771)	1.058 (6.021)	0.705 (3.721)	1.078 (6.337)	0.721 (4.117)	1.126 (5.837)	0.710 (4.927)	1.160 (5.644)	0.909 (4.316)	0.879 (7.775)	0.809 (6.371)

Table XI: *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, TK or TK1M). 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, alphas of Carhart (1997)'s 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), 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 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.*

	(1)	(2)	(3)	(4)	(5)
LP	3.907 (6.626)	2.226 (10.875)	2.216 (6.940)	1.763 (5.001)	1.022 (3.097)
LP*Size	-0.283 (-2.922)				
LP*Illiq		0.361 (2.964)			
LP*Ivola			0.001 (0.005)		
LP*Analyst				0.300 (1.813)	
LP*IO					2.076 (0.967)
Beta	0.136 (1.028)	0.14 (1.061)	0.136 (1.030)	0.195 (1.320)	0.110 (0.662)
Size	-0.026 (-0.389)	-0.174 (-4.595)	-0.175 (-4.675)	-0.122 (-2.580)	-0.162 (-3.938)
BM	0.209 (3.577)	0.208 (3.575)	0.208 (3.561)	0.222 (3.725)	0.220 (3.535)
MOM	0.007 (5.210)	0.007 (5.195)	0.007 (5.222)	0.006 (4.294)	0.006 (3.854)
Rev	-0.002 (-0.439)	-0.001 (-0.181)	-0.006 (-1.133)	0.000 (0.096)	0.003 (0.572)
Illiq	0.037 (2.161)	-0.153 (-2.583)	0.037 (2.178)	0.016 (1.587)	0.018 (1.718)
IVola	-0.075 (-1.287)	-0.059 (-1.009)	-0.124 (-1.411)	-0.097 (-1.664)	-0.057 (-0.961)
Coskew	-0.003 (-0.679)	-0.003 (-0.641)	-0.003 (-0.718)	-0.002 (-0.355)	-0.003 (-0.475)
Tskew	-0.048 (-2.355)	-0.048 (-2.328)	-0.047 (-2.308)	-0.060 (-2.868)	-0.056 (-2.517)
Max	-0.238 (-5.080)	-0.252 (-5.315)	-0.208 (-4.311)	-0.215 (-4.414)	-0.227 (-4.543)
Analyst				-0.247 (-2.841)	
IO					0.168 (0.131)
Intercept	0.402 (0.843)	1.288 (4.210)	1.320 (4.682)	1.499 (3.673)	1.750 (4.275)
Adjusted R^2	7.379%	7.429%	7.418%	6.286%	6.111%
n	2206	2206	2206	2530	2659

Table XII: *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; Ivola, 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.*

