Prospect Theory and Stock Returns: An Empirical Test

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Abstract

We test the hypothesis that, when thinking about allocating money to a stock, investors mentally represent the stock by the distribution of its past returns and then evaluate this distribution in the way described by prospect theory. In a simple model of asset prices where some investors think in this way, a stock whose past return distribution has a high (low) prospect theory value earns a low (high) subsequent return, on average. We find empirical support for this prediction in the cross-section of U.S. stock returns, particularly among small-capitalization stocks where less sophisticated investors are likely to have a bigger impact on prices. We repeat our tests in 46 international stock markets and find a similar pattern in a majority of these markets.

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1 Introduction

A crucial ingredient in any model of asset prices is an assumption about how investors evaluate risk. Most of the available models assume that investors evaluate risk according to the expected utility framework, and models based on this assumption have been helpful for thinking about a number of empirical facts. Nonetheless, a large body of research shows that, at least in laboratory settings, attitudes to risk can depart significantly from the predictions of expected utility, and that an alternative theory – "prospect theory," due to Kahneman and Tversky (1979) and Tversky and Kahneman (1992) – captures these attitudes more accurately. This raises an obvious question: Can models in which some investors evaluate risk according to prospect theory help us make more sense of the evidence on prices and returns? In this paper, we present new evidence on this question. Specifically, we derive the predictions, for the cross-section of stock returns, of a simple prospect theory-based model and test these predictions in both U.S. and international data.

Applying prospect theory outside the laboratory presents a challenge for researchers. To see why, it is helpful to think of decision-making under prospect theory as involving two steps: "representation" and "valuation." First, for any risk that an agent is considering, he forms a mental representation of that risk. More precisely, since, under prospect theory, people are assumed to derive utility from gains and losses, the agent forms a mental representation of the gains and losses he associates with taking the risk. Second, the agent evaluates this representation – this distribution of gains and losses – to see if it is appealing.

The second step, valuation, is straightforward: Tversky and Kahneman (1992) provide detailed formulas that specify the value that a prospect theory agent would assign to any given distribution of gains and losses. The difficult step, for the researcher, is the first one: representation. Given a risk that the agent is considering, how does he mentally represent it? In experimental settings, the answer is clear: laboratory subjects are typically *given* a representation for any risk they are asked to consider – a 50:50 bet to win $110 or lose $100, say. Outside the laboratory, however, the answer is much less clear: how does an investor who is thinking about a stock represent that stock in his mind?[1]

We suggest that, for many investors, their mental representation of a stock is given by the *distribution of the stock's past returns*. The most obvious reason why people might adopt this representation is because they believe the past return distribution to be a good and

[1]Representation plays less of a role in the expected utility framework because of the strong convention that the argument of the utility function is the final wealth level. In prospect theory, by contrast, the agent derives utility from "gains and losses." Kahneman and Tversky (1979) offer relatively little guidance on how these gains and losses should be defined. As a result, the question of representation becomes important.

easily accessible proxy for the object they are truly interested in, namely the distribution of the stock's *future* returns. This belief may be mistaken: a stock with a high mean return over the past few years typically has a low subsequent return (De Bondt and Thaler, 1985); and a stock whose past returns are highly skewed does not necessarily exhibit high skewness in its future returns. Nonetheless, many investors may *think* that a stock's past return distribution is a good approximation of its future return distribution, and therefore adopt the past return distribution as their mental representation of the stock.

In this paper, we test the pricing implications of the joint hypothesis laid out above: that some investors in the economy think about stocks in terms of their historical return distributions; and that they evaluate these distributions according to prospect theory. To understand the implications of this hypothesis, we construct a simple model of asset prices in which some investors allocate money across stocks in the following way. For each stock in the cross-section, they take the stock's historical return distribution and compute the prospect theory value of this distribution. If the prospect theory value is high, they tilt toward the stock in their portfolios; after all, by assumption, the stock is appealing to these investors. Conversely, if the prospect theory value is low, they tilt away from the stock; again, by assumption, the stock is unappealing to these investors. The model makes a simple prediction, one that we test in our empirical work: that stocks with high prospect theory values will have low subsequent returns, on average, while stocks with low prospect theory values will have high subsequent returns. The intuition is clear: stocks with high prospect theory values are appealing to some investors; these investors tilt toward these stocks in their portfolios, causing them to become overvalued and to earn low subsequent returns.

We expect our prediction about returns to hold more strongly among stocks that are more heavily traded by individual investors – for example, among small-cap stocks. This is because the investor behavior that underlies our prediction is relatively unsophisticated, and therefore likely a better description of what individual investors do, than of what institutional investors do. For example, the investors we describe engage in "narrow framing": when thinking about a stock, they evaluate the return distribution of the stock itself; more sophisticated investors would evaluate the return distribution of the overall portfolio that results from tilting toward the stock. Moreover, the investors in our framework evaluate the stock's *past* returns; more sophisticated investors would try to forecast the stock's future returns, and would evaluate those.

To test our prediction – that the prospect theory value of a stock's past return distribution predicts the stock's subsequent return with a negative sign – we need to define what we mean by "past return distribution." The most obvious way that investors can learn about a stock's past return distribution is by looking at a chart of the stock's past price movements – specifically, at the chart that usually appears, front and center, when they look up information about the stock. In defining "past return distribution," we therefore take guidance from the typical format of these charts. In the internet era, these charts come in a variety of formats. Most of our data is drawn from the pre-internet era, however, and during this period, the main sources of information about a stock for retail investors were so-called investment handbooks, such as the Value Line Investment Survey. These handbooks feature charts prominently and present them using a fairly standard format. Based on a review of these sources, we suggest that a natural mental representation of a stock's past return distribution is the distribution of its monthly returns over the previous five years.

In summary, then, our main empirical prediction is that stocks whose historical return distributions have high (low) prospect theory values will have low (high) subsequent returns. We expect this prediction to hold primarily among small-cap stocks, in other words, among stocks where individual investors play a more important role.

In our empirical analysis, we find support for this prediction. We conduct a variety of tests, but it is easiest to understand our main result in a Fama-MacBeth framework. Each month we compute, for each stock in the cross-section, the stock's prospect theory value – the prospect theory value of the distribution of the stock's monthly returns over the previous five years. For each month in the sample, we then run a cross-sectional regression of subsequent stock returns on this prospect theory value, including as controls the important known predictors of returns. Consistent with our hypothesis, we find that the coefficient on the stock's prospect theory value, averaged across all the monthly regressions, is significantly negative: stocks with higher prospect theory values have lower subsequent returns. We also find, again consistent with our framework, that this result is particularly strong among small-cap stocks.

Further analysis provides additional support for our hypothesis. For example, we show that the predictive power of prospect theory value for subsequent stock returns is stronger among stocks that are less subject to arbitrage – for example, among illiquid stocks and stocks with high idiosyncratic volatility. And in an important out-of-sample test, we repeat our analysis in each of 46 international stock markets covered by Datastream. We find support for our prediction in a large majority of these markets as well.

Our tests assume that investors evaluate a stock's past return distribution according to prospect theory. We also consider the possibility that they instead evaluate the distribution according to expected (power) utility. In this case, the analogous prediction is that a stock whose historical return distribution has a high (low) *power* utility value will have low (high) subsequent returns. We find no empirical support for this prediction. This suggests that our results are driven by the specific way in which prospect theory weights stocks' past returns – it is not that *any* weighting of past returns would deliver similar results.

In our final set of results, we try to understand what exactly it is about a high prospect theory value stock that might be especially appealing, and what it is about a low prospect theory value stock that might be aversive. We find that a significant part of prospect theory value's predictive power for returns comes from the "probability weighting" component of prospect theory. Under probability weighting, the agent overweights the *tails* of a return distribution, a device that, among other things, captures the widespread preference for lottery-like gambles. The fact that probability weighting plays an important role in our results suggests – and we confirm this in the data – that a high prospect theory value stock is a stock whose past returns are positively skewed. Part of what may be driving our results, then, is that when investors observe the stock's past return distribution, perhaps by looking at a price chart, they see the skewness, which, in turn, leads them to think of the stock as a lottery-like gamble and hence to find it appealing. By tilting toward the stock in their portfolios, they cause it to become overvalued and to earn a low subsequent return.

The trading behavior we propose in this paper has an important precedent in Benartzi and Thaler's (1995) influential work on the equity premium puzzle. In their paper, Benartzi and Thaler propose that people evaluate the stock market by computing the prospect theory value of its historical return distribution; and similarly, that they evaluate the bond market by computing the prospect theory value of *its* historical return distribution. The individuals in our framework think in a similar way: they evaluate a stock by computing the prospect theory value of its historical return distribution. In this sense, our analysis can be thought of as the stock-level analog of Benartzi and Thaler (1995), one that, surprisingly, has not yet been investigated.

Our research is also related to prior work that uses prospect theory to think about the cross-section of average returns. Barberis and Huang (2008) study asset prices in a one-period economy in which investors derive prospect theory utility from the change in their wealth over the course of the period. This framework generates a new prediction, one that does not emerge from the traditional analysis based on expected utility, namely that a security's expected future skewness – even idiosyncratic skewness – will be priced: a stock whose future returns are expected to be positively skewed, say, will be "overpriced" and will earn a lower average return. Over the past few years, several papers, using various measures of expected skewness, have presented evidence in support of this prediction (Kumar 2009; Boyer, Mitton, and Vorkink 2010; Bali, Cakici, and Whitelaw 2011; Conrad, Dittmar, and Ghysels 2013). Moreover, the idea that expected skewness is priced has been used to shed light on the low average returns of IPO stocks, distressed stocks, high volatility stocks, stocks sold in over-the-counter markets, and out-of-the-money options (these assets have positively skewed returns); the diversification discount; and the lack of diversification in many household portfolios.[2]

In this paper, we examine the cross-section of average stock returns using a different implementation of prospect theory, one that makes a different assumption about the representation of gains and losses that investors have in their minds when thinking about a stock. In Barberis and Huang's (2008) framework, investors apply prospect theory to gains and losses in the value of their overall *portfolios*; and, more important, the portfolio gains and losses they are thinking about are *future* gains and losses. By contrast, in our framework, investors apply prospect theory to *stock*-level gains and losses (narrow framing), and react to *past* gains and losses. Put simply, in our framework, investors overvalue stocks whose past return distributions are appealing under prospect theory; in other frameworks, investors overvalue stocks whose future return distributions are appealing under prospect theory. Since a stock's past return distribution may be quite different from its expected future return distribution, the two approaches make distinct empirical predictions.

In Section 2, we discuss our conceptual framework in more detail. In Section 3, we present the results of our empirical tests. Section 4 concludes.

2 Conceptual Framework

Our assumption about investor behavior is that, for some investors, how much they allocate to a stock depends, in part, on the prospect theory value of the stock's historical return distribution. In this section, we discuss our conceptual framework in more detail. In Section 2.1, we review the mechanics of prospect theory. In Section 2.2, we discuss the issue of how "historical return distribution" should be defined. And in Section 2.3, we present a simple model that formalizes our main empirical prediction – that a stock's prospect theory value will predict its subsequent return with a negative sign in the cross-section.

[2]For more discussion of these applications, see Mitton and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), Boyer and Vorkink (2013), and Eraker and Ready (2014).

2.1 Prospect theory

In this section, we review the elements of prospect theory. Readers already familiar with this material may prefer to jump to Section 2.2.

The original version of prospect theory is described in Kahneman and Tversky (1979). While this paper contains all of the theory's essential insights, the specific model it presents has some limitations: it can be applied only to gambles with at most two nonzero outcomes, and it predicts that people will sometimes choose dominated gambles. Tversky and Kahneman (1992) propose a modified version of the theory known as cumulative prospect theory that resolves these problems. This is the version that is typically used in economic analysis and is the version we adopt in this paper.[3]

To see how cumulative prospect theory works, consider the gamble

$$(x_{-m}, p_{-m}; \ldots; x_{-1}, p_{-1}; x_0, p_0; x_1, p_1; \ldots; x_n, p_n), \tag{1}$$

which should be read as "gain x_{-m} with probability p_{-m}, x_{-m+1} with probability p_{-m+1}, and so on, independent of other risks," where $x_i < x_j$ for $i < j$, $x_0 = 0$, and $\sum_{i=-m}^{n} p_i = 1$. For example, a 50:50 bet to win \$110 or lose \$100 would be written as $(-\$100, \frac{1}{2}; \$110, \frac{1}{2})$. In the expected utility framework, an agent with utility function $U(\cdot)$ evaluates the gamble in (1) by computing

$$\sum_{i=-m}^{n} p_i U(W + x_i), \tag{2}$$

where W is his current wealth. A cumulative prospect theory agent, by contrast, assigns the gamble the value

$$\sum_{i=-m}^{n} \pi_i v(x_i), \tag{3}$$

where

$$\pi_i = \begin{cases} w^+(p_i + \ldots + p_n) - w^+(p_{i+1} + \ldots + p_n) & \text{for} \quad 0 \le i \le n \\ w^-(p_{-m} + \ldots + p_i) - w^-(p_{-m} + \ldots + p_{i-1}) & \phantom{\text{for}} \quad -m \le i < 0 \end{cases}, \tag{4}$$

and where $v(\cdot)$ is known as the value function and $w^+(\cdot)$ and $w^-(\cdot)$ as probability weighting

[3]While our analysis is based exclusively on cumulative prospect theory, we often abbreviate this to "prospect theory."

functions.[4] Tversky and Kahneman (1992) propose the functional forms

$$v(x) = \begin{cases} x^{\alpha} & \text{for} \quad x \geq 0 \\ -\lambda(-x)^{\alpha} & \phantom{\text{for}} \quad x < 0 \end{cases} \tag{5}$$

and

$$w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{1/\gamma}}, \quad w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{1/\delta}}, \tag{6}$$

where α, γ, $\delta \in (0,1)$ and $\lambda > 1$. The left panel in Figure 1 plots the value function in (5) for $\alpha = 0.5$ and $\lambda = 2.5$. The right panel in the figure plots the weighting function $w^{-}(P)$ in (6) for $\delta = 0.4$ (the dashed line), for $\delta = 0.65$ (the solid line), and for $\delta = 1$, which corresponds to no probability weighting at all (the dotted line). Note that $v(0) = 0$, $w^{+}(0) = w^{-}(0) = 0$, and $w^{+}(1) = w^{-}(1) = 1$.

