First Impressions: "System 1" Thinking and the Cross-section of Stock Returns

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Abstract

For each stock in the U.S. universe in turn, we take the stock's distribution of past returns, and compute the value that would be assigned to this distribution by (cumulative) prospect theory. We find that this "prospect theory value" predicts subsequent returns in the cross-section, with a negative sign. This is particularly true for stocks traded primarily by individual investors and for stocks that are hard to arbitrage. We repeat our tests in 46 international markets, and find a similar pattern in a majority of those markets. Our conjecture is that some investors are influenced in their trading by the quick initial impression of a stock that they form after glancing at a chart of the stock's historical price movements – a so-called "system 1" impression that we quantify as the stock's prospect theory value. Stocks with high prospect theory values make a positive impression on these investors, who tilt toward them, causing them to be overpriced and to earn low subsequent returns.

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1 Introduction

In this paper, we propose that the trading decisions of some investors – particularly individual investors – are influenced by a specific cognitive process. We first describe this process and then explain the motivation for it.

Under the process we propose, an individual determines his allocation to a stock by taking the distribution of the stock's past returns, and then evaluating this distribution in the way described by (cumulative) prospect theory. A stock with a high "prospect theory value" – a stock whose past return distribution has a high prospect theory value – is appealing to him, and he tilts towards it. Conversely, a stock with a low prospect theory value is unappealing, and he tilts away from it. If enough investors act in this way, stocks with high prospect theory values will become overvalued and will subsequently earn low average returns, while those with low prospect theory values will become undervalued and will subsequently earn high average returns. This is the prediction that we test – and find empirical support for – in this paper.

Our approach is motivated by a widely-used framework in psychology known as the two-system framework (Kahneman, 2011). Under this framework, people have two modes of thinking. The first, "system 1," is fast, automatic, and possibly unconscious. This system is in continuous operation while we are awake, and generates spontaneous impressions and feelings. The second mode of thinking, "system 2," is slower, more deliberate, and involves effortful reasoning. It is only engaged occasionally – for example, if system 1 is unable to form a clear impression of a situation, or feels that it may have made an error. A broadly held view in psychology is that, because system 2 is not always engaged, many of our decisions are guided by system 1. Indeed, even if system 2 *is* engaged, the initial impression generated by system 1 may still influence a person's final decision.

The trading heuristic we described above is an attempt to capture an individual's system 1 response in an investing context. We have in mind someone who is looking through a business-oriented newspaper, magazine, or website, and who chances on a chart showing a stock's historical price movements. As soon as he sees the chart, the investor is likely to have an immediate reaction to it. The cognitive process we proposed above is an attempt to capture this immediate reaction. In particular, we conjecture that, as soon as he sees the chart, the individual forms a quick impression of the stock's historical return distribution; and that, just as quickly, he evaluates this distribution in the way described by prospect theory. Under this view, a stock with a high prospect theory value is one whose historical price chart makes a positive impression on the investor. Our conjecture is that this positive

impression then nudges him toward buying the stock. Conversely, a stock with a low prospect theory value is one whose price chart leaves a negative impression, one that leads the investor to avoid the stock.

There are three features of our trading heuristic that make it a good candidate for capturing system 1 thinking. First, under this trading rule, the individual uses *prospect theory* to evaluate the risk he is considering. Prospect theory, due to Kahneman and Tversky (1979) and Tversky and Kahneman (1992), has long been associated with system 1; indeed, it is widely viewed as the best available description of people's immediate reaction to a risk or gamble they are facing.

Second, under our trading heuristic, the individual evaluates the return distribution of the stock itself, considered in isolation. Evaluating a risk in isolation, separately from other concurrent risks, is known as *narrow framing*, and is also closely associated with system 1 thinking. The reason is that, in many cases, the first point of contact we have with a risk, gamble, or investment is a piece of information about the gamble itself, taken alone. For example, when we see an article about a stock, the first thing that catches our attention is often the accompanying chart showing the stock's performance.

The third element of our trading rule is that the individual evaluates the distribution of *past* returns on the stock. Once again, this is a natural feature of system 1 thinking: since discussions of a stock in the media often include a chart of past performance, information about past returns is immediately available to the reader.

The system 1 thinking we have described – evaluating a stock's historical distribution according to prospect theory – is likely to differ from any subsequent system 2 thinking that the individual does. Such system 2 thinking is likely to involve *broad* rather than narrow framing: instead of evaluating the stock in isolation, the investor will think about how adding the stock to his portfolio will impact the overall return of the portfolio. It is also likely to entail thinking about the stock's *future* returns, rather than forming an impression purely based on its past returns. And it may involve the use of expected utility, rather than prospect theory.

As we noted above, a widely-held view in psychology is that, since system 2 often fails to engage, it is system 1 that drives many of our decisions. However, since investing in stocks carries significant financial consequences, one might assume that system 2 *will* engage in investing contexts, and therefore that the system 1 process we describe above will have little influence on actual trading. This is not necessarily the case. System 2 engages when system 1 suspects that it has made an error. But many investors may fail to realize that there

is something wrong with the system 1 process laid out above. We often judge objects by looking at how they have performed in the past; it may therefore seem entirely reasonable to judge a stock by its past performance.

In summary, we think of the trading heuristic we described at the start – evaluating a stock's past returns according to prospect theory – as capturing an investor's immediate, automatic, system 1 response to a stock, and, in particular, his immediate response to a chart showing the stock's historical price movements. As noted above, the prediction that we test – a prediction that depends on a sufficient number of people basing their trading decisions on this heuristic – is that stocks with high (low) prospect theory values will earn low (high) subsequent returns, on average. We expect this prediction to hold primarily among small-cap stocks, in other words, among stocks where individual investors play a more important role. We do not expect the prediction to hold strongly, or indeed at all, among large-cap stocks. Trading in large-cap stocks is dominated by institutional investors. While these investors may exhibit a system 1 response to a stock as described above, they are much more likely to engage system 2 before trading; this, in turn, makes it more likely that system 1 will be overruled.

In order to test our hypothesis that the prospect theory value of a stock's historical return distribution will predict subsequent returns, we need to take a stand on what we mean by "historical return distribution." We discuss this issue in detail in Section 2.2. In short, the distribution we use is guided by the structure of the charts that the financial media typically use to present a stock's past performance. Based on a review of these media, we construct the distribution of past returns using the stock's monthly returns, in excess of the market return, over the previous five years.

In our empirical analysis, we find significant support for our prediction. We conduct a variety of tests, but it is easiest to understand our main result in a Fama-Macbeth framework. Specifically, each month, and for each stock in the cross-section, we compute the stock's prospect theory value – the prospect theory value of the distribution of its monthly excess returns over the past five years. We then run a cross-sectional regression of subsequent returns on this prospect theory value, including as controls the important known predictors of cross-sectional returns. Consistent with our prediction, we find a significant negative coefficient on the stock's prospect theory value: stocks with higher prospect theory values have lower subsequent returns. Also consistent with our framework, we find that this result is particularly strong among small-cap stocks.

We conduct a number of robustness checks. The most important of these is that we

repeat our analysis in each of the 49 international markets covered by Datastream. We find significant support for our prediction in these markets as well.

Our empirical work focuses on testing whether a stock's prospect theory value can predict its subsequent return in the cross-section. However, we also examine whether the prospect theory value variable can help explain known anomalies, such as the size premium and the value premium. In other words, perhaps the reason the typical small stock (or value stock) has a high average return is because the distribution of this stock's past returns is unappealing to prospect theory investors, who push its price down, thereby causing the stock to earn high returns later. We test this hypothesis and find that the prospect theory value variable appears to explain about 20% of the value premium, but only a smaller fraction of the small stock premium.