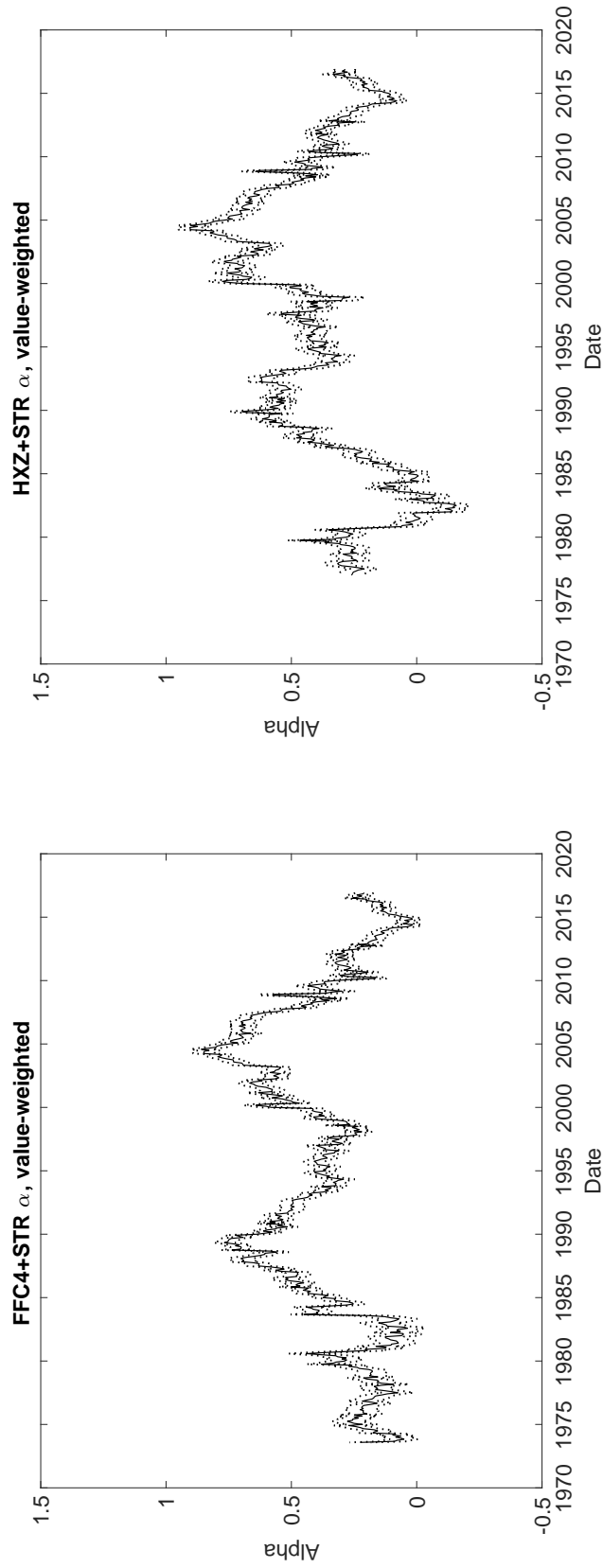


Figure 1: Ten-year trailing alpha of the difference portfolio. Each month, stocks are sorted into deciles based on LP. The figure presents alpha from Carhart (1997)'s four-factor model augmented with the short-term reversal factor (FFC4+STR α , left panel), and alpha from Hou et al. (2015)'s four-factor 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,

$$r_d = a + b_1 MKT_d + \epsilon_d, \quad (9)$$

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

$$\text{Downside beta} = \frac{\text{cov}(r_d, MKT_d | MKT_d < \mu_{MKT})}{\text{var}(MKT_d | MKT_d < \mu_{MKT})}, \quad (10)$$

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

$$Illiq = \frac{1}{D} \sum_{d=1}^D \frac{|R_d|}{VOLD_d}, \quad (11)$$

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

$$EL = \frac{1}{D} \sum_{d=1}^D \mathbb{1}_{R_d < 0} |R_d|, \quad (12)$$

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; $\mathbb{1}_{R_d < 0}$ is an indicator function equal one if $R_d < 0$ and zero otherwise.

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

$$LP = \frac{\sum_{d=1}^D \mathbb{1}_{R_d < 0}}{D}, \quad (13)$$

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; $\mathbb{1}_{R_{i,d} < 0}$ is an indicator function equal to one if $R_{i,d} < 0$ 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. We follow Bali et al. (2017) to construct Max with the average five highest daily stock returns. However, our results are robust to using the highest daily return 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

$$r_d = a + b_1 MKT_d + b_2 MKT_d^2 + \epsilon_d. \quad (14)$$

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,

$$TK = \sum_{j=-m}^{-1} v(r_j) \left[w^- \left(\frac{j+m+1}{N} \right) - w^- \left(\frac{j+m}{N} \right) \right] + \sum_{j=1}^n v(r_j) \left[w^+ \left(\frac{n-j+1}{N} \right) - w^+ \left(\frac{n-j}{N} \right) \right], \quad (15)$$

where N is the number of valid monthly returns in the five years' period; r_j is the stock's j th monthly return²³ over the past five years, in ascending order from

$(r_{-m}, r_{-m+1}, \dots, r_{-1}, r_1, \dots, r_{n-1}, r_n)$ with r_{-m} the lowest monthly return, r_{-1} the largest negative monthly return, r_1 the smallest non-negative monthly return, and r_n the largest monthly return ($m + n = N$); $v(\cdot)$, $w^+(\cdot)$, $w^-(\cdot)$ are given by

$$v(x) = \begin{cases} x^\alpha, & x \geq 0 \\ -\lambda(-x)^\alpha, & x < 0, \end{cases} \quad (16)$$

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}, \quad w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{1/\delta}}, \quad (17)$$

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

$$Semivar = \frac{1}{D} \sum_{d=1}^D \mathbb{1}_{R_d < 0} R_d^2, \quad (18)$$

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; $\mathbb{1}_{R_d < 0}$ is an indicator function equal to one if $R_d < 0$ and zero otherwise.

²³To be consistent with LP, we use 0 as the reference point.