There are four important differences between (2) and (3). First, the carriers of value in cumulative prospect theory are gains and losses, not final wealth levels: the argument of $v(\cdot)$ in (3) is x_i, not $W + x_i$. Second, while $U(\cdot)$ is typically differentiable everywhere, the value function $v(\cdot)$ is kinked at the origin, as shown in Figure 1, so that the agent is more sensitive to losses – even small losses – than to gains of the same magnitude. This element of cumulative prospect theory is known as loss aversion and is designed to capture the widespread aversion to bets such as $(-\$100, \frac{1}{2}; \$110, \frac{1}{2})$. The severity of the kink is determined by the parameter λ; a higher value of λ implies a greater relative sensitivity to losses. Tversky and Kahneman (1992) estimate $\lambda = 2.25$ for their median subject.

Third, while $U(\cdot)$ is typically concave everywhere, $v(\cdot)$ is concave only over gains; over losses, it is convex. This pattern can be seen in Figure 1. While we take account of this concavity/convexity in our analysis, it plays a very minor role in our results. One reason for this is that the curvature estimated by Tversky and Kahneman (1992) is very mild: using experimental data, they estimate $\alpha = 0.88$. To a first approximation, then, $v(\cdot)$ is piecewise-linear.

Finally, under cumulative prospect theory, the agent does not use objective probabilities when evaluating a gamble, but rather, transformed probabilities obtained from objective probabilities via the weighting functions $w^{+}(\cdot)$ and $w^{-}(\cdot)$. Equation (4) shows that, to obtain the probability weight π_i for an outcome $x_i \geq 0$, we take the total probability of all outcomes equal to or better than x_i, namely $p_i + \ldots + p_n$, the total probability of all outcomes strictly better than x_i, namely $p_{i+1} + \ldots + p_n$, apply the weighting function $w^{+}(\cdot)$ to each,

[4] When $i = n$ or $i = -m$, equation (4) reduces to $\pi_n = w^{+}(p_n)$ and $\pi_{-m} = w^{-}(p_{-m})$, respectively.

and compute the difference. To obtain the probability weight for an outcome $x_i < 0$, we take the total probability of all outcomes equal to or worse than x_i, the total probability of all outcomes strictly worse than x_i, apply the weighting function $w^-(\cdot)$ to each, and compute the difference.

The main consequence of the probability weighting in (4) and (6) is that the agent overweights the *tails* of any distribution he faces. In equations (3)-(4), the most extreme outcomes, x_{-m} and x_n, are assigned the probability weights $w^-(p_{-m})$ and $w^+(p_n)$, respectively. For the functional form in (6) and for γ, $\delta \in (0, 1)$, $w^-(P) > P$ and $w^+(P) > P$ for low, positive P; the right panel of Figure 1 illustrates this for $\delta = 0.4$ and $\delta = 0.65$. If p_{-m} and p_n are small, then, we have $w^-(p_{-m}) > p_{-m}$ and $w^+(p_n) > p_n$, so that the most extreme outcomes – the outcomes in the tails – are overweighted.

The overweighting of tails in (4) and (6) is designed to capture the simultaneous demand many people have for both lotteries and insurance. For example, people typically prefer $(\$5000, 0.001)$ to a certain \$5, but also prefer a certain loss of \$5 to $(-\$5000, 0.001)$.[5] By overweighting the tail probability of 0.001 sufficiently, cumulative prospect theory can capture both of these choices. The degree to which the agent overweights tails is governed by the parameters γ and δ; lower values of these parameters imply more overweighting of tails. Tversky and Kahneman (1992) estimate $\gamma = 0.61$ and $\delta = 0.69$ for their median subject.

2.2 Construction of return distributions

Every application of prospect theory outside the laboratory requires an assumption about "representation," in other words, about how the agent mentally represents the risk he is thinking about. Our assumption in this paper is that, when thinking about a stock, many investors mentally represent it by the distribution of its past returns, most likely because they see the past return distribution as a good and easily accessible proxy for the stock's *future* return distribution. In the Introduction, we noted an intuitive implication of this assumption for the cross-section of stock returns, namely that the prospect theory value of a stock's past return distribution should negatively predict the stock's subsequent return. We formalize this prediction in Section 2.3 and test it in Section 3.

To test the hypothesis that the prospect theory value of a stock's past return distribution has predictive power for subsequent returns, we need to define what we mean by "past return distribution." The most obvious way for an investor to learn about a stock's past return distribution is by looking at a chart that shows the stock's historical price movements. Price

[5] We abbreviate $(x, p; 0, q)$ as (x, p).

charts are ubiquitous in the financial world and usually appear front and center when an investor looks up information about a stock. In defining "past return distribution," we therefore take guidance from the way these charts are typically presented.

In the internet era, investors have a number of different chart formats at their disposal. However, most of the data that we use in our empirical analysis comes from the pre-internet era, a time when the main reference sources on stocks for retail investors were so-called investment handbooks, the most popular of which was the Value Line Investment Survey. The Value Line Survey presents a page of information about each stock. The page is dominated by a chart of historical price fluctuations that goes back several years. All of the other investment handbooks that we have examined also present charts spanning several years. The average time window across the various sources is, very approximately, five years. On these charts, the daily and weekly fluctuations are not discernible, but the monthly fluctuations are, and make a clear impression on the viewer – merely by glancing at the chart, the investor gets a quick sense of the distribution of monthly returns on the stock over the past few years. A large body of evidence in the field of judgment and decision-making suggests that people often passively accept the representation that is put in front of them.[6] Under this view, if the monthly return distribution over the past few years is the distribution that jumps out at the investor when he looks at a chart, it is plausible that this is the representation that he adopts when thinking about the stock. In short, then, when computing the prospect theory value of a stock's past return distribution, we take "past return distribution" to mean the distribution of monthly returns over the past five years.

The final thing we need to specify is whether the monthly returns we use to construct the historical distribution are raw returns, or something else – returns in excess of the risk-free rate, say, or returns in excess of the market return. On the one hand, it is raw returns that are closest to what is being depicted in a chart of past price fluctuations. On the other hand, an investor looking at a stock chart is likely to have a sense of the performance of the overall market over the period in question, and this may affect his reaction to the chart. For example, if he sees a chart showing a decline in the price of a stock, he may react neutrally, rather than negatively, if he knows that the market also performed poorly over the same period. In our benchmark results, we therefore use stock returns in excess of the market return. However, we also present results based on raw returns and returns in excess of the risk-free rate; these results are similar to those for the benchmark case.

In summary, then, when thinking about a stock, some of the investors in our framework

[6]See, for example, Gneezy and Potters (1997), Thaler et al. (1997), Benartzi and Thaler (1999), and Gneezy, Kapteyn, and Potters (2003).

mentally represent it as the distribution of its monthly returns in excess of the market over the past five years. To determine their allocation to the stock, they evaluate this distribution according to prospect theory, thereby obtaining the stock's prospect theory value. We now explain more precisely how this prospect theory value is computed.

Given a specific stock, we record the stock's return in excess of the market in each of the previous 60 months and then sort these 60 excess returns in increasing order, starting with the most negative through to the most positive. Suppose that m of these returns are negative, while the remaining $n = 60 - m$ are positive. Consistent with the notation of Section 2.1, we label the most negative return as r_{-m}, the second most negative as r_{-m+1}, and so on, through to r_n, the most positive return, where r is a monthly return in excess of the market. The stock's historical return distribution is then

$$(r_{-m}, \frac{1}{60}; r_{-m+1}, \frac{1}{60}; \ldots; r_{-1}, \frac{1}{60}; r_1, \frac{1}{60}; \ldots; r_{n-1}, \frac{1}{60}; r_n, \frac{1}{60}), \tag{7}$$

in other words, the distribution that assigns an equal probability to each of the 60 excess returns that the stock posted over the previous 60 months. From Section 2.1, the prospect theory value of this distribution is

$$\mathrm{TK} \equiv \sum_{j=-m}^{-1} v(r_j) \left[w^-(\frac{j+m+1}{60}) - w^-(\frac{j+m}{60}) \right] + \sum_{j=1}^{n} v(r_j) \left[w^+(\frac{n-j+1}{60}) - w^+(\frac{n-j}{60}) \right]. \tag{8}$$

Note that we label a stock's prospect theory value as "TK," which stands for Tversky and Kahneman (1992), the paper that first presented cumulative prospect theory.[7]

To compute the expression in (8), we need to specify the value function parameters α and λ in equation (5) and the weighting function parameters γ and δ in (6). We use the parameter estimates obtained by Tversky and Kahneman (1992) from experimental data, namely

$$\begin{aligned} \alpha &= 0.88,\ \lambda = 2.25 \\ \gamma &= 0.61,\ \delta = 0.69. \end{aligned}$$

[7]An obvious feature of TK is that it does not depend on the order in which the 60 excess returns occur in time. In reality, investors may pay more attention to more recent returns. We do not pursue this line of thinking in great detail because it is not clear how much investors downweight distant past returns. However, in a tentative investigation, we used data on portfolio holdings to try to obtain an estimate of the relative weight investors put on distant as opposed to recent returns. A modified TK measure that incorporates this estimate produces results that are qualitatively similar to those that we present in Section 3.

Subsequent to Tversky and Kahneman (1992), several papers have used more sophisticated techniques, in conjunction with new experimental data, to estimate these parameters (Gonzalez and Wu 1999; Abdellaoui 2000). Their estimates are similar to those obtained by Tversky and Kahneman (1992).

2.3 Model

Our assumption about investor behavior is that, when allocating across stocks, a significant fraction of investors are influenced by the prospect theory value of each stock's historical return distribution. In the Introduction, we noted an intuitive implication of this assumption for the cross-section of stock returns, namely that a stock's prospect theory value should predict its subsequent return with a negative sign. We now present a simple model that formalizes this prediction.

We work in a mean-variance framework. There is a risk-free asset with a fixed return of r_f. There are J risky assets, indexed by j. Asset j has return $\widetilde{r}_j$ whose mean and standard deviation are μ_j and σ_j, respectively. The covariance between the returns on assets i and j is $\sigma_{i,j}$. More generally, given a portfolio p, we use $\widetilde{r}_p$, μ_p, σ_p, and $\sigma_{p,q}$ to denote the portfolio's return, mean, standard deviation, and covariance with portfolio q, respectively.

There are two types of trader in the economy. Traders of the first type are traditional mean-variance investors who hold the tangency portfolio that, among all combinations of risky assets, has the highest Sharpe ratio. The tangency portfolio has return $\widetilde{r}_t$, mean μ_t, and standard deviation σ_t. The weights of the J risky assets in the tangency portfolio are given by the $J \times 1$ vector ω_t.

Traders of the second type are "prospect theory" investors. These investors construct their portfolio holdings by taking the tangency portfolio w_t and then adjusting it, increasing their holdings of stocks with high prospect theory values and decreasing their holdings of stocks with low prospect theory values. Formally, they hold a portfolio p whose risky asset weights are given by

$$\omega_p = (1-k)\omega_t + k\omega_{TK}, \tag{9}$$

for some $k \in (0,1)$, and where ω_{TK}^j, the j'th element of ω_{TK}, is given by

$$\omega_{TK}^j = f(\mathrm{TK}_j), \tag{10}$$

where TK_j, defined in (8), is the prospect theory value of stock j's past returns – specifically, as described in Section 2.2, the prospect theory value of the distribution of the 60 past monthly returns on the stock in excess of the market – and $f(\cdot)$ is a strictly increasing function with $f(0) = 0$. In other words, relative to the benchmark tangency portfolio, these investors tilt toward stocks with positive prospect theory values, and do so all the more, the higher their prospect theory values. Conversely, they tilt away from stocks with negative prospect theory values, and do so all the more, the more negative these values are.

Our assumption about the behavior of the prospect theory investors is consistent with a principle emphasized by Koszegi and Rabin (2006, 2009), namely that, when incorporating prospect theory into an economic framework, we should model agents whose decisions are determined by both prospect theory considerations *and* traditional expected utility considerations, not agents whose decisions are determined by prospect theory alone. The thinking is that, even if, as Kahneman and Tversky (1979) argue, people derive utility from gains and losses, they surely also derive utility from absolute wealth levels and it would be a mistake to ignore this. Equation (9) reflects the spirit of Koszegi and Rabin's (2006, 2009) prescription: the stock allocations of the prospect theory agents are affected by both traditional considerations (the ω_t term) and prospect theory considerations (the ω_{TK} term).

If the fraction of traditional mean-variance investors in the overall population is π, so that the fraction of prospect theory investors is $1-\pi$, the market portfolio ω_m can be written

$$\begin{aligned} \omega_m &= \pi\omega_t + (1-\pi)((1-k)\omega_t + k\omega_{TK}) \\ &= (1-(1-\pi)k)\omega_t + (1-\pi)k\omega_{TK} \\ &= (1-\eta)\omega_t + \eta\omega_{TK}, \end{aligned} \tag{11}$$

where $\eta = (1-\pi)k$.

In the Appendix, we prove the following proposition, which guides our empirical work. In the proposition, β_x is the market beta of asset or portfolio x.

Proposition 1. *In the economy described above, the mean return μ_j of asset j is given by*

$$\frac{\mu_j - r}{\mu_m - r} = \beta_j - \frac{\eta s_{j,TK}}{\sigma_m^2(1-\eta\beta_{TK})}, \tag{12}$$

where $s_{j,TK}$ is the covariance between the residuals $\widetilde{\varepsilon}_j$ and $\widetilde{\varepsilon}_{TK}$ obtained from regressing asset j's excess return and portfolio TK's excess return, respectively, on the market portfolio:

$$\widetilde{r}_j = r_f + \beta_j(\widetilde{r}_m - r_f) + \widetilde{\varepsilon}_j \tag{13}$$

$$\widetilde{r}_{TK} = r_f + \beta_{TK}(\widetilde{r}_m - r_f) + \widetilde{\varepsilon}_{TK}. \tag{14}$$

Under the additional assumption that $Cov(\tilde{\varepsilon}_i, \tilde{\varepsilon}_j) = 0$ for $i \neq j$, we obtain

$$\begin{aligned} \frac{\mu_j - r}{\mu_m - r} &= \beta_j - \frac{\eta w_{TK}^j s_j^2}{\sigma_m^2 (1 - \eta \beta_{TK})} \\ &= \beta_j - \frac{\eta f(\mathrm{TK}_j) s_j^2}{\sigma_m^2 (1 - \eta \beta_{TK})}. \end{aligned} \tag{15}$$

Equation (15) captures the prediction that we test in the next section: that stocks with higher prospect theory values (higher TK_j) will have lower alphas.