The trading heuristic we propose in this paper may seem unusual by the standards of the finance literature, but, in a sense, it is not new: it 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 very 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 a cross-sectional counterpart to Benartzi and Thaler's (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) analyze a one-period economy in which investors derive prospect theory utility from their end-of-period wealth. This framework generates a new prediction, one that does not emerge from the traditional analysis based on expected utility, namely that a security's skewness – even idiosyncratic skewness – will be priced: a positively skewed stock, say, will be "overpriced" and will earn a lower average return. In the past few years, several papers, using a variety of measures of skewness, have presented evidence in support of this prediction (Boyer, Mitton, and Vorkink 2010; Bali, Cakiki, and Whitelaw 2011; Conrad, Dittmar, and Ghysels 2012). Moreover, the idea that skewness is priced has been used to shed light on the low average returns of IPO stocks, distressed stocks, high volatility stocks, stocks sold over-the-counter, and out-of-the-money options (the assets in these categories have positively skewed returns); the diversification

discount; and the lack of diversification in many household portfolios.[1]

In this paper, we examine the cross-section of average stock returns using a different implementation of prospect theory, one that is more consistent with system 1 thinking. In Barberis and Huang's (2008) framework, investors apply prospect theory to gains and losses in the value of their overall *portfolios*; and the portfolio gains and the losses they are thinking about are *future* gains and losses. These assumptions are more consistent with system 2: thinking about portfolio gains and losses and about future gains and losses requires significant cognitive effort. By contrast, in our framework, investors apply prospect theory to *stock*-level gains and losses (narrow framing), and react to *past* gains and losses, rather than thinking about future gains and losses. These assumptions are more consistent with the fast, automatic nature of system 1.

2 Conceptual Framework

Our hypothesis is that the trading of some investors is based, in part, on the first impression that they form of a stock after seeing a chart of its historical price movements, an impression that we quantify as the prospect theory value of the stock's past return distribution. In this section, we fill in some conceptual details. In Section 2.1, we remind the reader of the mechanics of prospect theory. In Section 2.2, we discuss the issue of how "past 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 returns with a negative sign in the cross-section.

2.1 Prospect theory

The original version of prospect theory was described by 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 only be applied 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 it is the version we use in this paper.[2]

[1] For more discussion of these applications, see Mitton and Vorkink (2007), Mitton and Vorkink (2010), Boyer, Mitton, and Vorkink (2010), Mitton and Vorkink (2012), and Eraker and Ready (2012).

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

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 $\sum_{i=-m}^{n} p_i = 1$. In the expected utility framework, an agent with utility function $U(\cdot)$ evaluates this gamble 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[3]

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

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

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

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,

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

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 $(\$110, \frac{1}{2}; -\$100, \frac{1}{2})$. 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 minimal 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, $v(\cdot)$ 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, 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, subjects typically prefer $(\$5000, 0.001)$ to a certain \$5, but also prefer a certain loss of \$5 to $(-\$5000, 0.001)$.[4] 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

[4] We abbreviate $(x, p; 0, q)$ to (x, p).

the parameters γ and δ; lower values of these parameters implies 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

Before we can test our hypothesis – that the prospect theory value of a stock's distribution of past returns has predictive power for future returns – we need to take a stand on what we mean by a stock's "distribution of past returns." Are these annual, monthly, weekly, or daily returns? How far back should we go when we compute them? Are they raw returns, returns in excess of the risk-free rate, or returns in excess of the market return?

To answer this question, we recall the original motivation for the trading rule we propose: the trading rule is intended to capture an investor's immediate reaction to a chart showing a stock's historical price movements – a chart that he comes across while browsing the business-oriented media. The return distribution that we use should therefore be guided by how these media typically construct the charts that they present to their readers.

To learn more about this, we review some of the most important information sources for retail investors over the course of the 20th century: the *Valueline Investment Survey*; *Barron's* financial weekly; and the *Wall Street Journal*. For decades, Valueline has used a consistent format in its stock charts: it shows a stock's fluctuations over the previous ten years. Barron's also uses a consistent format: it shows a stock's fluctuations over the previous five years. The Wall Street Journal does not use a single format on a consistent basis – the charts it presents depend on the subject of the accompanying article – but most of its charts show stock fluctuations over the previous year, two years, or three years.

This informal survey suggests that many, if not most, of the charts investors are exposed to present price fluctuations over the course of several years. To reflect this, we use the previous five years of data when constructing our prospect theory variable. For a chart that presents several years of data, daily and weekly fluctuations are not discernible, but monthly fluctuations are, and make a clear impression on the reader. We therefore construct our prospect theory variable using monthly returns.

Finally, we need to specify whether the monthly returns we compute 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. However, an investor looking at a stock chart is likely to have a strong sense of the performance of the overall market over the same period, and this may influence his immediate reaction to the chart. For example, if he sees a chart showing

a decline in the price of a stock, he react neutrally, rather than negatively, if he knows that the market also performed poorly over the same period. In our benchmark results, we use stock returns in excess of the market; but we also examine the robustness of our results to using raw returns, or returns in excess of the risk-free rate.

In summary, then, we use as our main definition of "past return distribution" the distribution of a stock's monthly returns in excess of the market over the past five years. While we have tried to use the format of actual charts to guide this definition, we recognize it involves a large element of subjectivity. We therefore also conduct extensive robustness checks. Fortunately, we find that our results are not very sensitive to the exact way in which the historical return distribution is defined.

Now that we have defined what we mean by "past return distribution," we can define a stock's "prospect theory value" more precisely. 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 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 introduced in 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. The distribution of past returns for the stock 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; here, r denotes the stock's monthly excess return. From Section 2.1, we know that the prospect theory value of this distribution is

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

Note that we label a stock's prospect theory value as "TK." The two letters stand for Tversky and Kahneman (1992), the paper that first presented cumulative prospect theory.

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

$$\alpha = 0.88, \lambda = 2.25$$

$$\gamma = 0.61, \delta = 0.69.$$

Subsequent to Tversky and Kahneman (1992), several papers have used more sophisticated techniques, in conjunction with new experimental data, to estimate these parameters. However, their estimates largely confirm those of Tversky and Kahneman's (1992).

In Section 3, we will present evidence that the TK variable predicts future returns in the cross-section of stocks. It is natural to ask which of prospect theory's features is most responsible for this predictive power. To help answer this question, we conduct our main empirical tests not only for TK, but also for a variable that we label PW, which stands for Probability Weighting. As its label suggests, this variable takes account *only* of probability weighting, and removes the loss aversion and concavity/convexity features of prospect theory. In other words, it sets $\alpha = 1$ and $\lambda = 1$ in (5), so that the value function becomes the identity function $v(x) \equiv x$; however, it maintains $\gamma = 0.61$ and $\delta = 0.69$. Formally,

$$\text{PW} \equiv \sum_{j=-m}^{-1} r_j \left[w^-(\frac{j+m+1}{60}) - w^-(\frac{j+m}{60}) \right] + \sum_{j=1}^{n} r_j \left[w^+(\frac{n-j+1}{60}) - w^+(\frac{n-j}{60}) \right]. \quad (9)$$

2.3 Model

Our empirical prediction is that a stock's prospect theory value should predict the stock's subsequent return with a negative sign in the cross-section. In this section, we present a simple model that formalizes this idea.

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 $\widetilde{r}_j$, mean μ_j, and standard deviation σ_j. 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 traders 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 weight of the J risky assets in the tangency portfolio is given by the $J \times 1$ vector ω_t.