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

$$r_d = a + b_1 MKT_d + b_2 SMB_d + b_3 HML_d + \epsilon_d, \quad (19)$$

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,

$$\bar{r} = \frac{\sum_{d=1}^D r_d}{D}, \quad s^2 = \frac{\sum_{d=1}^D (r_d - \bar{r})^2}{D - 1}, \quad (20)$$

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,

$$LP_p = P[r < 0] = \frac{1}{\sqrt{2\pi}s} \int_{-\infty}^0 \exp\left(-\frac{(x - \bar{r})^2}{2s^2}\right) dx. \quad (21)$$

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 empirical distribution of stock returns exhibiting skewness and leptokurtosis is given by,

$$f_{ST}(z; \nu, \lambda) = \begin{cases} bc \left(1 + \frac{1}{\nu-2} \left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-\frac{\nu+1}{2}} & \text{if } z < -\frac{a}{b} \\ bc \left(1 + \frac{1}{\nu-2} \left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-\frac{\nu+1}{2}} & \text{if } z \geq -\frac{a}{b} \end{cases}, \quad (22)$$

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

$$\begin{aligned} a &= 4\lambda c \left(\frac{\nu-2}{\nu-1}\right), \quad b^2 = 1 + 3\lambda^2 - a^2, \\ c &= \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi(\nu-2)}\Gamma\left(\frac{\nu}{2}\right)}, \end{aligned} \quad (23)$$

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

Parameters of the ST PDF are estimated by maximizing the log-likelihood function,²⁴ 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,

$$LP_p = P[r < 0] = P[z < -\mu/\sigma] = \int_{-\infty}^{-\mu/\sigma} f_{ST}(x; \nu, \lambda) dx. \quad (24)$$

²⁴See 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)	(10)
LP	1.800 (4.953)	2.510 (8.228)	2.467 (8.723)	2.188 (7.229)	2.198 (7.293)	1.914 (6.085)	1.574 (5.053)	2.194 (7.307)	2.053 (6.636)	1.979 (6.398)
Beta		-0.183 (-1.006)	-0.022 (-0.125)	-0.030 (-0.180)	-0.002 (-0.015)	0.004 (0.022)	-0.013 (-0.080)	0.247 (0.888)	-0.079 (-0.468)	0.012 (0.073)
Size		-0.048 (-1.478)	-0.098 (-3.134)	-0.101 (-3.274)	-0.103 (-3.342)	-0.097 (-3.168)	-0.091 (-2.965)	-0.101 (-3.324)	-0.077 (-2.411)	-0.102 (-3.329)
BM		0.068 (1.025)	0.052 (0.805)	0.059 (0.898)	0.064 (0.968)	0.059 (0.896)	0.062 (0.946)	0.059 (0.898)	0.100 (1.467)	0.059 (0.893)
MOM		0.006 (3.587)	0.007 (3.911)	0.007 (3.967)	0.007 (4.037)	0.007 (4.108)	0.007 (4.100)	0.007 (3.999)	0.007 (4.052)	0.007 (4.088)
Illiq			0.014 (0.328)	0.011 (0.265)	0.008 (0.194)	0.010 (0.242)	0.026 (0.613)	0.012 (0.287)	-0.005 (-0.148)	0.011 (0.267)
IVola			-0.178 (-2.372)	-0.214 (-2.485)	-0.188 (-2.099)	-0.082 (-0.841)	-0.018 (-0.195)	-0.205 (-2.426)	-0.229 (-2.842)	-0.154 (-1.720)
Coskew			0.007 (1.125)	0.005 (0.899)	0.004 (0.750)	0.006 (1.004)	0.005 (0.967)	-0.002 (-0.223)	0.006 (1.023)	0.004 (0.764)
Tskew			-0.023 (-0.817)	-0.020 (-0.712)	-0.021 (-0.698)	-0.038 (-1.306)	-0.040 (-1.353)	-0.020 (-0.678)	-0.033 (-1.212)	-0.031 (-1.049)
Max			-0.054 (-1.245)	-0.025 (-0.354)	-0.007 (-0.085)	-0.026 (-0.382)	0.036 (0.517)	-0.031 (-0.458)	-0.015 (-0.226)	0.000 (-0.003)
Rev				-0.006 (-0.842)	-0.009 (-0.776)	-0.015 (-1.939)	-0.028 (-3.297)	-0.006 (-0.855)	-0.010 (-1.255)	-0.026 (-2.469)
EL					-0.137 (-0.455)					
Min						0.061 (2.862)				
Semivar							-11.925 (-5.195)			
Downside beta								-0.262 (-1.364)		
TK									-0.030 (-1.533)	
TK1M										0.136 (2.176)
Intercept	-0.349 (-1.587)	-0.251 (-0.777)	0.413 (1.295)	0.566 (1.730)	0.582 (1.662)	0.676 (2.036)	0.571 (1.730)	0.562 (1.749)	0.455 (1.270)	0.718 (2.073)
Adjusted R^2	1.417%	12.880%	14.944%	15.502%	15.817%	15.801%	15.725%	15.912%	16.008%	15.813%
n	2775	2243	2206	2206	2206	2206	2206	2206	2187	2206

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.*