3 Empirical Analysis

In this section, we test the predictions of the framework described in Section 2. Our main prediction is that stocks with higher prospect theory values TK – stocks whose past return distributions have higher prospect theory values – will subsequently earn lower returns, on average. As noted earlier, we expect this prediction to hold primarily for stocks with lower market capitalizations, in other words, for stocks where individual investors play a more important role. After all, it is these individual investors who are more likely to make buying and selling decisions based on the thinking we have described.

3.1 Data

Our data come from standard sources. For U.S. firms, the stock price and accounting data are from CRSP and Compustat. Our analysis includes all stocks in the CRSP universe from 1926 to 2010 for which the variable TK can be calculated – in other words, all stocks with at least five years of monthly return data. Compustat does not cover the first part of our sample period; for these early years, our data on book equity are from Kenneth French's website. Stock price and accounting data for non-U.S. firms are from Datastream. Finally, we obtain quarterly data on institutional stock holdings from 1980-2010 from the Thomson Reuters (formerly CDA/Spectrum) database.

Table 1 presents summary statistics for the variables we use in our analysis. Panel A reports means and standard deviations; Panel B reports pairwise correlations. TK is the prospect theory variable defined in (8) whose predictive power is the focus of the paper. "Beta" is a stock's beta computed as in Fama and French (1992) using monthly returns over the previous five years; equation (15) indicates that beta should be included in our tests. The next few variables are known predictors of stock returns in the cross-section; we use them as controls in some of our tests. Their time t values are defined as follows:

Size: the market value of the firm's outstanding equity at the end of month $t-1$[8]

BM: the log of the firm's book value of equity divided by market value of equity, where book-to-market is computed following Fama and French (1992) and Fama and French (2008); firms with negative book value are excluded from the analysis

MOM: the stock's cumulative return from the start of month $t-12$ to the end of month $t-2$, a control for momentum

ILLIQ: Amihud's (2002) measure of illiquidity, computed using daily data from month $t-1$

REV: the stock's return in month $t-1$, a control for the short-term reversal phenomenon

LT REV: the stock's cumulative return from the start of month $t-60$ to the end of month $t-13$, a control for the long-term reversal phenomenon

IVOL: the volatility of the stock's daily idiosyncratic returns over month $t-1$, as in Ang et al. (2006).

Later in the paper, we propose that some of the predictive power of the TK variable may be related to the fact that the returns of high TK stocks are more positively skewed than those of the typical stock, a characteristic that may be appealing to investors when they observe it in a chart of historical price fluctuations. Some skewness-related variables have already been studied in the context of the cross-section of stock returns. To understand the relationship of TK to these other variables, we include them in some of our tests. They are:

MAX: a stock's maximum one-day return in month $t-1$, as in Bali, Cakici, and Whitelaw (2011)

MIN: (the negative of) a stock's minimum one-day return in month $t-1$, as in Bali, Cakici, and Whitelaw (2011)

Skew: the skewness of a stock's monthly returns over the previous five years

EISKEW: a stock's expected idiosyncratic return skewness, as in Boyer, Mitton, and Vorkink (2010)

Coskew: a stock's coskewness, computed using monthly returns over the previous five years in the way described by Harvey and Siddique (2000), namely as $E(\varepsilon_{i,t}\varepsilon^2_{M,t})/(E(\varepsilon^2_{M,t})\sqrt{E(\varepsilon^2_{i,t})})$, where $\varepsilon_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{M,t}$ are the residuals in a regression of excess stock returns $R_{i,t}$ on excess market returns $R_{M,t}$ and where $\varepsilon_{M,t} = R_{M,t} - \mu_M$ are the residuals after de-meaning the market returns.

[8] We adopt the convention that month $t-j$ spans the interval from time $t-j$ to time $t-j+1$.

To be clear, MAX, MIN, EISKEW, and Coskew have been shown to have predictive power for subsequent returns; see, for example, the papers referenced in the definitions of these variables. Skew, however, does not predict returns in a statistically significant way.

We compute the summary statistics in Table 1 using the full data sample, starting in July 1931 and ending in December 2010. The only exception is for EISKEW; this variable is available starting only in January 1988.[9]

To a first approximation, the prospect theory value of a gamble is increasing in the gamble's mean; decreasing in the gamble's standard deviation (due to loss aversion); and increasing in the gamble's skewness (due to probability weighting). The results in the column labeled "TK" in Panel B of Table 1 are consistent with this. Across stocks, TK is positively correlated with measures of past returns (REV, MOM, LT REV), negatively correlated with a measure of volatility (IVOL), and positively correlated with past skewness (Skew). High TK stocks also tend to have higher market capitalizations, probably because large-cap stocks are less volatile; they are also more likely to be growth stocks.

3.2 Time-series tests

Our main hypothesis is that the prospect theory value of a stock's past return distribution – the stock's TK value – will predict the stock's subsequent return in the cross-section. In this section, we test this hypothesis using decile sorts. In Section 3.4, we test it using the Fama-MacBeth methodology.

We conduct the decile sort test as follows. At the start of each month, beginning in July 1931 and ending in December 2010, we sort stocks into deciles based on TK. We then compute the average return of each TK decile portfolio over the next month, both value-weighted and equal-weighted. This gives us a time series of monthly returns for each TK decile. We use these time series to compute the average return of each decile over the entire sample. More precisely, in Table 2, we report the average return of each decile in excess of the risk-free rate; the 4-factor alpha for each decile (the return adjusted by the three Fama-French factors and the momentum factor); the 5-factor alpha for each decile (the return adjusted by the three Fama-French factors, the momentum factor, and the Pastor and Stambaugh (2003) liquidity factor); and the characteristics-adjusted return for each decile, computed in the way described by Daniel et al. (1997) and denoted DGTW. In the right-most column, we report the difference between the returns of the two extreme decile portfolios, in other words,

[9] Boyer, Mitton, and Vorkink (2010), who introduce EISKEW to the literature, construct this variable starting in 1988 because detailed data on the trading volume of NASDAQ stocks only becomes available in the 1980s.

the return of a "low-high" zero investment portfolio that buys the stocks in the lowest TK decile and shorts the stocks in the highest TK decile. As noted above, our analysis covers the full sample period, starting in July 1931 and ending in December 2010. The only exception is for the 5-factor alpha: we begin this analysis in January 1968 because that is when data on the liquidity factor become available.

The most important column in Table 2 is the right-most column, which reports the average return of the low-high portfolio. Our prediction is that this return will be significantly positive. Recall that we expect this prediction to hold more strongly for equal-weighted returns – in other words, for small stocks, where individual investors play a more important role. Ex-ante, we do not necessarily expect to find a significant result for value-weighted returns.

The right-most column of Table 2 supports our hypothesis. The average equal-weighted return on the low TK portfolio is significantly higher than on the high TK portfolio across all four types of returns that we compute (excess return, 4-factor alpha, 5-factor alpha, and DGTW return). As we predicted, the difference in average returns is larger for equal-weighted returns than for value-weighted returns. Nonetheless, we find a significant effect even for value-weighted returns. Moreover, the economic magnitudes of the excess returns and alphas in the right-most column are sizeable.[10]

Figure 2 presents a graphical view of the results in Table 2. It plots the equal-weighted (top panel) and value-weighted (bottom panel) 4-factor alphas on the ten TK decile portfolios. The figure makes it easy to see another aspect of the results in Table 2, namely that the alphas on the TK portfolios decline in a near-monotonic fashion as we move from the lowest TK portfolio to the highest TK portfolio.

We also examine whether TK can predict stock returns beyond the first month after portfolio construction. In Table 2 and Figure 2, we looked at whether TK calculated using returns from month $t-60$ to $t-1$ can predict the return in month t. To examine the longer horizon predictive power of TK, we again sort stocks into decile portfolios at time t using TK calculated from month $t-60$ to $t-1$, but now look at the returns of these portfolios not only in month t, but also in months $t+1$, $t+2$, and so on. Figure 3 shows the results.

[10]The reader can infer from the t-statistics in Table 2 that the long-short low-TK minus high-TK portfolio is fairly volatile – similarly volatile to a long-short value minus growth portfolio. This, in turn, suggests that stocks with similar TK values comove in their prices. This is indeed the case. We find that a stock in a given TK decile comoves more with other stocks in the same TK decile than with stocks in other TK deciles, even after controlling for the three Fama-French factors. This comovement may be due to investors having a similarly positive or negative attitude to stocks in the same TK decile, leading them to trade these stocks in a correlated way.

The top chart corresponds to equal-weighted returns; the bottom chart, to value-weighted returns. The figures plot 4-factor alphas. Specifically, the alpha that corresponds to the $t+k$ label on the horizontal axis is the 4-factor alpha of a long-short portfolio that, each month, buys stocks that were in the lowest TK decile k months previously and shorts stocks that were in the highest TK decile k months previously.

The figure shows that TK has predictive power for returns several months after portfolio construction. It also shows that a non-trivial fraction of TK's predictive power comes in the first month after the moment at which TK is computed. However, we do not attach much importance to this finding because it appears to be primarily a feature of U.S. data: in our tests with international data in Section 3.6, we find that skipping a month between the moment at which TK is computed and the moment at which we start measuring returns has little effect on TK's predictive power.

Table 3 reports the factor loadings for the low TK minus high TK portfolio for both a 4-factor and a 5-factor model, and for both equal-weighted and value-weighted returns. The results are consistent with those in Table 1: low TK portfolios comove with small stocks, value stocks, and low momentum stocks.

3.3 Robustness of time-series results

In the next section, Section 3.4, we test our main hypothesis using a Fama-MacBeth methodology. Before moving to this analysis, however, we first examine the robustness of the decile-sort results in Table 2. The results are in Table 4, whose six panels correspond to six different kinds of robustness checks. The two right-most columns report 4-factor alphas for the low TK minus high TK portfolio, based on either equal-weighted (EW) or value-weighted (VW) returns.

First, we check whether our results hold not only in the full sample, but also in each of two subperiods: one that starts in July 1931 and ends in June 1963, and another that starts in July 1963 and ends in December 2010. We choose July 1963 as the breakpoint to make our results easier to compare with those of the many empirical papers that, due to data availability, begin their analyses in July 1963. The first panel of Table 4 confirms that our main prediction holds in both subperiods: the long-short portfolio has a significantly positive alpha, particularly in the case of equal-weighted returns.

When constructing the past return distribution for a stock, we use monthly returns over the previous five years. The second panel of Table 4 shows that, if we instead use monthly returns over the previous three, four, or six years, we obtain similar results. Also, when we construct a stock's past return distribution, we use returns in excess of the market return. The third panel of the table shows that we obtain similar results if we instead use raw returns, returns in excess of the risk-free rate, or returns in excess of the stock's own sample mean. The fourth panel shows that the long-short alpha remains significantly positive if we exclude stocks whose price falls below $5 in the month before portfolio construction. And the fifth panel shows that, consistent with Figure 3, the long-short alpha declines somewhat in economic magnitude if we skip a month between the moment at which we sort stocks and the moment at which we start measuring the returns of the decile portfolios. However, as noted earlier, this decline is primarily a U.S. phenomenon: we do not observe it in our international results in Section 3.6. Moreover, even after skipping a month, our prediction is confirmed for equal-weighted returns, which is where we expect to see it hold more strongly.

Finally, when computing TK, we use the probability weighting function in (6). While this is the most commonly used functional form, there are others. Perhaps the best-known alternative is due to Prelec (1998). In the final panel of the table, we show that our results are similar when we use the Prelec specification.

3.4 Fama-MacBeth tests and double sorts

We now test our main hypothesis using the Fama-MacBeth methodology. One advantage of this methodology is that it allows us to examine the predictive power of TK while controlling for known predictors of returns. This is important because, as shown in Table 1, TK is correlated with some of these known predictors.

We implement the Fama-MacBeth methodology in the usual way. Each month, starting in July 1931 and ending in November 2010, we run a cross-sectional regression of stock returns in that month on TK measured at the start of the month, and, as controls, variables already known to predict returns. Table 5 reports the time-series averages of the coefficients on the independent variables. The nine columns in the table correspond to nine different regression specifications which differ in the number of control variables they include.

The table provides support for our prediction. The TK variable retains significant predictive power even after we include the major known predictors of returns. In columns (2) through (5), for example, we include controls such as market capitalization ("Size"), book-to-market ("BM"), various measures of past returns ("REV," "MOM," and "LT REV"), an illiquidity measure ("ILLIQ"), and idiosyncratic volatility ("IVOL"). The table shows that controlling for the past month's return ("REV") takes a substantial bite out of the economic magnitude of the coefficient on TK; however, the inclusion of the other controls leaves the coefficient largely unaffected.

In Section 3.8, we will suggest that the low returns to high TK stocks may be due, in part, to the fact that the past returns of high TK stocks are positively skewed. Since skewness-related variables have been studied before in connection with the cross-section of returns, columns (6) through (9) include these variables as additional controls. We find that, even after their inclusion, the coefficient on TK remains largely unaffected in magnitude and statistical significance.

Table 5 shows that, while TK predicts returns at conventional levels of statistical significance, its predictive power is not as strong as that of, say, book-to-market or idiosyncratic volatility. We emphasize, however, that the construction of TK is constrained by prior theory and evidence in a way that the construction of many other predictor variables is not. For example, we use the exact functional forms suggested by Tversky and Kahneman (1992) as well as the exact parameter values that they estimate; and, given the typical format of price charts, we restrict ourselves to five years of monthly data when computing TK. Given that we have tied our hands on these dimensions, the statistical significance with which TK predicts returns is, if anything, strikingly high, rather than low. The only specification in Table 5 where the statistical significance of the coefficient on TK falls below conventional levels is the one in column (7) that includes past return skewness as a control. However, we suggest in Section 3.8 that past skewness is an integral part of the prospect theory interpretation we are proposing; as such, it is not clear that it should even be included as a control. We also note that the t-statistics in Table 5 are computed using a particularly conservative specification of standard errors, namely Newey-West adjusted with 12 lags.[11]

One of the assumptions of our framework is that, when investors observe a stock's historical return distribution, they evaluate it according to prospect theory. We now consider the possibility that they instead evaluate it according to expected (power) utility. The prediction in this case is that a stock whose historical return distribution has a high (low) *expected utility* value will have low (high) subsequent returns. To test this prediction, we replace TK in the regression in column (6) of Table 5 with the variable EU, defined as

$$\mathrm{EU} \equiv \sum_{j=-m}^{n} \frac{1}{60} \frac{(1+r_j)^{1-\theta}}{1-\theta}, \tag{16}$$

[11]Harvey, Liu, and Zhu (2014) argue that, due to the prevalence of data mining, it is desirable to hold empirical results to a higher level of statistical significance than is typically the case. However, they also note that an exception should be made for tests, like ours, that are heavily motivated and constrained by prior theory and evidence. In Section 3.6, we address the data mining concern directly by conducting an out-of-sample test of our hypothesis in international data.

where, using the notation of Section 2.2, $\{r_{-m}, \ldots, r_n\}$ are the stock's monthly returns over the previous 60 months.