Traders of the second type are "prospect theory value" investors. These investors construct their portfolio holdings by starting with 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 assets weights are given by

$$\omega_p = (1-k)\omega_t + k\omega_{PT}, \tag{10}$$

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

$$\omega_{PT}^j = f(\mathrm{TK}_j), \tag{11}$$

where TK_j, defined in (8), is the prospect theory value of stock j's past returns – specifically, as described in Sections 2.1 and 2.2, the prospect theory value of the distribution of 60 past monthly excess returns on the stock – 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.

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

$$\begin{aligned} \omega_m &= \pi\omega_t + (1-\pi)((1-k)\omega_t + k\omega_{PT}) \\ &= (1-(1-\pi)k)\omega_t + (1-\pi)k\omega_{PT} \\ &= (1-\eta)\omega_t + \eta\omega_{PT}. \end{aligned} \tag{12}$$

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*

$$\frac{\mu_j - r}{\mu_m - r} = \beta_j - \frac{\eta s_{j,PT}}{\sigma_m^2(1-\eta\beta_{PT})}, \tag{13}$$

where $s_{j,PT}$ is the covariance between the idiosyncratic risks of asset j and portfolio PT, in other words, the covariance between the residuals $\widetilde{\varepsilon}_j$ and $\widetilde{\varepsilon}_{PT}$ obtained from regressing asset j's excess return and portfolio PT's excess return, respectively, on the market portfolio:

$$\widetilde{r}_j = r_f + \beta_j(\widetilde{r}_m - r_f) + \widetilde{\varepsilon}_j \tag{14}$$

$$\widetilde{r}_{PT} = r_f + \beta_{PT}(\widetilde{r}_m - r_f) + \widetilde{\varepsilon}_{PT}. \tag{15}$$

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

$$\begin{aligned} \frac{\mu_j - r}{\mu_m - r} &= \beta_j - \frac{\eta w_{PT}^j s_j^2}{\sigma_m^2 (1 - \eta \beta_{PT})} \\ &= \beta_j - \frac{\eta f(\mathrm{TK}_j) s_j^2}{\sigma_m^2 (1 - \eta \beta_{PT})}. \end{aligned} \tag{16}$$

Equation (16) captures the prediction that we test in the next section: that stocks with a higher prospect theory value (higher TK_j) will have lower alphas.

3 Empirical Analysis

In this section, we test our main hypothesis: 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. We emphasize that 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 system 1 thinking that our trading heuristic is trying to capture. Institutional investors, by contrast, are more likely to override system 1 with system 2 reasoning.

3.1 Data

Our data comes from standard sources. For U.S. firms, the stock price and accounting data are from CRSP and Compustat, respectively. We use the entire CRSP universe from 1926 to 2010. The first part of this sample period is not covered by Compustat; for these early years, we use data on book equity obtained from Kenneth French's website. Stock price data and accounting information for non-U.S. firms are from Datastream.

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. Full definitions of each variable can be found in the table caption and in Table A1 of the Appendix, but we also describe them briefly here. TK and PW are the two prospect theory variables whose predictive power is the focus of the paper; they are defined in (8) and (9), respectively. The next few variables are known predictors of cross-sectional stock returns that we will use as controls in some of our tests. They are:

- Beta

- Size (a stock's log market capitalization at the end of the previous month)
- BM (log book-to-market ratio)
- MOM (medium-term past return)
- ILLIQ (a measure of illiquidity)
- REV (short-term past return)
- LTREV (long-term past return)
- IVOL (idiosyncratic volatility of daily returns over the past month).

Later in the paper, we note that some of the predictive power of the TK variable may stem from the fact that high TK stocks are more positively skewed than the typical stock, a characteristic that may be appealing to investors. Some skewness-related variables have already been linked to the cross-section of stock returns. To study the relationship of TK to these other variables, we introduce them here. They are:

- MAX (a stock's maximum one-day return over the past month)
- MIN (a stock's minimum one-day return over the past month)
- Skew (the skewness of the stock's monthly returns)
- Industry Skew (the cross-sectional skewness of the previous month's returns on stocks in the same industry)
- EISKEW (a stock's expected idiosyncratic skewness)

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, which we compute starting from January 1988.

Recall that, in general, 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 labelled "TK" in Panel B are consistent with this. Across stocks, TK is positively correlated with measures of past returns (REV, MOM, LTREV), negatively correlated with a measure of volatility (STD), and positively correlated with measures of past skewness (Skew, Industry Skew). High TK stocks also tend to be larger-cap stocks – probably because large-cap stocks are less volatile – and 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 return in the cross-section. In this section, we test the 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, 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 Panel A of Table 2, we report the average return of each decile in excess of the risk-free rate; the 4-factor adjusted return (the return adjusted by the three Fama-French factors and the momentum factor); the 5-factor adjusted return (the return adjusted by the three Fama-French factors, the momentum factor, and the Pastor and Stambaugh (2003) liquidity risk factor); and the characteristics-adjusted return, 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, the return of a "low-high" portfolio, a zero investment portfolio that goes long the stocks in the lowest TK decile and shorts the stocks in the highest TK decile. Our analysis uses the full sample period, starting in July 1931 and ending in December 2010. The only exception is for the 5-factor adjusted return: due to data availability, we start this analysis in January 1968.

The most important column in Table 2 is the right-most one, which reports the average return of the low-high portfolio. Our prediction is that this return difference 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.

Panel A of the table presents significant support for our hypothesis. The average equal-weighted return on the low TK portfolio is significantly higher than for the high TK portfolio. As expected, the difference in average returns is higher for equal-weighted returns than for value-weighted returns. Nonetheless, we find a significant effect even for value-weighted returns.

Panel B repeats the analysis in Panel A using PW in place of TK. The findings are similar: the results for equal-weighted returns are strong, and stronger than those for value-

weighted returns; nonetheless, for most return measures, we obtain significant results even for the value-weighted returns. The strong results for PW suggest that a significant fraction of the predictive power of TK is driven by the probability weighting component of prospect theory.

Figure 2 presents a graphical view of the results in Table 2. It shows the 4-factor adjusted alpha for the ten decile portfolios, for both TK and PW, and for both value-weighted and equal-weighted returns.

We also examine whether TK (or PW) can predict stock returns beyond the first month after portfolio construction. Note that, in Table 2 and Figure 2, we use TK/PW calculated from month $t-60$ to $t-1$ to look at returns in month t. To examine the longer horizon predictive power of TK/PW, we use TK/PW calculated from month $t-60$ to $t-1$ and look at returns in months $t+1$, $t+2$, and so on. Figure 3 shows the 4-factor adjusted alphas for the four different long-short portfolios, by different lengths of time between the construction of TK/PW and the return evaluation period. The figure shows that TK (PW) has predictive power for returns several months after portfolio construction.

Table 3 reports the factor loadings for the low-high portfolio for both TK and PW-based portfolios, for both equal-weighted and value weighted returns, and for both a 4-factor model and a 5-factor model. The table is consistent with the pattern that emerged from the summary statistics in Table 1: high TK portfolios comove with large stocks, growth stocks, and high momentum stocks.

3.3 Robustness of time-series results

In the next section, we test our main hypothesis using a Fama-Macbeth methodology. Before we do this, however, we first examine the robustness of the decile-sort results in Table 2. The results of these robustness tests are in Table 4.

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 prediction holds in both subperiods.

When constructing the past return distribution for each 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 compute 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. In short, the "reference point" the investor uses when judging a stock's historical performance does not appear to play a large role in our results. The fourth panel of the table shows that we obtain similar results if we exclude stocks whose price at the beginning of the five year period that we use to construct TK is below $5.

Finally, when computing TK (or PW) for each stock, we use the functional form in (6) for the probability weighting functions. 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 regression methodology. One advantage of this methodology is that it allows us to examine the predictive power of TK and PW while controlling for known predictors of returns. This is important because, as shown in Table 1, our TK and PW variables are correlated with some of these predictors.