We consider several values of θ, ranging from 0.5 to 10, but find no evidence that, after controlling for the important known predictors in column (6), the EU variable has any predictive power for subsequent returns.[12] This suggests that the results in Table 5 are driven by something specific about the way prospect theory weights stocks' past returns – it is not that *any* weighting of past returns delivers similar results.

Fama-MacBeth regressions allow us to examine the predictive power of TK while controlling for known predictors, but they do have a limitation: they assume that the relationship between stock returns and the various predictors is linear. We therefore also use double-sorts to study the robustness of TK's predictive power. Specifically, we use the following procedure. Suppose that we want to see whether the predictive power of TK is subsumed by control variable X. At the beginning of each month, we sort stocks into quintiles based on X. Within each quintile, we again sort stocks into quintiles, this time based on TK. The returns, over the next month, of the five TK quintile portfolios are then averaged across different quintiles of the control variable X. More precisely, if $r_{i,j}$ is the return, over the next month, of the portfolio of stocks in the i'th quintile of X and j'th quintile of TK, we compute, for $j = 1, \ldots, 5$,

$$\overline{r}_j = \frac{r_{1,j} + \ldots + r_{5,j}}{5}. \tag{17}$$

We then compute

$$\overline{r} = \overline{r}_1 - \overline{r}_5 = \frac{(r_{1,1} - r_{1,5}) + \ldots + (r_{5,1} - r_{5,5})}{5} \tag{18}$$

as a measure of the return of the low TK minus high TK portfolio, controlling for variable X.

We report the results of this exercise in Table 6. Each column corresponds to a specific control variable. Within each column, we report, on both an equal-weight (EW) and value-weight (VW) basis, the 4-factor alphas of the five TK quintile portfolios – in other words, $\overline{r}_1$, $\overline{r}_2$, $\overline{r}_3$, $\overline{r}_4$, and $\overline{r}_5$, defined above, adjusted for the four Carhart factors – and, in the bottom row of each column, the 4-factor alpha of the low-TK minus high-TK portfolio, in other words, $\overline{r}_1 - \overline{r}_5$ adjusted for the four factors. The control variables we consider are the past month's return (REV); the Amihud (2002) illiquidity measure (ILLIQ); the long-term past return (LT REV); idiosyncratic volatility (IVOL); the maximum one-day return over the past month (MAX); skewness of past returns (Skew); expected idiosyncratic skewness

[12]These results are available on request.

(EISKEW); and coskewness of past returns (Coskew).

The most important row in Table 6 is the bottom one. It shows that, consistent with the Fama-MacBeth results in Table 5, the TK variable retains significant predictive power for returns even after controlling for known predictors of returns.

3.5 The role of limits to arbitrage

We expect the predictive power of TK to be stronger for stocks whose pricing is less subject to the forces of arbitrage – for example, stocks with low market capitalizations, illiquid stocks, stocks with high idiosyncratic volatility, and stocks with low institutional ownership. We now test this hypothesis.

At the end of each month, we sort stocks into two groups based on size, illiquidity, idiosyncratic volatility, or institutional ownership. Size is market capitalization at the end of the previous month; illiquidity (ILLIQ) is defined as in Amihud (2002); idiosyncratic volatility (IVOL) is computed as in Ang et al. (2006); and institutional ownership is the log of one plus the fraction of a stock's outstanding shares that are held by institutional investors. In the case of the Size variable, the breakpoint is the median for NYSE-listed firms; in the case of ILLIQ and IVOL, the breakpoints are the medians in the full sample of stocks. The breakpoint for institutional ownership is the 66.67% percentile in the sample. We do not use the median as the breakpoint because average institutional ownership is very low in the early years of the sample. If we were to use the median as the breakpoint, many stocks with low levels of institutional ownership would be classified into the high institutional ownership group.[13]

Within each of the size, ILLIQ, IVOL, and institutional ownership portfolios, we then sort stocks into deciles based on TK and compute the return on each decile over the next month. Repeating this each month gives us a time series of returns for each TK decile portfolio. In Table 7, we report, on both an equal-weight (EW) and value-weight (VW) basis, the excess return, 4-factor alpha, 5-factor alpha, and DGTW return for a long-short portfolio that goes long the lowest TK decile and short the highest TK decile. Our analysis is based on the full sample, from 1931 to 2010, except in the case of institutional holdings, where, due to data availability, the sample begins in 1980.

[13]For any stock in any quarter, we obtain its institutional holdings by aggregating the positions of different institutions. Different institutional funds may have different report dates; we assume that fund managers do not trade between the report date and the quarter end. If the Thomson Reuters database does not have data on a particular stock, we set its institutional holdings to zero. We also winsorize the institutional ownership variable at 1% in both tails and lag it by one quarter to match returns.

The results in Table 7 are consistent with our hypothesis. The predictive power of TK is uniformly stronger among stocks where the forces of arbitrage are likely to be weaker.

Table 8 also presents results on the role of limits to arbitrage, but does so using a Fama-MacBeth analysis rather than through double sorts. Specifically, we run a Fama-MacBeth regression that is the same as that in column (6) of Table 5, except that it also includes four other independent variables: TK interacted with Size, TK interacted with ILLIQ, TK interacted with IVOL, and TK interacted with institutional ownership. The coefficients on the four interaction terms confirm our hypothesis that the predictive power of TK is greater for stocks with low market capitalizations, illiquid stocks, stocks with high idiosyncratic volatility, and stocks with low institutional ownership.

3.6 International evidence

Our hypothesis is that a stock's prospect theory value can predict its subsequent return in the cross-section. We have provided some evidence for this hypothesis using data on U.S. stocks. In this section, we conduct an important out-of-sample test: we test our hypothesis using data from Datastream on 46 international stock markets.

For each stock market in turn, we conduct a test that is similar to the decile sort tests in Table 2. Each month, we sort stocks into quintiles based on TK and record the return of each quintile over the next month. This gives us a time series of returns for each TK quintile. We use these time series to compute the average return of each quintile over the entire sample, and hence also the average return of a long-short portfolio that goes long the stocks in the low TK quintile and short the stocks in the high TK quintile. Specifically, we compute, on both an equal-weight and value-weight basis, the raw average return of the long-short portfolio, but also the average return of the long-short portfolio adjusted for "global factors," for "international factors," and for "local factors." For a given country C, the local factors are the four Carhart factors constructed from the universe of stocks traded in country C; the global factors are the four Carhart factors constructed from the universe of *all* stocks across all 46 markets; and the international factors are a set of eight factors: the four local factors supplemented by the four global factors (Hou, Karolyi, and Kho, 2011). As before, we expect our prediction to hold more strongly for equal-weighted returns.

In Panel A of Table 9, we report the average value, across the 46 countries, of the eight types of long-short portfolio return we compute in each country ("Average alpha"); the number of countries for which the portfolio return is positive/negative and significant/insignificant at the 10% level; and the percentage of countries in which the portfolio return is positive, or positive and significant. In Panel B, we report analogous results for the case in which we skip a month between the moment of portfolio construction and the moment at which we start measuring returns.[14]

The international evidence is consistent with our prediction. Panel A of the table shows that, across all specifications, the vast majority of the countries we consider – as many as 80% to 90% of them – generate an average long-short portfolio return with the predicted positive sign. And for equal-weighted returns, the average return is positive in a statistically significant way in a strong majority of the 46 countries.

In Section 3.2, we noted that, in U.S. data, a non-trivial fraction of the predictive power of TK comes in the first month after portfolio construction. Panel B of Table 9 shows that, by contrast, in the international data, skipping a month between the moment when TK is computed and the month in which portfolio returns are measured has little effect on our results: even after skipping a month, the vast majority of countries generate a long-short equal-weighted alpha with the predicted positive sign, and the effect is statistically significant in most countries. Even in the value-weighted case, there is evidence that TK has predictive power for subsequent returns.

3.7 Explaining anomalies

Our central assumption about investor behavior is that some investors allocate across stocks based on the prospect theory value of each stock's historical return distribution. In previous sections, we presented evidence consistent with a basic implication of this assumption, namely that a stock's prospect theory value will predict its subsequent return in the cross-section. Another natural question is: Can the investor behavior we have proposed explain anomalies such as the size and value premia? Under this view, small stocks and value stocks have high average returns because the distribution of past returns of the typical small-cap or value stock has a low prospect theory value, making these stocks unappealing to some investors. By tilting away from such stocks, the investors cause them to become undervalued and therefore to earn high subsequent returns.

We carry out two tests of this hypothesis: a double-sort test, where we sort stocks on TK and either size or book-to-market, and then check whether, controlling for TK, size and book-to-market still predict returns; and a Fama-MacBeth test, where we examine whether introducing TK into a Fama-MacBeth regression shrinks the coefficients on size and book-to-market. The results, which we do not report but which are available on request, suggest

[14] The table caption contains additional information about our methodology.

that the investor behavior we describe here does not play a major role in explaining the size and value premia.

The potential explanation for the size and value premia that comes out of our framework – an explanation that we have just cast doubt on – is that value stocks and small stocks earn high average returns because the distribution of their past returns is unappealing to prospect theory investors. Another potential explanation of these premia, one that emerges from "forward-looking" implementations of prospect theory such as that of Barberis and Huang (2008), is that value stocks and small stocks earn high average returns because the distribution of their *future* returns is unappealing to prospect theory investors. These are distinct explanations: a stock that is classified as a value stock *today* may not have been a value stock five years ago; the distribution of its returns over the past five years may therefore be quite different from the distribution of its returns over the next five. To our knowledge, this alternative explanation of size and value premia has not yet been examined.

3.8 Mechanism

In previous sections, we presented evidence that a stock's prospect theory value predicts its subsequent return in the cross-section. Our interpretation of this is that, when thinking about a stock, some investors mentally represent it by its historical return distribution and then evaluate this distribution according to prospect theory. They tilt their portfolios toward stocks whose past return distributions are appealing under prospect theory, thereby causing these stocks to become overvalued and to earn low subsequent returns. Similarly, they tilt away from stocks whose past returns are unappealing under prospect theory, causing these stocks to become undervalued and to earn high subsequent returns.

A natural question is: What is it exactly about the past returns of stocks with high prospect theory values that makes them appealing to investors? Conversely, what is it about stocks with low prospect theory values that makes them unappealing? To answer this, we start by digging more deeply into the characteristics of low TK and high TK stocks. In general, gambles with high prospect theory values have a high mean payoff; a low standard deviation (loss aversion lowers the prospect theory value of a gamble with a high standard deviation); and high skewness (probability weighting raises the prospect theory value of a positively skewed gamble). Given this, we expect stocks with high TK values to be stocks with high past returns, low past volatility, and high past skewness.

To examine this conjecture, we sort stocks each month into deciles based on TK and, for a variety of characteristics, record the average value of each characteristic across all stocks in each decile at that time. We repeat this exercise in every month, from July 1931 to December 2010, and then, for each decile in turn, compute the time series averages of the characteristics across all months in the sample. In effect, this exercise allows us to dig further into the correlations listed in Panel B of Table 1.

The results, reported in Table 10, confirm our conjecture to some extent, but also indicate some subtleties. As expected, measures of past returns (REV, MOM, LT REV) increase monotonically from TK decile 1 to TK decile 10. Past skewness ("Skew") also generally increases from TK decile 1 to TK decile 10; however, the increase in skewness occurs largely from deciles 8 to 9, and from 9 to 10. Interestingly, while measures of past volatility – "Beta", "IVOL", and "STD", the standard deviation of monthly returns over the past five years – decrease monotonically from TK decile 1 to TK decile 8, they increase slightly in decile 9 and then rise significantly in decile 10; indeed, far from being the least volatile stocks, the stocks in decile 10 are *more* volatile than average. The reason for this is that volatility and skewness are correlated in the cross-section; since stocks in TK decile 10 are much more skewed than the average stock, they are also more volatile than the average stock. Put differently, the stocks in decile 10 are those that trade off past return, volatility, and skewness in a way that is maximally attractive to a prospect theory agent. Table 10 shows that these are stocks with high past returns and high past skewness, but, if anything, higher past volatility than the average stock.

Given that high TK stocks have much higher past returns than low TK stocks, one might conjecture that the negative relation between TK and subsequent returns in the cross-section has something to do with the negative relation between REV / LT REV and subsequent returns in the cross-section. However, in our earlier tests, using two different methodologies, we saw that controlling for REV and LT REV did not take away TK's predictive power. Nor is it easy to argue that TK's predictive power is related to the predictive power of volatility for subsequent returns: the volatility of stocks in decile 1 is not very different from the volatility of stocks in decile 10. A more promising avenue is to focus on skewness: high TK stocks are much more highly skewed than low TK stocks.

Some evidence that suggests a role for skewness comes from examining which component of prospect theory is most responsible for TK's ability to predict returns. Table 11 presents some results on this. The seven columns in the table correspond to seven different Fama-MacBeth regressions. The regressors in each case are a prospect theory variable (first row) and, as controls, ten well-known predictors of returns, such as market capitalization and book-to-market. The control variables are the same across the seven regression specifications;

it is only the prospect theory variable that changes.

The right-most column uses TK as the prospect theory variable; this column therefore corresponds to the Fama-MacBeth regression we ran previously in column (6) of Table 5.[15] In the other six columns, we "turn off" one or more features of prospect theory. For example, the label "LA" in the first column stands for "loss aversion." The prospect theory variable in this regression features only loss aversion, and turns off probability weighting and the concavity/convexity feature of the value function; in other words, it is the quantity on the right-hand side of equation (8), computed using $\lambda = 2.25$ as before, but also using $(\alpha, \gamma, \delta) = (1, 1, 1)$ in place of $(0.88, 0.61, 0.69)$. Similarly, in the column labeled "PW" ("probability weighting"), the prospect theory variable uses $(\gamma, \delta) = (0.61, 0.69)$, as in our basic analysis, but also $(\alpha, \lambda) = 1$, thereby retaining probability weighting but turning off loss aversion and concavity/convexity; and in the column labeled "CC" ("concavity/convexity"), we use $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 1)$. The column labeled "LA,CC" retains loss aversion and concavity/convexity but turns off probability weighting; in other words, it corresponds to $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 2.25)$. "LA,PW" and "CC,PW" are defined in a similar way.

The results in Table 11 suggest that the element of prospect theory that is primarily responsible for the predictive power of TK is probability weighting: the four most significant coefficients in the first row of the table correspond to prospect theory variables that involve probability weighting (columns (2), (5), (6), (7)), while for the three least significant coefficients, probability weighting has been turned off (columns (1), (3), (4)). Put another way, by comparing columns (4) and (7), we see that, if we remove probability weighting from the TK variable while retaining the other features of prospect theory, the significance of the coefficient on the prospect theory variable drops markedly. We stress that this evidence on the role of probability weighting is tentative: comparing t-statistics across columns does not constitute a formal statistical test.

Table 12, which has the same general structure as Table 11, makes the same point in a slightly different way. The eleven columns in Table 12 correspond to eleven different Fama-MacBeth regressions. As before, the regressors in each specification are a prospect theory variable (first row) and a set of control variables, with only the prospect theory variable changing across specifications. In this table, we vary only the values of the probability weighting parameters. Specifically, each specification sets the loss aversion and concav-

[15]The regression coefficients in column (7) of Table 11 are different from those in column (6) of Table 5. In Table 11, we normalize each independent variable to have a mean of 0 and a standard deviation of 1. This makes it easier to compare the coefficients on the various prospect theory variables in the first row of the table. In Table 5, the independent variables are *not* normalized, thereby enabling comparison with other empirical studies that follow the same procedure.

ity/convexity parameters to $\alpha = 0.88$ and $\lambda = 2.25$ as before, but varies the probability weighting parameters γ and δ, giving them the values listed at the top of each column. Recall that the baseline parameter values are $\gamma = 0.61$ and $\delta = 0.69$, the values used in column (4).

The table shows that the most statistically significant results correspond to values of γ and δ that are below 1, in other words, to values that imply *over*-weighting of tails. By contrast, the predictive power of the prospect theory variable drops markedly in columns (8)-(11); these columns correspond to values of γ and δ that are greater than 1, in other words, values that imply under-weighting of tails. This leads to the, again, tentative suggestion that the predictive power of the prospect theory variable is related to the over-weighting of tails generated by probability weighting.

The fact that probability weighting appears to play a significant role in our results suggests that the skewness of a stock's past returns may be important for understanding the predictive power of TK: under probability weighting, the appeal of a stock depends, in part, on the skewness of its returns. Consistent with this, Table 10 shows that the past returns of high TK stocks are indeed highly skewed. In short, then, part of what may be driving the predictive power of TK is that, when investors observe the past returns of a high TK stock – for example, by looking at a chart of its past price movements – the skewness they see leads them to mentally represent the stock as a lottery-like gamble. Since they find such gambles appealing, they tilt toward the stock, causing it to become overpriced and to earn low subsequent returns.

An additional piece of evidence that skewness is, in part, driving the predictive power of TK comes from column (7) of Table 5, which shows that the predictive power of TK diminishes somewhat when past skewness ("Skew") is included as a control. However, the same regression also suggests that skewness is unlikely to be the whole story: while TK predicts subsequent returns, a stock's past skewness ("Skew") does not. This suggests that TK may be capturing what people find appealing, or not appealing, about the extremes of a return distribution in a way that simple measures of skewness are too crude to do. We also note that probability weighting does not affect only the tails of a distribution. In other words, TK is likely capturing what people find appealing, or not appealing, about the *entire* distribution of past returns – an appeal not captured by mean, volatility, or skewness alone.

4 Conclusion

In this paper, we investigate whether a model in which some investors evaluate stocks according to prospect theory can shed light on the cross-section of stock returns. Any application of prospect theory outside the laboratory requires an assumption about how people mentally represent the risks they are considering. Here, we assume that, when thinking about a stock, some investors represent it in their minds as the distribution of its past returns. Our framework predicts that stocks whose past return distributions have a high (low) prospect theory value will have low (high) subsequent returns, on average. We find support for this prediction in both U.S. and international data.

Prior research has tested the implications of prospect theory for stock returns under the assumption that investors use a *forward*-looking representation of stock returns, in other words, that they apply prospect theory to estimates of a stock's future return distribution. In this paper, we test prospect theory under the assumption that investors use a *backward*-looking representation. Both the prior literature and the current paper present evidence that supports their respective assumptions. This suggests not only that prospect theory is helpful for understanding the cross-section of returns, but also that both forward- *and* backward-looking representations of stocks may be commonly used by investors. For example, sophisticated investors may exert effort to try to forecast a stock's future return distribution; less sophisticated investors, on the other hand, may content themselves with thinking about a stock in terms of its past returns. As we learn more about both the representation and valuation stages of economic decision-making, we are likely to be able to make sharper predictions about stock returns.

5 Appendix

Proof of Proposition 1. We know that, in this economy,

$$\mu_j - r = \frac{\sigma_{j,t}}{\sigma_t^2}(\mu_t - r). \tag{19}$$

Note also that, from equation (11),

$$\begin{aligned}
\mu_m - r &= (1-\eta)(\mu_t - r) + \eta(\mu_{TK} - r) \\
\sigma_{j,m} &= (1-\eta)\sigma_{j,t} + \eta\sigma_{j,TK} \\
\sigma_m^2 &= (1-\eta)^2\sigma_t^2 + \eta^2\sigma_{TK}^2 + 2(1-\eta)\eta\sigma_{t,TK}.
\end{aligned}$$

Rearranging each of these equations in turn, we obtain:

$$\begin{aligned}
\mu_t - r &= \frac{\mu_m - r - \eta(\mu_{TK} - r)}{1-\eta} \\
\sigma_{j,t} &= \frac{\sigma_{j,m} - \eta\sigma_{j,TK}}{1-\eta} \\
\sigma_t^2 &= \frac{\sigma_m^2 - \eta^2\sigma_{TK}^2 - 2(1-\eta)\eta\sigma_{t,TK}}{(1-\eta)^2} \\
&= \frac{\sigma_m^2 - \eta^2\sigma_{TK}^2 - 2\eta(\sigma_{m,TK} - \eta\sigma_{TK}^2)}{(1-\eta)^2} \\
&= \frac{\sigma_m^2 + \eta^2\sigma_{TK}^2 - 2\eta\sigma_{m,TK}}{(1-\eta)^2}.
\end{aligned}$$

Substituting these expressions into (19), we find

$$\mu_j - r = \frac{\sigma_{j,m} - \eta\sigma_{j,TK}}{\sigma_m^2 + \eta\sigma_{TK}^2 - 2\eta\sigma_{m,TK}}(\mu_m - r - \eta(\mu_{TK} - r)). \tag{20}$$

This implies

$$\mu_{TK} - r = \frac{\sigma_{m,TK} - \eta\sigma_{TK}^2}{\sigma_m^2 + \eta^2\sigma_{TK}^2 - 2\eta\sigma_{m,TK}}(\mu_m - r - \eta(\mu_{TK} - r)). \tag{21}$$

Rearranging (21), we obtain

$$\frac{\mu_{TK} - r}{\mu_m - r} = \frac{\sigma_{m,TK} - \eta\sigma_{TK}^2}{\sigma_m^2 - \eta\sigma_{m,TK}} = \frac{\beta_{TK} - \eta(\beta_{TK}^2 + s_{TK}^2/\sigma_m^2)}{1 - \eta\beta_{TK}} = \beta_{TK} - \frac{\eta s_{TK}^2}{\sigma_m^2(1-\eta\beta_{TK})}, \tag{22}$$

where $s_{TK}^2 = var(\widetilde{\varepsilon}_{TK})$, and where $\widetilde{\varepsilon}_{TK}$ is the residual in a regression of the excess return of portfolio TK on the excess market return.

Substituting (22) back into (20), we obtain

$$\mu_j - r = \frac{\beta_j - \eta\sigma_{j,TK}/\sigma_m^2}{1 - \eta\beta_{TK}}(\mu_m - r). \tag{23}$$

Given the decomposition in Proposition 1, we have $\sigma_{j,TK} = \beta_j\beta_{TK}\sigma_m^2 + s_{j,TK}$. Substituting this into (23) gives

$$\frac{\mu_j - r}{\mu_m - r} = \beta_j - \frac{\eta s_{j,TK}}{\sigma_m^2(1-\eta\beta_{TK})}. \tag{24}$$

This is equation (12).

Under the additional assumption that $cov(\widetilde{\varepsilon}_i, \widetilde{\varepsilon}_j) = 0$, we have $s_{j,TK} = \omega_{TK}^j s_j^2$. Substituting this into (24) gives equation (15).

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Table 1. Data Summary

The table presents summary statistics for our sample: the mean and standard deviation of each variable (Panel A), and the correlations between them (Panel B). We compute the means, standard deviations, and correlations from the cross-section month by month and report the time-series averages of the monthly cross-sectional statistics. TK is the prospect theory value of a stock's historical return distribution; the details of its construction are in Section 2.2 of the main text. Beta is calculated from monthly returns over the previous five years, following Fama and French (1992). Size is the log market capitalization at the end of the previous month. BM is the log book-to-market ratio. When the book value of equity is missing in Compustat, we use data from Davis, Fama, and French (2002); cases with negative book value are deleted. MOM is the cumulative return from the start of month t-12 to the end of month t-2. ILLIQ is the Amihud (2002) measure of illiquidity. REV is the return in month t-1. LT REV is the cumulative return from the start of month t-60 to the end of month t-13. IVOL is idiosyncratic return volatility, as in Ang et al. (2006). MAX and MIN are the maximum and the negative of the minimum daily return in month t-1, as in Bali, Cakici, and Whitelaw (2011). Skew is the skewness of monthly returns from month t-60 to month t-1. EISKEW is expected idiosyncratic skewness, as in Boyer, Mitton, and Vorkink (2010). Coskew is coskewness, computed as in Harvey and Siddique (2000) using five years of monthly returns. The sample period runs from July 1931 to December 2010, except in the case of EISKEW, where it starts in January 1988 due to data availability.

Panel A. Means and standard deviations

	TK	Beta	Size	BM	MOM	ILLIQ	REV	LT REV	IVOL	MAX	MIN	Skew	EISKEW	Coskew
Mean	**-0.05**	1.16	11.03	-0.16	0.15	0.58	0.01	0.80	0.02	0.06	0.05	0.66	0.47	-0.00
Standard deviation	**0.03**	0.57	1.82	0.86	0.44	2.518	0.12	1.58	0.02	0.06	0.04	0.80	0.47	0.24

Panel B: Correlations

	TK	Beta	Size	BM	MOM	ILLIQ	REV	LT REV	IVOL	MAX	MIN	Skew	EISKEW	Coskew
TK	**1**													
Beta	**-0.03**	1												
Size	**0.36**	-0.13	1											
BM	**-0.34**	0.05	-0.42	1										
MOM	**0.32**	-0.01	0.11	-0.14	1									
ILLIQ	**-0.25**	0.08	-0.44	0.25	-0.11	1								
REV	**0.11**	-0.01	0.04	0.01	0.00	0.02	1							
LT REV	**0.56**	0.04	0.19	-0.35	-0.02	-0.12	-0.01	1						
IVOL	**-0.31**	0.26	-0.49	0.21	-0.09	0.58	0.14	-0.13	1					
MAX	**-0.22**	0.24	-0.37	0.17	-0.07	0.50	0.32	-0.10	0.88	1				
MIN	**-0.29**	0.26	-0.42	0.18	-0.06	0.49	-0.18	-0.09	0.79	0.59	1			
Skew	**0.22**	0.22	-0.37	0.11	0.07	0.20	0.03	0.00	0.30	0.25	0.24	1		
EISKEW	**-0.21**	0.20	-0.61	0.24	-0.13	0.33	-0.03	-0.07	0.44	0.35	0.37	0.39	1	
Coskew	**0.04**	0.22	0.07	0.04	-0.02	-0.01	-0.00	-0.05	0.01	0.01	0.02	0.23	-0.04	1

Table 2. Decile Portfolio Analysis

The table reports excess returns and alphas, on both an equal-weight (EW) and value-weight (VW) basis, of portfolios of stocks sorted on TK, the prospect theory value of a stock's historical return distribution; the details of TK's construction are in Section 2.2 of the main text. Each month, all stocks are sorted into deciles based on TK. For each of the decile portfolios, P1 (low TK) through P10 (high TK), we report the average excess return, 4-factor alpha (following Carhart), 5-factor alpha (Carhart 4-factor model augmented by Pastor and Stambaugh's (2003) liquidity factor), and characteristics-adjusted return calculated as in Daniel et al. (1997) and denoted DGTW. The sample runs from July 1931 to December 2010, except in the case of the 5-factor alpha, where it starts in January 1968 due to constraints on the availability of the liquidity factor.