We conduct the Fama-Macbeth regressions in the usual way. Each month, starting in July 1931 and ending in November 2010, we run a cross-sectional regression of stock returns on TK (or PW) and a set of control variables – variables 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 further empirical 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 "LTREV"), an illiquidity measure ("ILLIQ"), and idiosyncratic volatility ("IVOL"). We noted earlier that the low returns to high TK stocks may, in part, be due to the fact that the past returns of 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 some of these variables as additional controls. We find that, even after their inclusion, the coefficient on TK remains significant.

While Fama-Macbeth regressions allow us to examine the predictive power of TK while

controlling for known predictors, they do have a limitation: they assume a linear relationship between stock returns and the various predictors. We therefore examine the robustness of TK's predictive power through double-sorts. The general idea is this. Suppose that we want to see whether the predictive power of TK is subsumed by control variable X. We first sort stocks into quintiles based on X. Within each of these quintiles, we again sort stocks into quintiles, this time based on TK (or PW). The returns of the five TK/PW quintile portfolios are then averaged across different quintiles of the control variable X. We take the difference between the average return on the low TK portfolio and the average return on the high TK portfolio as our factor-controlled long-short return.

We report the results of this exercise in Table 6. Each column corresponds to a specific control variable, and to either equal-weighted or value-weighted returns. Within each column, we report the average return of the five TK quintile portfolios, as discussed above, and also the average return difference between the lowest and highest TK quintiles. The control variables we consider are short-term reversal (REV); the Amihud liquidity measure (ILLIQ); the maximum daily return of the past month (MAX); idiosyncratic volatility (IVOL); expected idiosyncratic skewness (EISKEW); past realized skewness (Skew), past realized cross-sectional skewness within one industry (Industry Skew); and long-term reversal (LTREV).

The crucial row in the table is the bottom one. Consistent with our Fama-Macbeth results, it shows that the TK variable retains significant predictive power for returns even after controlling for the other known predictors of returns.

3.5 Role of limits to arbitrage

We expect the predictive power of TK to be stronger for stocks where arbitrage is more difficult – for example, for stocks with low market capitalizations, for illiquid stocks, and for stocks with high idiosyncratic volatility. We now test this hypothesis.

Each month, we sort stocks into two groups based on size, illiquidity, or idiosyncratic volatility. Size is defined as the market capitalization at the end of the last month. Illiquidity is defined as in Amihud (2002). Idiosyncratic volatility is the IVOL variable we have used earlier, computed as in Ang et al. (2006). In the case of the size variable, the breakpoint we use is the median of NYSE listed firms; in the case of ILLIQ and IVOL, the breakpoints are the sample medians. Within each of the size, ILLIQ, and IVOL portfolios, we sort stocks into deciles based on TK (or PW) 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 the excess return, the four-factor alpha, the five-factor alpha, and DGTW-adjusted returns for a long-short portfolio that goes long the lowest TK decile and short the highest TK decile.

The results in the table are consistent with our hypothesis. The predictive power of TK is generally stronger among stocks where arbitrage is likely to be more difficult. Figure 3 shows these results graphically: it plots equal-weighted 4-factor alphas for the long-short portfolio among hard-to-arbitrage stocks (small, illiquid, and volatile stocks), and among stocks that are easier to arbitrage (large, liquid, and less volatile stocks).

3.6 International results

Our hypothesis is that a stock's prospect theory value can predict its subsequent return in the cross-section. We have provided some supportive 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 very similar to the decile sort tests in Table 2. Each month, we sort stocks into deciles based on TK (or PW) and record the return of each decile over the next month. This gives us a time series of returns for each TK decile. We use these time series to compute the average return of each decile over the entire sample, and hence also the return of a long-short portfolio that goes long the stocks in the low TK decile and short the stocks in the high TK decile. In particular, in Table 8, we report the raw average return of the long-short portfolio, but also the average return adjusted for global factors, for international factors, and for local factors; and for both value-weighted and equal-weighted returns. Long-short average returns that are significant at the 10% level are indicated in bold. As before, our hypothesis is that the results should be stronger for equal-weighted returns.

The table shows that the international evidence is supportive of our prediction. To see this, it may be most useful to look at the summary results at the bottom of the table. First, we note that, across all specifications, the vast majority of the countries we consider – as many as 80% to 90% of them – generate an effect with the predicted positive sign. And for equal-weighted returns – the place where we expect our result to hold more strongly – the predicted effect is significantly positive in a strong majority of the 46 countries.

3.7 Explaining anomalies

Our focus thus far has been on testing whether a stock's prospect theory value can predict its subsequent return. We now turn to a different question: We ask whether the trading heuristic we have proposed can help explain well-known anomalies such as the size premium and the value premium. Under this view, small stocks and value stocks have high average returns because they have low prospect theory values, in other words, because the typical small-cap stock or value stock has a distribution of past returns that is unappealing to prospect theory investors. By tilting away from such stocks, these investors cause them to become undervalued, and therefore to earn high subsequent returns.

The potential explanation for the size and value premia that comes out of our current framework is different, in a crucial way, from the potential explanation of these premia that emerges from other, more "forward-looking" implementations of prospect theory, such as that of Barberis and Huang (2008). In Barberis and Huang's (2008) framework, value stocks and small stocks will earn high average returns if the distribution of their *future* returns is unappealing to prospect theory investors. By contrast, in our current framework, value and small stocks will earn high average returns if the distribution of their *past* 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. As a result, the distribution of its returns over the past five years may be quite different from the distribution of its returns over the next five.

To test the idea that the trading heuristic we describe in this paper is driving the size and value premia, we conduct two types of tests: double sorts; and a Fama-Macbeth regression. In the double-sort analysis, we sort stocks each month into quintiles based on the TK (or PW) measure. Then, within each quintile, we again sort stocks into quintiles based on size or book-to-market. If TK or PW is driving the size and value premia, then, within each quintile, the size and value premia should be significantly lower than when these premia are computed unconditionally.

Table 9 presents the results of this double-sort analysis. Panel A focuses on the value premium, and Panel B, on the size premium. We look first at Panel A. The first subpanel reports the unconditional value premium. In other words, each month, we sort stocks into quintiles based on book-to-market and report the returns of the long-short portfolio that goes long value stocks and shorts growth stocks. We look at both value-weighted and equal-weighted returns, and at returns adjusted for various factors. Subpanel B repeats this exercise, but restricts the sample to stocks for which data on TK and PW are also available.

Panel C conducts the double-sort we described above. Each month, we sorts stocks into quintiles based on the TK measure. Then, within each quintile, we further sort stocks based on book-to-market. We compute the value premium within each quintile – the return of a strategy that goes long the highest book-to-market quintile and shorts the lowest book-to-market quintile – and then average this premium across the five TK quintiles. Panel C reports the result of this calculation for both equal-weighted and value-weighted returns, and for returns adjusted for various factors. Finally, subpanel D repeats this exercise using PW in place of TK.

Panel A of Table 9 suggests that the trading heuristic we describe in this paper may be able to explain some portion of the value premium: the long-short returns in subpanels C and D are generally somewhat smaller than the long-short returns in subpanels A and B. However, the portion of the value premium that we can explain is small.

Panel B of Table 9 repeats this analysis for the size premium. Comparing the long-short returns in subpanels C and D with those in subpanels A and B suggests that the trading heuristic we describe has little explanatory power for the size premium.