		P1 low TK	P2	P3	P4	P5	P6	P7	P8	P9	P10 high TK	TK low-high portfolio
Excess return	EW	**2.144**	**1.320**	**1.155**	**1.073**	**0.996**	**0.988**	**0.925**	**0.904**	**0.889**	**0.798**	**1.346**
		(5.39)	(4.51)	(4.28)	(4.28)	(4.31)	(4.48)	(4.59)	(4.50)	(4.43)	(3.50)	(5.05)
	VW	**1.216**	**0.969**	**0.909**	**0.903**	**0.752**	**0.703**	**0.679**	**0.667**	**0.695**	**0.537**	**0.679**
		(3.57)	(3.38)	(3.68)	(3.93)	(3.52)	(3.39)	(3.74)	(3.66)	(3.99)	(2.83)	(2.62)
4-factor alpha	EW	**1.025**	**0.343**	**0.204**	**0.167**	**0.112**	**0.112**	**0.081**	0.038	-0.018	**-0.210**	**1.236**
		(6.05)	(4.19)	(3.39)	(3.24)	(2.27)	(2.37)	(1.89)	(0.79)	(-0.34)	(-3.19)	(6.83)
	VW	**0.405**	**0.261**	**0.242**	**0.318**	**0.141**	**0.098**	**0.098**	0.005	0.040	**-0.218**	**0.622**
		(2.72)	(2.39)	(2.73)	(4.01)	(1.89)	(1.48)	(1.80)	(0.09)	(0.73)	(-3.66)	(3.67)
5-factor alpha (1968 onward)	EW	**1.242**	**0.330**	**0.181**	**0.170**	**0.169**	**0.177**	**0.135**	0.057	0.066	-0.057	**1.300**
		(4.98)	(2.82)	(2.19)	(2.63)	(3.03)	(3.46)	(2.61)	(1.03)	(1.06)	(-0.73)	(5.21)
	VW	**0.551**	0.115	**0.251**	**0.320**	**0.192**	0.132	**0.155**	0.011	0.010	**-0.155**	**0.706**
		(2.40)	(0.76)	(2.14)	(3.27)	(2.07)	(1.62)	(2.12)	(0.16)	(0.13)	(-2.17)	(2.88)
DGTW	EW	**0.720**	**0.156**	0.061	0.046	0.051	0.051	0.037	-0.012	-0.046	**-0.110**	**0.830**
		(6.56)	(2.70)	(1.42)	(1.23)	(1.51)	(1.50)	(1.08)	(-0.32)	(-1.19)	(-2.22)	(6.61)
	VW	**0.255**	0.077	**0.096**	**0.113**	0.009	0.066	0.038	-0.044	-0.025	**-0.096**	**0.351**
		(2.16)	(1.02)	(1.68)	(2.20)	(0.18)	(1.62)	(1.14)	(-1.31)	(-0.76)	(-2.46)	(2.65)

Table 3. Factor Loadings

The table reports the factor loadings of a long-short portfolio that, each month, buys stocks whose TK values at the start of the month are in the bottom decile and shorts stocks whose TK values are in the top decile. We report results for two factor models – the Carhart 4-factor model and a 5-factor model (the 4-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor) – and on both an equal-weight (EW) and value-weight (VW) basis. The sample runs from July 1931 to December 2010, except in the case of the 5-factor alpha, where it starts in January 1968 due to constraints on the availability of the liquidity factor.

Model/Measure	MktRf	SMB	HML	UMD	PS_Liq
4-factor model	-0.116	1.172	0.613	-0.679	-
EW	(-3.20)	(21.02)	(11.60)	(-16.51)	
4-factor model	0.027	1.044	0.469	-0.752	-
VW	(0.78)	(19.98)	(9.47)	(-19.48)	
5-factor model	0.100	0.967	0.671	-0.710	-0.057
EW	(1.77)	(12.33)	(7.85)	(-12.99)	(-0.86)
5-factor model	0.226	1.132	0.673	-0.858	-0.158
VW	(4.10)	(14.70)	(8.02)	(-15.99)	(-2.40)

Table 4. Robustness

The table presents the results of several robustness checks. The right column reports the equal-weight (EW) and value-weight (VW) 4-factor alphas of a long-short portfolio that, each month, buys (shorts) stocks with TK values in the lowest (highest) decile. The first panel presents results for two subperiods. In the second panel, we use 3, 4, or 6 years of monthly returns to compute TK. In the third panel, we compute TK using raw returns, returns in excess of the risk-free rate, and returns in excess of the sample mean. In the fourth panel, we exclude stocks whose price falls below $5 in the month before portfolio construction. In the fifth panel, we skip a month between the moment of TK construction and the moment at which we start measuring returns. In the sixth panel, we use the probability weighting function proposed by Prelec (1998). The sample period runs from July 1931 to December 2010.

		TK	
		EW	VW
Subperiods	1931/07-1963/06	**1.252**	**0.459**
		(4.35)	(1.89)
	1963/07-2010/12	**1.211**	**0.634**
		(5.34)	(2.81)
Window for constructing TK	Past 3 years	**1.283**	**0.674**
		(6.72)	(3.77)
	Past 4 years	**1.244**	**0.557**
		(6.79)	(3.24)
	Past 6 years	**1.193**	**0.643**
		(6.56)	(3.71)
Other return measures	Raw returns	**1.204**	**0.464**
		(5.48)	(2.17)
	Returns in excess of the risk-free rate	**1.049**	**0.282**
		(6.31)	(1.69)
	Returns in excess of the sample mean	**0.797**	**0.543**
		(4.07)	(2.94)
Exclude low priced stocks	price>=5$	**0.373**	**0.365**
		(3.71)	(2.85)
Skip a month		**0.779**	**0.299**
		(4.58)	(1.86)
Alternative weighting function	Prelec (1998)	**1.238**	**0.530**
		(6.89)	(3.26)

Table 5. Fama-MacBeth Regression Analysis

The table reports the results of Fama-MacBeth regressions. TK is the prospect theory value of a stock's historical return distribution; the details of its construction are in Section 2.2 of the main text. Beta is calculated from monthly returns over the previous five years, following Fama and French (1992). Size is the log market capitalization at the end of the previous month. BM is the log book-to-market ratio. When the book value of equity is missing in Compustat, we use data from Davis, Fama, and French (2002); cases with negative book value are deleted. MOM is the cumulative return from the start of month t-12 to the end of month t-2. ILLIQ is the Amihud (2002) measure of illiquidity. REV is the return in month t-1. LT REV is the cumulative return from the start of month t-60 to the end of month t-13. IVOL is idiosyncratic return volatility, as in Ang et al. (2006). MAX and MIN are the maximum and the negative of the minimum daily returns in month t-1, as in Bali, Cakici, and Whitelaw (2011). Skew is the skewness of monthly returns from month t-60 to month t-1. EISKEW is expected idiosyncratic skewness, as in Boyer, Mitton, and Vorkink (2010). Coskew is coskewness, computed as in Harvey and Siddique (2000) using five years of monthly returns. The reported coefficients on Beta, Size, BM, ILLIQ, and LT REV are scaled up by 100. The sample period runs from July 1931 to December 2010, except in the case of EISKEW, where it starts in January 1988 due to data availability. The t-statistics are Newey-West adjusted with 12 lags.

	Controls					Skewness Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TK	**-0.107**	**-0.108**	**-0.059**	**-0.050**	**-0.043**	**-0.043**	**-0.046**	**-0.067**	**-0.043**
	(-3.77)	(-4.94)	(-3.07)	(-2.60)	(-2.16)	(-2.18)	(-1.92)	(-2.28)	(-2.16)
Beta		0.132	0.166	0.192	**0.240**	**0.243**	**0.249**	**0.480**	**0.243**
		(1.14)	(1.22)	(1.40)	(1.99)	(2.07)	(2.11)	(2.59)	(2.00)
Size		**-0.132**	**-0.125**	**-0.078**	**-0.097**	**-0.089**	**-0.092**	**-0.066**	**-0.092**
		(-4.07)	(-3.65)	(-2.44)	(-3.38)	(-3.24)	(-3.55)	(-1.94)	(-3.27)
BM		**0.151**	**0.203**	**0.177**	**0.126**	**0.127**	**0.112**	0.121	**0.124**
		(2.7)	(3.44)	(3.06)	(2.26)	(2.29)	(2.03)	(1.31)	(2.27)
MOM		**0.010**	**0.009**	**0.009**	**0.008**	**0.009**	**0.008**	**0.005**	**0.009**
		(7.99)	(6.47)	(6.73)	(6.39)	(6.47)	(6.30)	(3.44)	(6.55)
REV			**-0.079**	**-0.079**	**-0.078**	**-0.081**	**-0.082**	**-0.053**	**-0.092**
			(-16.39)	(-16.28)	(-15.20)	(-16.47)	(-16.02)	(-9.64)	(-15.85)
ILLIQ				**0.286**	**0.597**	**0.622**	**0.631**	**1.299**	**0.620**
				(2.37)	(4.90)	(5.08)	(5.20)	(6.88)	(5.11)
LT REV					-0.041	-0.039	**-0.035**	-0.000	-0.033
					(-1.40)	(-1.31)	(-1.70)	(-0.04)	(-1.13)
IVOL					**-0.138**	0.068	0.067	0.073	0.068
					(-4.27)	(1.43)	(1.43)	(1.03)	(1.44)
MAX						**-0.036**	**-0.036**	-0.022	**-0.036**
						(-3.45)	(-3.42)	(-1.36)	(-3.45)
MIN						**-0.059**	**-0.060**	**-0.093**	**-0.059**
						(-4.50)	(-4.61)	(-6.72)	(-4.56)
Skew							0.013		
							(0.30)		
EISKEW								-0.194	
								(-1.61)	
Coskew									-0.039
									(-0.41)
N	954	954	954	954	954	954	954	276	954

Table 6. Double Sorts

Each month, stocks are sorted into quintiles based on a control variable (one of REV, ILLIQ, LT REV, IVOL, MAX, Skew, EISKEW, or Coskew). Then, within each quintile, stocks are further sorted into quintiles based on TK. The returns of the five TK portfolios over the next month are averaged across the five control variable quintiles. We report the 4-factor alphas, on both an equal-weight (EW) and value-weight (VW) basis, of the five TK portfolios and of the low-TK minus high-TK long-short portfolio. TK is the prospect theory value of a stock's historical return distribution. REV is the return in month t-1. ILLIQ is the Amihud (2002) measure of illiquidity. LT REV is the cumulative return from the start of month t-60 to the end of month t-13. IVOL is idiosyncratic return volatility, as in Ang et al. (2006). MAX is the maximum daily return in month t-1, as in Bali, Cakici, and Whitelaw (2011). Skew is the skewness of monthly returns from month t-60 to month t-1. EISKEW is expected idiosyncratic skewness, as in Boyer, Mitton, and Vorkink (2010). Coskew is coskewness, computed as in Harvey and Siddique (2000) using five years of monthly returns. The sample period runs from July 1931 to December 2010, except in the case of EISKEW, where it starts in January 1988 due to data availability.

TK	REV		ILLIQ		LT REV		IVOL		MAX		Skew		EISKEW		Coskew	
	EW	VW	EW	VW	EW	VW	EW	EW	EW	VW	EW	VW	EW	VW	EW	VW
Low 1	0.493	0.267	0.626	0.285	0.572	0.295	0.511	0.511	0.764	0.281	0.684	0.234	0.690	0.267	0.693	0.259
	(4.77)	(2.93)	(7.59)	(3.57)	(6.56)	(3.61)	(5.78)	(5.78)	(7.87)	(3.13)	(5.93)	(2.36)	(6.23)	(2.92)	(6.13)	(2.68)
2	0.186	0.261	0.262	0.061	0.249	0.169	0.212	0.212	0.201	0.048	0.167	0.119	0.202	0.229	0.163	0.199
	(3.87)	(3.77)	(5.37)	(1.27)	(5.09)	(3.08)	(4.71)	(4.71)	(4.00)	(0.78)	(3.36)	(1.77)	(4.25)	(3.61)	(3.45)	(2.93)
3	0.154	0.095	0.120	-0.051	0.147	0.074	0.111	0.111	0.086	-0.054	0.100	0.072	0.114	0.114	0.121	0.093
	(3.75)	(1.92)	(2.99)	(-1.22)	(3.84)	(1.52)	(3.02)	(3.02)	(2.23)	(-1.06)	(2.60)	(1.45)	(2.77)	(2.23)	(3.10)	(1.85)
4	0.105	0.091	0.049	-0.111	0.060	-0.008	0.106	0.106	0.002	-0.136	0.035	-0.022	0.043	0.058	0.034	0.059
	(2.60)	(2.33)	(1.14)	(-2.77)	(1.60)	(-0.18)	(2.71)	(2.71)	(0.05)	(-2.91)	(0.87)	(-0.52)	(1.12)	(1.47)	(0.83)	(1.53)
High 5	-0.007	-0.061	-0.127	-0.345	-0.100	-0.120	-0.079	-0.079	-0.118	-0.141	-0.056	-0.170	-0.100	-0.059	-0.079	-0.078
	(-0.14)	(-1.35)	(-2.59)	(-6.44)	(-2.05)	(-2.53)	(-1.75)	(-1.75)	(-2.55)	(-2.83)	(-1.30)	(-4.24)	(-2.10)	(-1.44)	(-1.64)	(-1.93)
1-5	**0.500**	**0.328**	**0.753**	**0.630**	**0.673**	**0.416**	**0.590**	**0.590**	**0.882**	**0.421**	**0.740**	**0.403**	**0.790**	**0.326**	**0.772**	**0.337**
	(4.34)	(2.94)	(7.94)	(6.23)	(7.02)	(4.11)	(5.91)	(5.91)	(8.15)	(3.79)	(5.77)	(3.47)	(6.38)	(2.95)	(6.18)	(2.93)

Table 7. Limits to Arbitrage

At the start of each month, we sort stocks into two groups based on one of Size, ILLIQ, IVOL, or Institutional Holding. Size is log market capitalization at the end of the previous month; ILLIQ is the Amihud (2002) measure of illiquidity; IVOL is idiosyncratic return volatility, as in Ang et al. (2006); and Institutional Holding is log of one plus the fraction of shares outstanding held by institutional investors. For Size, the breakpoint is the median value of the variable across NYSE-listed firms; for ILLIQ and IVOL, the breakpoint is the median value of the variable across all firms in the sample; for Institutional Holding, as explained in the main text, the breakpoint used to distinguish 'High' from 'Low' is the 66.67% percentile. Within each of the Size/ILLIQ/IVOL/Institutional Holding portfolios, stocks are sorted into deciles based on TK. We report, on both an equal-weight (EW) and value-weight (VW) basis, the excess return, 4-factor alpha, 5-factor alpha (4-factor model augmented by the Pastor and Stambaugh (2003) liquidity factor), and characteristics-adjusted (DGTW) return, of the long-short portfolio that, each month, buys (shorts) stocks in the lowest (highest) TK decile that month. The characteristics-adjusted return is adjusted for size, book-to-market, and momentum, as in Daniel et al. (1997).