We also use Fama-Macbeth regressions to test whether our proposed trading heuristic can explain the size and value premia. These regressions are presented in Table 10. Each column in the table corresponds to a different regression. To understand our approach, look at the first three columns. In column (1), we run a standard Fama-Macbeth regression with size, book-to-market, momentum, and beta as explanatory variables. In columns (2) and (3), we include TK and PW as explanatory variables, respectively. The idea is that, if our trading heuristic is a driver of the size and value premia, we should see the magnitude and significance of the coefficients on "size" and "book-to-market" go down as soon as we include TK or PW as independent variables. The remaining regressions in the table have a similar structure – they differ simply in the number of predictors included as independent variables.

The Fama-Macbeth regressions point to the same conclusion as the double-sort analysis in Table 9. A stock's prospect theory value seems to have little ability to explain the size premium. Depending on the specification, there is some evidence that it can explain the value premium, but even here, the effect is small.

3.8 Mechanism

In previous sections, we have presented evidence that a stock's prospect theory value can predict its subsequent return in the cross-section. Our interpretation is that this is because some investors are influenced in their trading by their initial impression of a stock when they

see a chart of its past price movements – an impression that we quantify as the prospect theory value of the stock's past returns. In short, high prospect theory value stocks are stocks that have appealing past return distributions, which, in turn, leads some investors to tilt towards them.

A natural question is: What is it 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? In general, gambles with high prospect theory values will tend to have high mean payoffs; low standard deviation (due to loss aversion), and high skewness (due to probability weighting). Given this, we would expect stocks with high TK values to be stocks with high past returns, with low past volatility, and with high past skewness.

To examine this conjecture, we sort stocks each month into deciles based on TK and record the average characteristic of the stocks in each decile at that time. We repeat this each month and then compute the average characteristics, across our full sample, of the typical stock in each decile.

The results, reported in Table 11, confirm our prediction to some extent, but also indicate some subtleties. As expected, measures of past returns (REV, MOM, LTREV) increase monotonically from TK decile 1 to TK decile 10. Skewness also generally increases from TK decile 1 to TK decile; however, the increase in skewness occurs largely from deciles 8 to 9, and from 9 to 10. Interestingly, volatility does *not* decrease monotonically from TK decile 1 to TK decile 10; indeed, far from containing the least volatile stocks, the stocks in decile 10 are more volatile than average. The reason is that stocks with low volatility are also much less skewed, and therefore have lower prospect theory values; as a result, the decile 10 stocks cannot have a volatility that is too low. Put differently, the decile 10 stocks are those that trade off past return, volatility, and skewness in a way that makes them maximally attractive to a prospect theory agent.

Given that stocks with high TK values tend to be stocks with high past returns and high past skewness, one might conjecture that the predictive power of TK stems from the predictive power of past returns or past skewness. However, in our earlier tests, and using several different methodologies, we controlled both for past returns (REV, MOM, LTREV) and for skewness-related variables (Skew, Industry Skew, EISKEW). These controls failed to take away TK's predictive ability.

A more informative clue as to what is driving our results comes from examining which feature of prospect theory is most responsible for TK's ability to predict returns. Table 12

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, eight 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; in other words, this column corresponds to the Fama-Macbeth regression we ran previously in Table 5. 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 ignores 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 $(\alpha, \gamma, \delta) = (1, 1, 1)$. Similarly, in the column labelled "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 labelled "CC" ("concavity/convexity"), we use $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 1)$. The column labelled "LACC" uses $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 2.25)$, retaining loss aversion and concavity/convexity, but turning off probability weighting. "LAPW" and "CCPW" are defined in a similar way.

We emphasize two lessons from Table 12. First, the element of prospect theory that is driving the predictive power of the TK variable is probability weighting: the four most significant coefficients in the first row of the table correspond to prospect theory variables that involve probability weighting, while for the three least significant coefficients, probability weighting has been turned off. 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 drops markedly.

The second lesson of Table 12 is that loss aversion tends to worsen the predictive power of the TK variable: by comparing columns (6) and (7), we see that removing loss aversion while retaining the other features of prospect theory improves the predictive power of our variable.

Tables 13 and 14, which have the same general structure as Table 12, make the same two points in a slightly different way. The 14 columns in Table 13 correspond to 14 different Fama-Macbeth regressions. As before, the regressors in each specification are a prospect theory variable and a set of control variables, with only the prospect theory variable chang-

ing across specifications. In this table, we vary only the probability weighting parameters. Specifically, each specification sets $\alpha = 0.88$ and $\lambda = 2.25$ as before, but the parameters γ and δ vary, taking the values listed at the top of each column. Recall that our baseline parameters are $\gamma = 0.61$ and $\delta = 0.69$, the values in column (4). The table shows that the most statistically significant results involve at least some degree of probability weighting – in particular, probability weighting that involves the overweighting of tails. Note that columns (9)-(14) also involve probability weighting, but here, probability weighting involves underweighting of tails. These specifications have much reduced predictive power.

Table 14 performs a similar exercise in the case of loss aversion. The nine columns correspond to nine Fama-Macbeth regressions. In each case, we compute the prospect theory variable using $\gamma = 0.61$, $\delta = 0.69$, and $\alpha = 0.88$, as in our benchmark results, but vary the loss aversion parameter λ from 0.5 up to 4. The table confirms the lesson of Table 12: the predictive power of the prospect theory variable is strengthened when λ is significantly below its benchmark level of 2.25; in this sense, loss aversion exerts a drag on TK's predictive power.

The fact that probability weighting is the main force behind the predictive power of TK sheds some light on *why* TK predicts returns. The main effect of probability weighting is to overweight the tails of the distribution it is applied. This suggests that the predictive power of TK *is* related to skewness in some way, but not in a way that can be captured by the usual measure of skewness. Put differently, TK may be capturing what people find appealing, or not appealing, about the extremes of distribution in a way that simple measures of skewness are unable to capture. However, we also note that probability weighting does not affect the tails of distribution alone. 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

For each stock in the U.S. universe in turn, we take the stock's distribution of past returns, and compute the value that would be assigned to this distribution by (cumulative) prospect theory. We find that this "prospect theory value" predicts subsequent returns in the cross-section, with a negative sign. This is particularly true for stocks traded primarily by individual investors and for stocks that are hard to arbitrage. We repeat our tests in 49 international markets, and find a similar pattern in a majority of those markets. Our con-

jecture is that some investors are influenced in their trading by the quick initial impression of a stock that they form after glancing at a chart of the stock's historical price movements – a so-called "system I" impression that we quantify as the stock's prospect theory value. Stocks with high prospect theory values make a positive impression on these investors, who tilt toward them, causing them to be overpriced and to earn low subsequent returns.

5 Appendix

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

$$\mu_j - r = \frac{\sigma_{j,t}}{\sigma_t^2}(\mu_t - r). \tag{17}$$

Note also that, from equation (12),

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

Rearranging each of these equations in turn, we obtain:

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

Substituting these expressions back into (17), we find

$$\mu_j - r = \frac{\sigma_{j,m} - \eta\sigma_{j,PT}}{\sigma_m^2 + \eta\sigma_{PT}^2 - 2\eta\sigma_{m,PT}}(\mu_m - r - \eta(\mu_{PT} - r)). \tag{18}$$

This implies

$$\mu_{PT} - r = \frac{\sigma_{m,PT} - \eta\sigma_{PT}^2}{\sigma_m^2 + \eta^2\sigma_{PT}^2 - 2\eta\sigma_{m,PT}}(\mu_m - r - \eta(\mu_{PT} - r)). \tag{19}$$

Rearranging (19), we obtain

$$\frac{\mu_{PT} - r}{\mu_m - r} = \frac{\sigma_{m,PT} - \eta\sigma_{PT}^2}{\sigma_m^2 - \eta\sigma_{m,PT}} = \frac{\beta_{PT} - \eta(\beta_{PT}^2 + s_{PT}^2/\sigma_m^2)}{1 - \eta\beta_{PT}} = \beta_{PT} - \frac{\eta s_{PT}^2}{\sigma_m^2(1 - \eta\beta_{PT})}, \tag{20}$$

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

Substituting (20) back into (18), we obtain

$$\mu_j - r = \frac{\beta_j - \eta\sigma_{j,PT}/\sigma_m^2}{1 - \eta\beta_{PT}}(\mu_m - r). \tag{21}$$

Given the decomposition in Proposition 1, we have $\sigma_{j,PT} = \beta_j\beta_{PT}\sigma_m^2 + s_{j,PT}$. Substituting this into (21) gives

$$\frac{\mu_j - r}{\mu_m - r} = \beta_j - \frac{\eta s_{j,PT}}{\sigma_m^2(1 - \eta\beta_{PT})}. \tag{22}$$

This is equation (13).

Under the additional assumption that $cov(\widetilde{\varepsilon}_i, \widetilde{\varepsilon}_j) = 0$, we have $s_{j,PT} = \omega_{PT}^j s_j^2$. Substituting this into (22) gives equation (16).

6 References

Amihud, Y. (2002), "Illiquidity and Stock Returns: Cross-section and Time-series Effects," *Journal of Financial Markets* 5, 31-56.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang (2006), "The Cross-section of Volatility and Expected Returns," *Journal of Finance* 61, 259-299.

Arkes, H., D. Hirshleifer, D. Jiang, and S. Lim (2010), "A Cross-cultural Study of Reference Point Adaptation: Evidence from China, Korea, and U.S.," *Organization Behavior and Human Decision Processes* 112, 99-111.

Bali, T., N. Cakici, and R. Whitelaw (2011), "Maxing Out: Stocks as Lotteries and the Cross-section of Expected Returns," *Journal of Financial Economics* 99, 427-446.

Barberis, N. and M. Huang (2008), "Stocks as Lotteries: The Implications of Probability Weighting for Security Prices," *American Economic Review* 98, 2066-2100.

Barberis, N., M. Huang, and R. Thaler (2006), "Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing," *American Economic Review* 96, 1069-1090.

Boyer, B., T. Mitton, and K. Vorkink (2010), "Expected Idiosyncratic Skewness," *Review of Financial Studies* 23, 169-202.

Carhart, M. (1997), "On Persistence in Mutual Fund Performance," *Journal of Finance* 52, 57-82.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers (1997), "Measuring Mutual Fund Performance with Characteristics-based Benchmarks," *Journal of Finance* 52, 1035-1058.

De Bondt, W. and R. Thaler (1985), "Does the Stock Market Overreact," *Journal of Finance* 40, 793-805.

Kahneman, D. (2011), *Thinking, Fast and Slow.* Farrar, Straus, and Giroux, New York.

Kahneman, D. and A. Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica* 47, 263-291.

Pastor, L. and R. Stambaugh (2003), "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* 111, 642-685.

Prelec, D. (1998), "The Probability Weighting Function," *Econometrica* 66, 497-527.

Tversky, D. and D. Kahneman (1992), "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk and Uncertainty* 5, 297-323.

Table 1. Data Summary

This table presents the summary statistics of the sample, including the mean and standard deviation for each variable, and the correlations between them. TK and PW are the two variables we used in this paper to capture the preference of prospect theory-utility investors. Beta is calculated from past five years' monthly return, following Fama and French (1992). Size is the natural log of firm market capitalization at the end of the previous month. BM is the natural log of book-to-market ratio. When the book value of equity is missing in Compustat, we use the data from Davis, Fama and French (2002). The cases with negative book value are deleted. MOM is momentum which is defined as the cumulative return from month t-12 to t-1. ILLIQ is the Amihud (2002) illiquidity measure. REV is the short term reversal measure which is the lagged monthly return. LT REV is the long term reversal measure which is the cumulative return from month t-60 to t-13. IVOL is idiosyncratic volatility, calculated following Ang, Hodrick, Xing and Zhang (2006). MAX and MIN are the maximum and minimum daily return in month t-1, defined following Bali, Cakici and Whitelaw (2011). Skew is skewness of monthly return from month t-60 to t-1. Industry skew is calculated following Zhang (2006). For a given firm, its industry skew is the cross-sectional skewness of month t-1 for all the stocks in its industry (Fama and French 48 industry). EISKEW is the expected idiosyncratic skewness measure, constructed following Boyer, Mitton and Vorkink (2010). The sample period is July 1931 to December 2010, except for EISKEW which is from January 1988 onward.

Panel A

	TK	**PW**	Beta	Size	BM	MOM	ILLIQ	REV	LT REV	IVOL	MAX	MIN	Skew	Industry skew	EISKEW
Mean	**-0.10**	**0.02**	1.10	11.6	1.20	0.15	2.76	0.01	0.85	0.03	0.07	-0.10	0.63	0.01	0.53
Standard deviation	**0.04**	**0.04**	0.68	2.20	6.40	0.64	37.28	0.15	2.19	0.02	0.08	0.05	0.90	0.18	0.68

Panel B:

Correlations

	TK	PW	Beta	Size	BM	MOM	ILLIQ	REV	LT REV	IVOL	MAX	MIN	Skew	Industry Skew	EISKEW
TK	**1**														
PW	**0.46**	**1**													
Beta	**-0.02**	**0.29**	1												
Size	**0.26**	**-0.16**	-0.05	1											
BM	**-0.23**	**-0.18**	-0.03	-0.45	1										
MOM	**0.26**	**0.23**	0.03	0.08	-0.13	1									
ILLIQ	**-0.08**	**0.05**	0.02	-0.15	0.13	-0.04	1								
REV	**0.10**	**0.10**	0.01	0.03	0.03	0.00	0.02	1							
LT REV	**0.42**	**0.24**	0.08	0.14	-0.28	-0.04	-0.03	-0.02	1						
IVOL	**-0.37**	**0.23**	0.11	-0.35	0.11	-0.10	0.25	0.14	-0.09	1					
MAX	**-0.26**	**0.21**	0.11	-0.26	0.09	-0.08	0.25	0.30	-0.07	0.90	1				
MIN	**0.37**	**-0.19**	-0.14	0.31	-0.08	0.08	-0.22	0.20	0.06	-0.81	-0.61	1			
Skew	**0.22**	**0.70**	0.15	-0.36	0.05	0.11	0.06	0.07	0.03	0.26	0.22	-0.20	1		
Industry Skew	**0.12**	**0.01**	0.05	-0.08	0.08	0.10	-0.01	0.11	-0.01	-0.09	-0.06	0.14	0.04	1	
EISKEW	**-0.26**	**0.28**	0.10	-0.46	0.18	-0.17	0.1	-0.03	-0.14	0.40	0.32	-0.35	0.33	-0.02	1

Table 2. Decile Portfolio Analysis

This table presents decile portfolio returns and alphas, sorted on PT measures of value. Panel A looks at TK and Panel B looks at PW, respectively, to capture the preferences of prospect theory-utility investors. The details of their construction can be found in the text. For each month, all the stocks are sorted into deciles based on PW/TK. We report the excess return, 4-factor alpha (following Carhart), 5-factor adjusted alpha (Carhart 4-factor augmented by Pastor and Stambaugh's (2003) liquidity factor), and, characteristics-adjusted abnormal returns calculated following Daniel, Grinblatt, Titman and Wermers (1997), denoted as DGTW. The sample runs from July 1931 to December 2010, except for the 5-factor adjusted alpha which starts from January 1968, due to constraints on the availability of the Pastor and Stambaugh (2003) liquidity risk factor.