	Size				ILLIQ				IVOL				Institutional Holding			
	Small		Large		Illiquid		Liquid		High		Low		Low		High	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Excess return	**1.538**	**0.712**	**0.347**	**0.425**	**1.772**	**0.83**	**0.391**	**0.442**	**1.985**	**1.043**	**0.287**	**0.391**	**1.692**	0.717	0.475	0.337
	(5.90)	(2.87)	(2.01)	(2.41)	(6.54)	(3.18)	(2.44)	(2.44)	(6.95)	(3.34)	(2.83)	(2.17)	(4.09)	(1.39)	(1.55)	(1.10)
4-factor	**1.564**	**0.757**	**0.466**	**0.489**	**1.782**	**0.809**	**0.521**	**0.515**	**1.961**	**1.003**	**0.322**	**0.414**	**1.765**	**0.711**	**0.49**	0.359
	(7.35)	(3.70)	(4.12)	(3.93)	(7.83)	(3.59)	(4.84)	(4.04)	(8.23)	(3.75)	(2.87)	(3.02)	(4.90)	(1.85)	(2.55)	(1.58)
5-factor	**1.469**	**0.676**	**0.407**	**0.387**	**1.807**	**0.553**	**0.433**	**0.412**	**2.06**	**0.962**	0.175	**0.338**	**1.897**	**0.989**	**0.511**	0.317
	(5.74)	(2.72)	(2.75)	(2.35)	(6.19)	(2.04)	(3.25)	(2.52)	(6.61)	(2.58)	(1.40)	(1.89)	(5.21)	(2.59)	(2.61)	(1.38)
DGTW	**1.196**	**0.505**	**0.161**	**0.222**	**1.399**	**0.62**	**0.225**	**0.227**	**1.511**	**0.682**	**0.137**	**0.242**	**1.677**	**0.617**	**0.398**	0.29
	(7.70)	(2.98)	(1.70)	(2.57)	(8.17)	(3.47)	(2.41)	(2.60)	(8.57)	(3.34)	(1.77)	(2.65)	(5.97)	(1.87)	(1.88)	(1.35)

Table 8. Fama-MacBeth Analysis of Limits to Arbitrage

The table reports the results of Fama-MacBeth regressions of stock returns on TK – the prospect theory value of a stock's historical return distribution -- and on TK interacted with four variables that proxy for limits to arbitrage: Size, the log market capitalization; ILLIQ, the Amihud (2002) measure of illiquidity; IVOL, idiosyncratic return volatility, as in Ang et al. (2006); and Institutional Holding, measured as log of one plus the fraction of outstanding shares held by institutional investors. The other variables are controls that are defined in the caption for Table 1. The sample runs from July 1931 to December 2010, except in the case of Institutional Holding where it starts in 1980. The reported coefficients on Beta, Size, BM, ILLIQ, and LT REV are scaled up by 100. The t-statistics are Newey-West adjusted with 12 lags.

Interactions of limits-to-arbitrage measures with TK	Size	ILLIQ	IVOL	Institutional Holding
	(1)	(2)	(3)	(4)
TK	**-0.314**	-0.025	0.002	**-0.055**
	(-4.79)	(-1.31)	(0.10)	(-1.88)
TK*Size	**0.029**			
	(4.90)			
TK*ILLIQ		**-0.060**		
		(-2.07)		
TK*IVOL			**-0.014**	
			(-2.41)	
TK*Institutional Holding				**0.014**
				(2.84)
Beta	0.254	0.124	0.258	0.240
	(2.15)	(2.24)	(2.17)	(1.48)
Size	0.042	-0.109	-0.106	-0.094
	(1.34)	(-3.92)	(-3.82)	(-2.74)
BM	0.128	0.124	0.124	0.233
	(2.32)	(2.24)	(2.23)	(2.99)
MOM	0.008	0.008	0.008	0.006
	(6.26)	(6.34)	(6.07)	(4.17)
REV	-0.081	-0.080	-0.080	-0.061
	(-16.42)	(6.34)	(-16.22)	(-12.45)
ILLIQ	0.501	0.084	0.568	0.405
	(3.80)	(0.36)	(4.46)	(3.69)
LT REV	-0.087	-0.063	-0.065	-0.011
	(-2.80)	(-2.17)	(-2.13)	(-0.50)
IVOL	0.060	0.072	-0.032	0.024
	(1.26)	(1.51)	(-0.57)	(0.41)
MAX	-0.034	-0.035	-0.039	0.012
	(-3.18)	(-3.28)	(-3.77)	(0.82)
MIN	-0.058	-0.058	-0.055	-0.065
	(-4.51)	(-4.43)	(-4.14)	(-5.04)
Institutional Holding				0.196
				(7.08)
N	954	954	954	366

Table 9. Quintile Portfolio Analysis in 46 International Stock Markets

For each of 46 international stock markets, we sort stocks each month into quintiles based on TK and compute, on both an equal-weight (EW) and value-weight (VW) basis, the average raw return and alphas from models with "global factors," "local factors," and "international factors," of the portfolio that, each month, buys (shorts) stocks in the lowest (highest) TK quintile. All the returns are in U.S. dollars. The risk free rate is the U.S. one-month treasury rate. For a given country C, the local factors are the four Carhart factors constructed from the universe of stocks traded in country C; the global factors are the four Carhart factors constructed from the universe of all stocks across all 46 countries; and the international factors are the union of the four local factors and four global factors (Hou, Karolyi, and Kho, 2011). In Panel A, we report the average value, across the 46 countries, of the eight types of long-short portfolio return we compute in each country ("Average alpha"); the number of countries for which the portfolio return is positive/negative and significant/insignificant at the 10% level; and the percentage of countries in which the portfolio return is positive, or positive and significant. In Panel B, we report analogous results for the case in which we skip a month between the moment of TK construction and the moment at which we start measuring returns.

Additional details: For each country, we include all common stocks listed on the major exchange(s) in that country. Following Griffin, Kelly, and Nardari (2010), we eliminate non-common stocks such as preferred stocks, warrants, unit or investment trusts, funds, REITs, ADRs, and duplicates. A cross-listed stock is included only in its home country sample. If a stock has multiple share classes, only the primary class is included; for example, we include only A-shares in the Chinese stock market and only bearer-shares in the Swiss stock market. To alleviate survivorship bias, both active and dead stocks are included. We filter out suspicious stock returns by setting returns above 100% to 100% and returns below -95% to -95% (Ang et al., 2009; Chui, Titman, and Wei, 2011). To be included in the sample, we require that a stock have no missing monthly return in the past five years. As in Table 2, we construct TK using returns in excess of the value-weighted market return; the results are similar if we instead use raw returns or returns in excess of the risk-free rate. We also require that, for a given month, the number of stocks with a valid TK measure is at least 50. Following Hou, Karolyi, and Kho (2011), for all three factor models, the value factor is constructed using the price-to-cash flow ratio rather than the price-to-book ratio.

	Long short		Global factors		International factors		Local factors	
	EW	VW	EW	VW	EW	VW	EW	VW
Panel A. Do not skip a month								
Average alpha (%)	1.017	0.494	1.237	0.692	1.471	0.878	1.397	0.892
Positive and significant	26	8	29	16	38	18	35	16
Positive and insignificant	12	24	13	19	5	23	8	23
Negative and significant	3	1	0	0	0	0	0	0
Negative and insignificant	5	13	4	11	3	5	3	7
Percent positive	83%	70%	91%	76%	93%	89%	93%	85%
Percent positive and significant	57%	17%	63%	35%	83%	39%	76%	35%
Panel B. Skip a month								
Average alpha (%)	0.745	0.264	0.946	0.460	1.208	0.695	1.132	0.690
Positive and significant	23	4	24	11	31	16	32	13
Positive and insignificant	16	22	18	21	12	21	11	26
Negative and significant	2	1	1	0	0	0	0	0
Negative and insignificant	7	19	3	14	3	9	3	7
Percent positive	81%	57%	91%	70%	93%	80%	93%	85%
Percent positive and significant	48%	9%	52%	24%	67%	35%	70%	28%

Table 10. Characteristics of TK portfolios

Each month, we sort stocks into deciles based on TK and compute the mean values of the characteristics listed in the top row of the table across all stocks in each decile. The table reports, for each TK decile, the time-series averages of these mean characteristic values. All but one of the variables is defined in the caption for Table 1. The remaining variable, STD, is the standard deviation of a stock's monthly returns over the past five years. The sample runs from July 1931 to December 2010, except in the case of EISKEW, where it starts in January 1988 due to data availability.

Portfolios	TK	Beta	Size	BM	MOM	REV	ILLIQ	LT REV	IVOL	MAX	MIN	Skew	EISKEW	Coskew	STD
Low TK	-0.110	1.312	9.357	0.433	-0.073	-0.010	3.417	-0.331	0.042	0.112	0.089	0.571	0.809	-0.017	0.161
2	-0.083	1.241	10.129	0.170	0.042	0.005	1.172	-0.018	0.030	0.081	0.065	0.579	0.625	-0.021	0.140
3	-0.071	1.187	10.544	0.028	0.086	0.009	0.677	0.183	0.026	0.070	0.057	0.580	0.545	-0.017	0.130
4	-0.062	1.139	10.859	-0.072	0.110	0.012	0.443	0.369	0.023	0.063	0.051	0.568	0.477	-0.013	0.122
5	-0.055	1.099	11.110	-0.157	0.134	0.014	0.314	0.544	0.021	0.057	0.047	0.569	0.433	-0.011	0.115
6	-0.048	1.076	11.320	-0.216	0.160	0.016	0.220	0.727	0.019	0.053	0.044	0.568	0.399	-0.007	0.110
7	-0.042	1.059	11.512	-0.301	0.186	0.018	0.197	0.928	0.018	0.051	0.042	0.581	0.369	0.002	0.106
8	-0.035	1.068	11.677	-0.377	0.219	0.020	0.174	1.170	0.017	0.049	0.040	0.632	0.353	0.012	0.106
9	-0.027	1.098	11.798	-0.472	0.265	0.023	0.176	1.547	0.017	0.049	0.040	0.730	0.356	0.020	0.109
High TK	-0.007	1.319	11.658	-0.669	0.432	0.037	0.572	2.919	0.021	0.063	0.048	1.314	0.483	0.033	0.156

Table 11. Fama-MacBeth Regressions using Different Components of Prospect Theory

We report the results of seven Fama-MacBeth regressions. The seven specifications vary which components of prospect theory are incorporated into the construction of the prospect theory variable TK. "LA," "PW," and "CC" indicate that only loss aversion, probability weighting, and concavity/convexity are incorporated into TK, respectively. "LA,CC" indicates that only loss aversion and concavity/convexity are incorporated; "LA,PW" and "CC,PW" are defined similarly. "TK" in column (7) incorporates all elements of prospect theory and is identical to the TK variable in previous tables. To compare more easily across the different specifications, we standardize all the independent variables to have mean 0 and standard deviation 1. The sample runs from July 1931 to December 2010. The t-statistics are Newey-West adjusted with 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LA	PW	CC	LA,CC	LA,PW	CC,PW	TK
TK components	**-0.219**	**-0.136**	**-0.149**	**-0.160**	**-0.152**	**-0.134**	**-0.162**
	(-1.90)	**(-2.29)**	**(-1.62)**	**(-1.46)**	**(-2.18)**	**(-2.37)**	**(-2.18)**
Beta	0.126	0.183	0.187	0.119	0.164	0.188	0.165
	(1.80)	(2.32)	(2.24)	(1.80)	(2.07)	(2.34)	(2.07)
Size	-0.172	-0.253	-0.233	-0.181	-0.198	-0.253	-0.195
	(-3.06)	(-3.88)	(-3.51)	(-3.23)	(-3.27)	(-3.86)	(-3.24)
BM	0.107	0.120	0.097	0.111	0.125	0.117	0.120
	(2.05)	(2.28)	(1.85)	(2.15)	(2.38)	(2.24)	(2.29)
MOM	0.537	0.544	0.576	0.511	0.549	0.557	0.556
	(6.05)	(5.35)	(6.78)	(5.62)	(6.22)	(5.71)	(6.47)
REV	-1.269	-1.272	-1.266	-1.277	-1.269	-1.268	-1.268
	(-16.55)	(-16.08)	(-16.71)	(-16.56)	(-16.42)	(-16.15)	(-16.47)
ILLIQ	3.095	3.059	3.123	3.104	3.046	3.065	3.058
	(5.21)	(4.99)	(5.08)	(5.23)	(5.05)	(5.00)	(5.08)
LT REV	-0.023	-0.190	-0.038	-0.099	-0.111	-0.163	-0.083
	(-0.32)	(-2.16)	(-0.44)	(-1.44)	(-1.66)	(-1.99)	(-1.31)
IVOL	0.133	0.213	0.159	0.146	0.175	0.208	0.169
	(1.23)	(1.73)	(1.33)	(1.36)	(1.46)	(1.68)	(1.43)
MAX	-0.283	-0.311	-0.303	-0.281	-0.306	-0.310	-0.303
	(-3.29)	(-3.57)	(-3.46)	(-3.28)	(-3.48)	(-3.55)	(-3.45)
MIN	0.298	0.284	0.281	0.297	0.293	0.284	0.293
	(4.64)	(4.35)	(4.30)	(4.62)	(4.50)	(4.34)	(4.50)
N	954	954	954	954	954	954	954