Panel A. TK

		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 onwards)	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)

Panel B. PW

		P1 low PW	P2	P3	P4	P5	P6	P7	P8	P9	P10 high PW	PW low-high portfolio
Excess Return	EW	**1.423**	**1.033**	**1.045**	**1.068**	**1.066**	**1.127**	**1.070**	**1.182**	**1.114**	**1.061**	**0.362**
		(5.16)	(4.83)	(4.92)	(5.13)	(4.90)	(4.92)	(4.47)	(4.46)	(3.87)	(3.17)	(1.93)
	VW	**0.759**	**0.688**	**0.666**	**0.714**	**0.794**	**0.675**	**0.663**	**0.708**	**0.842**	**0.604**	0.155
		(3.35)	(3.71)	(3.77)	(3.92)	(4.21)	(3.45)	(3.22)	(2.94)	(3.13)	(2.04)	(0.70)
4-factor Alpha	EW	**0.815**	**0.379**	**0.294**	**0.252**	**0.163**	**0.151**	0.020	0.072	-0.101	-0.190	**1.005**
		(7.62)	(5.84)	(5.48)	(5.15)	(3.20)	(2.80)	(0.38)	(1.21)	(-1.31)	(-1.59)	(6.63)
	VW	**0.392**	**0.251**	**0.105**	0.053	0.061	**-0.122**	**-0.177**	**-0.212**	**-0.243**	**-0.514**	**0.906**
		(3.85)	(3.68)	(1.77)	(0.87)	(0.97)	(-1.86)	(-2.69)	(-2.53)	(-2.29)	(-4.04)	(5.13)
5-factor alpha (1968 onwards)	EW	**0.840**	**0.290**	**0.263**	**0.214**	**0.220**	**0.213**	**0.152**	**0.208**	0.050	0.018	**0.823**
		(5.47)	(3.65)	(4.05)	(3.51)	(3.49)	(3.30)	(2.28)	(2.73)	(0.50)	(0.11)	(4.31)
	VW	**0.315**	**0.191**	**0.144**	0.106	0.044	-0.096	-0.081	-0.035	0.100	-0.144	**0.459**
		(2.17)	(2.29)	(1.77)	(1.28)	(0.55)	(-1.13)	(-0.91)	(-0.31)	(0.74)	(-0.84)	(1.89)
DGTW	EW	**0.377**	**0.097**	**0.070**	0.056	0.011	**0.136**	**0.086**	**0.105**	0.031	-0.019	**0.396**
		(5.67)	(2.26)	(1.73)	(1.60)	(0.29)	(3.76)	(2.29)	(2.42)	(0.55)	(-0.21)	(3.64)
	VW	0.087	0.029	0.006	0.012	-0.050	-0.009	-0.032	-0.095	0.051	-0.149	**0.236**
		(1.29)	(0.72)	(0.16)	(0.33)	(-1.34)	(-0.22)	(-0.67)	(-1.61)	(0.69)	(-1.49)	(1.81)

Table 3. Factor loadings

This table presents the factor loadings for different models (Carhart 4-factor model and the 5-factor model) and four different long-short portfolios. VW-TK, EW-TK, VW-PW, and EW-PW represent value weighted TK, equal weighted TK, value weighted PW and equal weighted PW portfolios, respectively. The sample is from July 1931 to December 2010, except for the 5-factor adjusted alpha which starts from January 1968, due to the availability of the Pastor and Stambaugh (2003) liquidity risk factor.

Measure/Model	MktRf	SMB	HML	UMD	PS_Liq
EW-TK	-0.116	1.172	0.613	-0.679	-
4-factor model	(-3.20)	(21.02)	(11.60)	(-16.51)	
VW-TK	0.027	1.044	0.469	-0.752	-
4-factor model	(0.78)	(19.98)	(9.47)	(-19.48)	
EW-TK	0.100	0.967	0.671	-0.710	-0.057
5-factor model	(1.77)	(12.33)	(7.85)	(-12.99)	(-0.86)
VW-TK	0.226	1.132	0.673	-0.858	-0.158
5-factor model	(4.10)	(14.70)	(8.02)	(-15.99)	(-2.40)
EW-PW	-0.323	-0.740	0.198	-0.454	-
4-factor model	(-10.59)	(-15.84)	(4.48)	(-13.17)	
VW-PW	-0.503	-0.649	0.326	-0.569	-
4-factor model	(-14.16)	(-11.93)	(6.33)	(-14.19)	
EW-PW	-0.106	-0.502	0.823	-0.411	0.035
5-factor model	(-2.46)	(-8.36)	(12.59	(-9.84)	(0.68)
VW-PW	-0.267	-0.419	1.078	-0.642	0.090
5-factor model	(4.89)	(-5.49)	(12.99)	(-12.10)	(1.38)

Table 4. Robustness

This table shows results for various robustness checks. The first set of results look at two sub-periods: one before July 1963 and one after. In the second set of results, we vary the window length of historical returns used to calculate TK/PW. The lengths we examine include past 3, 4 or 6 years. In the third set of results, we vary the reference point, including cash (0 as reference point), risk-free rate and the sample mean. In the four set of results, we exclude the stocks with beginning period of price lower than $5. In the last set of analysis, we use the probability weighting function proposed by Prelec (1998) instead of Tversky and Kahneman (1992) as the probability weighting function. The sample period covers July 1931 to December 2010. Reported are the 4-factor adjusted alphas.

		TK		PW	
		EW	VW	EW	VW
Sub-periods	1931/07-1963/06	**1.252**	**0.459**	**0.969**	**1.011**
		(4.346)	(1.89)	(4.06)	(4.23)
	1963/07-2010/12	**1.211**	**0.634**	**0.777**	**0.513**
		(5.34)	(2.81)	(4.46)	(2.32)
Window for constructing TK/PW	Past 3 years data	**1.283**	**0.674**	**1.195**	**0.943**
		(6.72)	(3.77)	(7.92)	(4.90)
	Past 4 years data	**1.244**	**0.557**	**0.997**	**0.675**
		(6.79)	(3.24)	(6.58)	(3.63)
	Past 6 years data	**1.193**	**0.643**	**0.949**	**0.916**
		(6.56)	(3.71)	(6.30)	(5.53)
Alternative reference points	Cash as reference	**1.204**	**0.464**	**0.800**	**0.603**
		(5.48)	(2.17)	(4.67)	(2.71)
	Risk-free rate as reference	**1.049**	**0.282**	**0.994**	**0.833**
		(6.31)	(1.69)	(6.64)	(4.63)
	Sample mean as reference	**0.797**	**0.543**	**0.465**	**0.679**
		(4.07)	(2.94)	(2.84)	(3.13)
Excluding low priced stocks	price>=5$	**0.373**	**0.365**	**0.827**	**0.679**
		(3.71)	(2.85)	(6.35)	(4.26)
Skip one month		**0.779**	**0.299**	**0.593**	**0.753**
		(4.58)	(1.86)	(4.13)	(4.40)
Prelec	Prelec's probability weighting	**1.238**	**0.530**	**1.018**	**0.817**
	Function instead of TK (1992)	(6.89)	(3.26)	(6.78)	(4.63)

Table 5. Fama-MacBeth Regression Analysis

This table shows results from Fama-MacBeth regressions. Panel A looks at TK and Panel B looks at PW, respectively, to capture the preferences of prospect theory-utility investors. The details of their construction can be found in the text. Beta is calculated from past five years' monthly return, following Fama and French (1992). Size is the natural log of firm market capitalization at the end of last month. BM is the natural log of book-to-market ratio. When the book value of equity is missing in Compustat, we use the data from Davis, Fama and French (2002). The cases with negative book value are deleted. MOM is momentum which is defined as the cumulative return from month t-12 to t-1. ILLIQ is the Amihud (2002) illiquidity measure. REV is the short term reversal measure which is the lagged monthly return. LT REV is the long term reversal measure which is the cumulative return from month t-60 to t-13. IVOL is the standard deviation of the idiosyncratic return, calculated following Ang, Hodrick, Xing and Zhang (2006). MAX and MIN are the maximum and minimum daily return in month t-1, defined following Bali, Cakici and Whitelaw (2011). Skew is skewness of monthly return from month t-60 to t-1. Industry skew is calculated following Zhang (2006). For a given firm, its industry skew is the cross-sectional skewness of month t-1 for all the stocks in its industry. Industry is defined as Fama and French 48 industry. EISKEW is the expected idiosyncratic skewness measure, constructed following Boyer, Mitton and Vorkink (2010). The sample period covers from July 1931 to December 2010, except for EISKEW which is from January 1988. All the t-statistics are Newey-West adjusted with 12 lags.