Table 12. Fama-MacBeth Regressions that Vary the Degree of Probability Weighting

We report the results of 11 Fama-MacBeth regressions. The 11 specifications differ in the values of the parameters γ and δ used to construct the prospect theory variable TK. These parameters control the degree of probability weighting; Tversky and Kahneman's (1992) estimates are 0.61 and 0.69, respectively. To compare more easily across different specifications, we standardize the independent variables to have mean 0 and standard deviation 1. The sample period runs from July 1931 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
γ / δ	0.31/0.39	0.41/0.49	0.51/0.59	0.61/0.69	0.71/0.79	0.81/0.89	0.91/0.99	1.01/1.09	1.11/1.19	1.21/1.29	1.31/1.39
TK	**-0.068**	**-0.090**	**-0.121**	**-0.162**	**-0.198**	**-0.206**	**-0.186**	**-0.143**	**-0.131**	**-0.109**	**-0.093**
	(-1.75)	**(-2.02)**	**(-2.16)**	**(-2.18)**	**(-2.09)**	**(-1.91)**	**(-1.69)**	**(-1.36)**	**(-1.30)**	**(-1.15)**	**(-1.02)**
Beta	0.161	0.166	0.167	0.165	0.155	0.141	0.131	0.124	0.127	0.127	0.129
	(2.07)	(2.09)	(2.09)	(2.07)	(2.00)	(1.91)	(1.86)	(1.85)	(1.88)	(1.90)	(1.92)
Size	-0.218	-0.216	-0.209	-0.195	-0.182	-0.176	-0.180	0.189	-0.194	-0.199	-0.204
	(-3.42)	(-3.40)	(-3.35)	(-3.24)	(-3.13)	(-3.10)	(-3.18)	(-3.34)	(-3.40)	(-3.49)	(-3.56)
BM	0.136	0.133	0.128	0.120	0.112	0.108	0.108	0.111	0.112	0.114	0.116
	(2.59)	(2.53)	(2.44)	(2.29)	(2.14)	(2.05)	(2.06)	(2.14)	(2.16)	(2.21)	(2.25)
MOM	0.519	0.530	0.543	0.556	0.558	0.548	0.532	0.509	0.507	0.500	0.495
	(5.63)	(5.83)	(6.14)	(6.47)	(6.53)	(6.32)	(6.03)	(5.61)	(5.59)	(5.45)	(5.36)
REV	-1.277	-1.275	-1.272	-1.268	-1.266	-1.268	-1.273	-1.279	-1.280	-1.282	-1.283
	(-16.31)	(-16.32)	(-16.38)	(-16.47)	(-16.55)	(-16.60)	(-16.62)	(-16.60)	(-16.63)	(-16.63)	(-16.63)
ILLIQ	3.026	3.031	3.042	3.058	3.076	3.092	3.104	3.116	3.122	3.128	3.133
	(4.96)	(4.98)	(5.02)	(5.08)	(5.14)	(5.19)	(5.21)	(5.23)	(5.22)	(5.23)	(5.22)
LT REV	-0.224	-0.196	-0.149	-0.084	-0.029	-0.018	-0.043	-0.102	-0.109	-0.132	-0.151
	(-2.48)	(-2.38)	(-2.08)	(-1.31)	(-0.43)	(-0.24)	(-0.59)	(-1.45)	(-1.54)	(-1.89)	(-2.15)
IVOL	0.192	0.191	0.184	0.169	0.151	0.140	0.142	0.153	0.157	0.163	0.168
	(1.55)	(1.55)	(1.51)	(1.43)	(1.32)	(1.27)	(1.31)	(1.41)	(1.44)	(1.49)	(1.53)
MAX	-0.307	-0.308	-0.307	-0.303	-0.295	-0.288	-0.285	-0.284	-0.286	-0.287	-0.289
	(-3.47)	(-3.49)	(-3.48)	(-3.45)	(-3.39)	(-3.33)	(-3.31)	(-3.31)	(-3.33)	(-3.34)	(-3.35)
MIN	0.287	0.288	0.290	0.293	0.295	0.295	0.295	0.295	0.293	0.293	0.292
	(4.42)	(4.43)	(4.46)	(4.50)	(4.55)	(4.58)	(4.58)	(4.59)	(4.56)	(4.55)	(4.54)
N	954	954	954	954	954	954	954	954	954	954	954

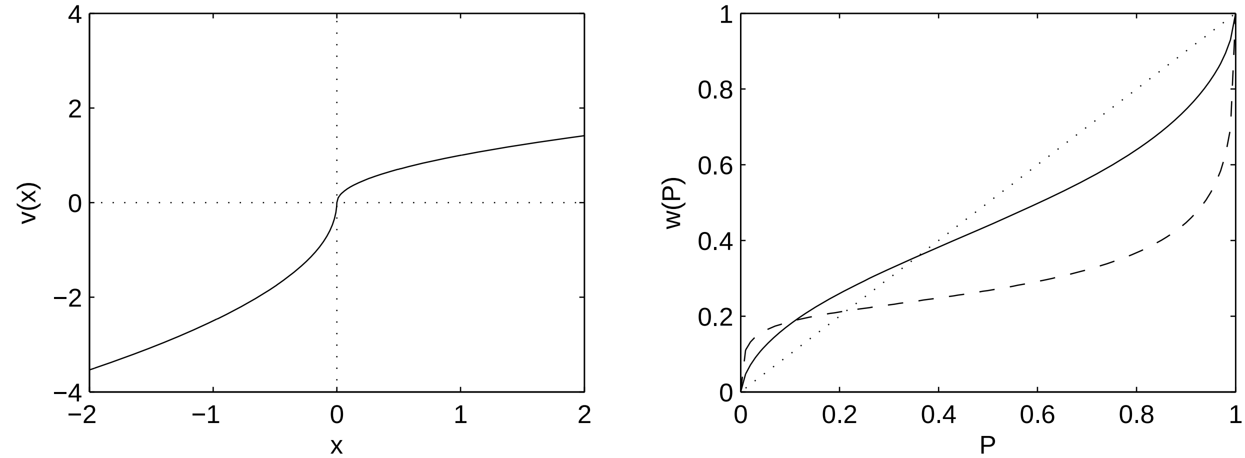

Figure 1. The prospect theory value function and probability weighting function. The left panel plots the value function proposed by Tversky and Kahneman (1992) as part of their cumulative prospect theory, namely $v(x) = x^{\alpha}$ for $x \geq 0$ and $v(x) = -\lambda(-x)^{\alpha}$ for $x < 0$, for $\alpha = 0.5$ and $\lambda = 2.5$. The right panel plots the probability weighting function they propose, namely $w(P) = P^{\delta}/(P^{\delta} + (1-P)^{\delta})^{1/\delta}$, for three different values of δ. The dashed line corresponds to $\delta = 0.4$, the solid line to $\delta = 0.65$, and the dotted line to $\delta = 1$.

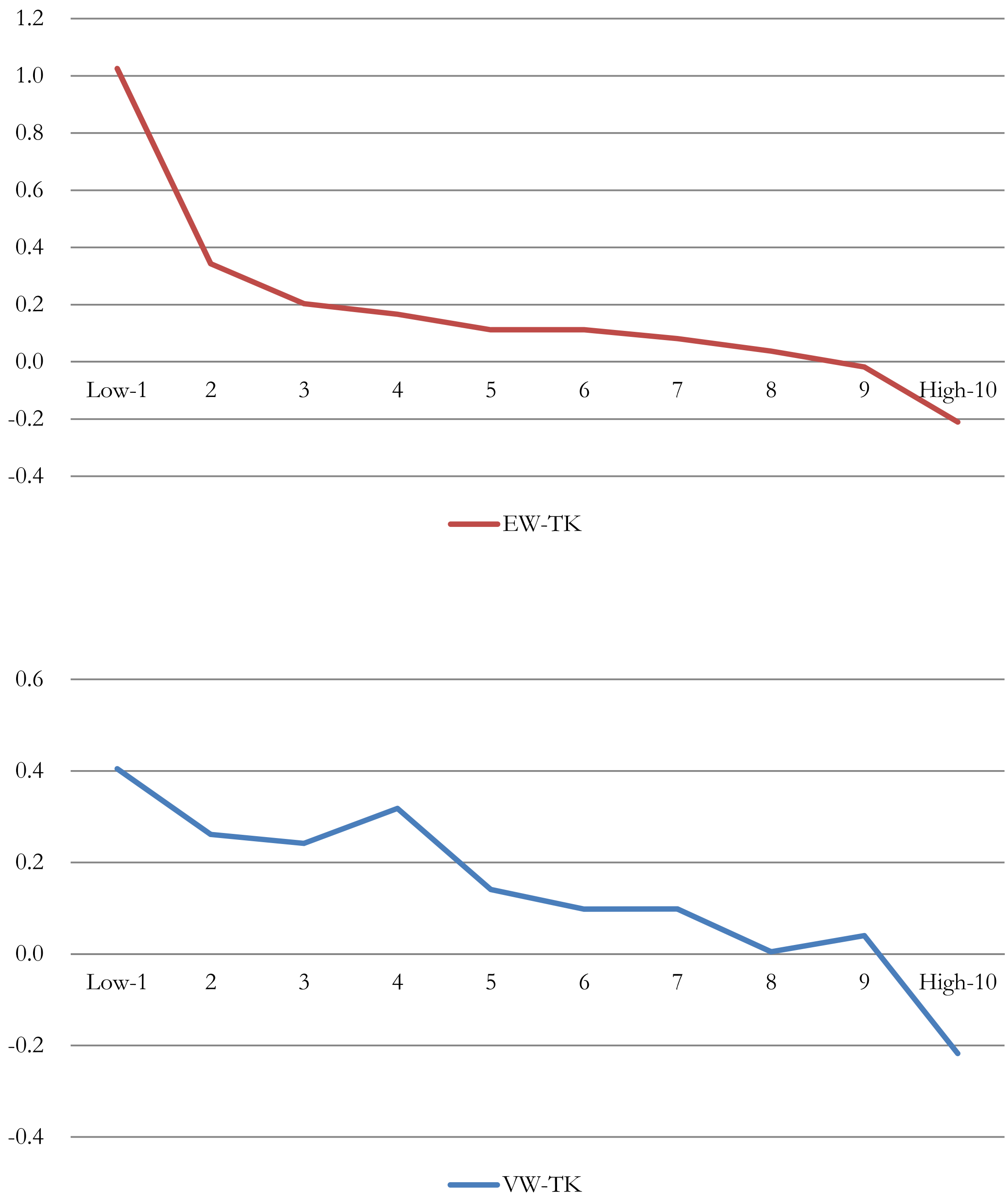

Figure 2. Performance of TK deciles

Each month, we sort all stocks into deciles by TK, the prospect theory value of a stock's historical return distribution, and record the average return of each decile over the next month on both an equal-weight (EW) and value-weight (VW) basis. Using the time series of average returns, we compute 4-factor alphas for the deciles and plot them in the figure. The top panel is for equal-weight returns; the bottom panel, for value-weight returns. The vertical axis is the monthly alpha, in percent; the horizontal axis marks the decile portfolio, from decile 1 (low TK) to decile 10 (high TK).

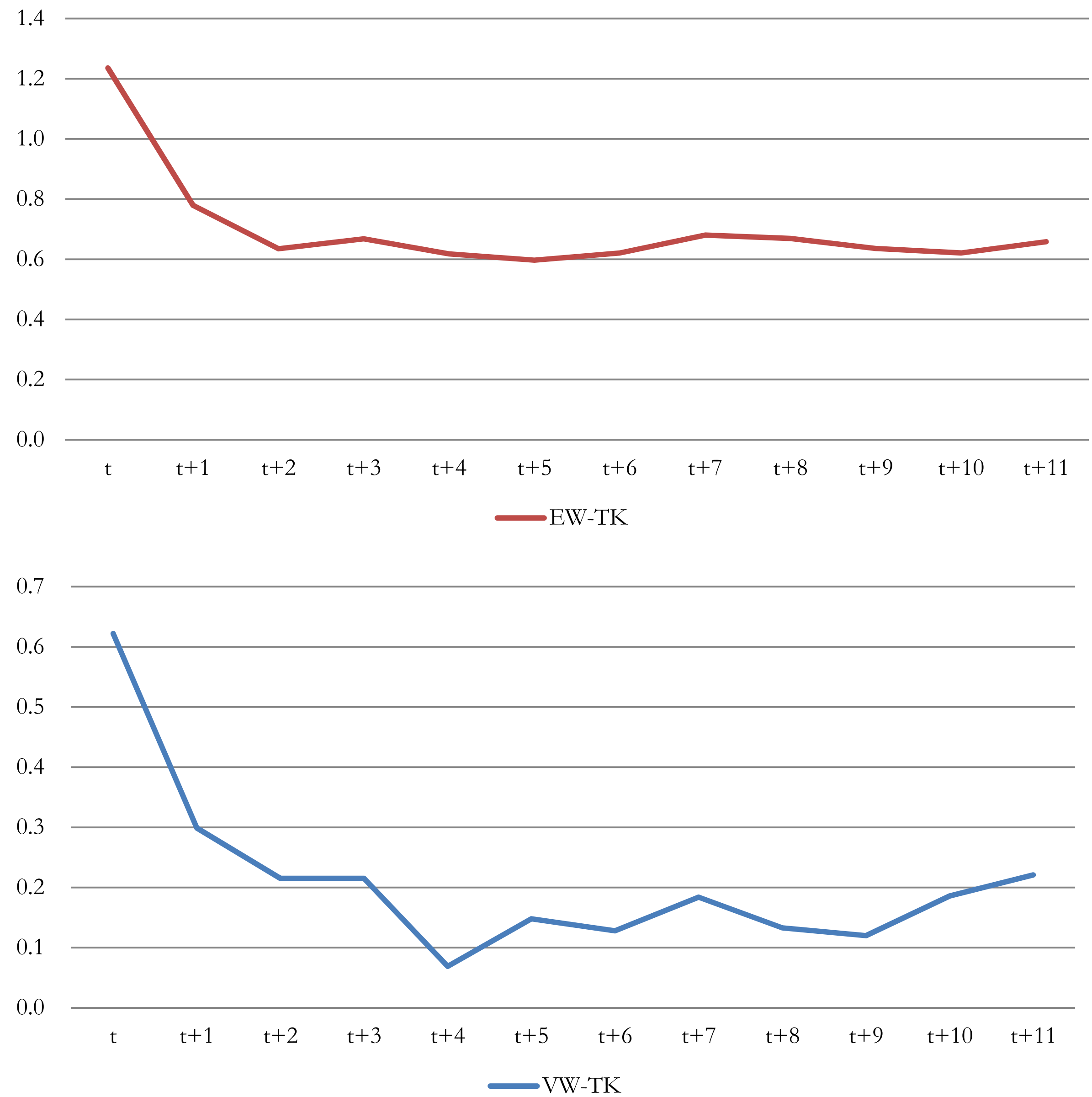

Figure 3. How do long-short portfolio returns decline over time?

The figure plots the 4-factor alpha, on both an equal-weight (EW) and value-weight (VW) basis, of a long-short portfolio that buys (shorts) stocks that were in the lowest (highest) TK decile at some point in the past. The vertical axis is the monthly alpha, in percent, of a decile portfolio; the horizontal axis indicates the time lag, in months, between the moment of portfolio construction and the moment at which we start measuring returns. The alpha plotted for $t+k$ is the alpha of the long-short portfolio that buys (shorts) stocks that were in the lowest (highest) TK decile k months previously.