Panel A. TK

	TK								
	Controls						Skewness Controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TK	**-0.1070**	**-0.1076**	**-0.0586**	**0.0500**	**-0.0431**	**-0.0434**	**-0.0457**	**-0.0417**	**-0.0665**
	(-3.77)	(-4.94)	(-3.07)	(-2.60)	(-2.16)	(-2.18)	(-1.92)	(-2.1)	(-2.28)
Beta		0.0013	0.0017	0.0019	0.002	**0.002**	0.003	0.002	**0.005**
		(1.14)	(1.22)	(1.40)	(1.99)	(2.07)	(2.11)	(1.94)	(2.59)
Size		**-0.0013**	**-0.0013**	**-0.0008**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
		(-4.07)	(-3.65)	(-2.44)	(-3.38)	(-3.24)	(-3.55)	(-3.19)	(-1.94)
BM		**0.0015**	**0.002**	**0.0018**	**0.001**	**0.001**	**0.001**	**0.001**	0.001
		(2.7)	(3.44)	(3.06)	(2.26)	(2.29)	(2.03)	(2.52)	(1.31)
MOM		**0.01**	**0.0085**	**0.0088**	**0.009**	**0.009**	**0.009**	**0.008**	**0.006**
		(7.99)	(6.47)	(6.73)	(6.39)	(6.47)	(6.30)	(6.28)	(3.44)
REV			**-.0793**	**-0.0793**	**-0.079**	**-0.081**	**-0.082**	**-0.082**	**-0.053**
			(-16.39)	(-16.28)	(-15.20)	(-16.47)	(-16.02)	(-16.53)	(-9.64)
ILLIQ				**285.53**	**596.83**	**621.95**	**631.13**	**587.83**	**1298.6**
				(2.37)	(4.9)	(5.08)	(5.20)	(4.89)	(6.88)
LT REV					-0.0004	-0.0004	-0.00040	-0.0003	-0.00002
					(-1.40)	(-1.31)	(-1.70)	(-1.20)	(-0.04)
IVOL					**-0.1384**	0.068	0.067	0.066	0.073
					(-4.27)	(1.43)	(1.43)	(1.35)	(1.03)
MAX						**-0.036**	**-0.036**	**-0.035**	-0.022
						(-3.45)	(-3.42)	(-3.23)	(-1.40)
MIN						**0.059**	**0.060**	**0.057**	**0.093**
						(4.50)	(4.61)	(4.17)	(6.72)
Skew							0.0001		
							(0.30)		
Industry Skew								**0.007**	
								(4.46)	
EISKEW									-0.002
									(-1.61)
N	954	954	954	954	954	954	954	954	276

Panel B. PW

	PW								
	Controls						Skewness controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PW	-0.0155	**-0.1138**	**-0.0510**	**0.0590**	**-0.0361**	**-0.0381**	**-0.0542**	**-0.0373**	**-0.0353**
	(-0.68)	(-6.54)	(-3.49)	(-4.02)	(-2.16)	(-2.29)	(-2.29)	(-2.18)	(-2.40)
Beta		**0.0024**	0.0021	**0.0025**	**0.003**	**0.0027**	**0.003**	**0.003**	**0.006**
		(2.18)	(1.59)	(1.88)	(2.19)	(2.32)	(2.42)	(2.15)	(2.76)
Size		**-0.0022**	**-0.0017**	**-0.0012**	**-0.001**	**-0.0012**	**-0.001**	**-0.001**	**-0.001**
		(-5.39)	(-4.35)	(-3.27)	(-3.98	(-3.88)	(-3.94)	(-3.78)	(-2.64)
BM		**0.0016**	**0.0021**	**0.0017**	**0.001**	**0.0013**	**0.001**	**0.001**	0.001
		(2.85)	(3.47)	(2.96)	(2.26)	(2.30)	(2.19)	(2.50)	(1.52)
MOM		**0.0101**	**0.0086**	**0.0091**	**0.008**	**0.0084**	**0.009**	**0.008**	**0.005**
		(7.36)	(5.64)	(6.05)	(5.17)	(5.35)	(5.49)	(5.12)	(2.63)
REV			**-.0791**	**-0.0787**	**-0.079**	**-0.0814**	**-0.082**	**-0.082**	**-0.054**
			(-15.98)	(-15.84)	(-14.76)	(-16.08)	(-15.82)	(-16.12)	(-9.98)
ILLIQ				**329.84**	**594.20**	**622.26**	**632.55**	**589.60**	**1303.6**
				(2.69)	(4.80)	(4.99)	(5.09)	(4.82)	(6.87)
LT REV					**-0.001**	**-0.0009**	-0.001	**-0.0008**	**-0.0005**
					(-2.24)	(-2.16)	(-1.75)	(-2.06)	(-1.73)
IVOL					**-0.1223**	**0.086**	**0.084**	0.083	0.093
					(-3.53)	(1.73)	(1.70)	(1.64)	(1.27)
MAX						**-0.0374**	**-0.037**	**-0.036**	-0.025
						(-3.57)	(-3.57)	(-3.33)	(-1.53)
MIN						**0.0568**	**0.056**	**0.055**	**0.089**
						(4.35)	(4.26)	(4.02)	(6.29)
Skew							0.000		
							(1.03)		
Industry Skew								**0.007**	
								(4.62)	
EISKEW									-0.002
									(-1.41)
N	954	954	954	954	954	954	954	954	276

Table 6. Double Sorts

All stocks are first sorted into quintiles, based on one of the control variables (REV, ILLIQ, MAX, IVOL, EISKEW, LT REV, Asset Growth, and Investment-to-Asset). Then within each quintile, stocks are sorted into quintiles based on TK/PW. The five TK/PW portfolios are averaged across different control variable quintiles. We report the 4-factor alpha of the five TK/PW portfolios. Panel A looks at TK and Panel B looks at PW, respectively, to capture the preferences of prospect theory-utility investors. Beta is calculated from past five years' monthly return, following Fama and French (1992). Size is the natural log of firm market capitalization at the end of the previous month. BM is the natural log of book-to-market ratio. When the book value of equity is missing in Compustat, we use the data from Davis, Fama and French (2002). The cases with negative book value are deleted. MOM is momentum which is defined as the cumulative return from month t-12 to t-1. ILLIQ is the Amihud (2002) illiquidity measure. REV is the short term reversal measure which is the lagged monthly return. LT REV is the long term reversal measure which is the cumulative return from month t-60 to t-13. IVOL is the standard deviation of the idiosyncratic return, calculated following Ang, Hodrick, Xing and Zhang (2006). MAX and MIN are the maximum and minimum daily return in month t-1, defined following Bali, Cakici and Whitelaw (2011). Skew is skewness of monthly return from month t-60 to t-1. Industry skew is calculated following Zhang (2006). For a given firm, its industry skew is the cross-sectional skewness of month t-1 for all the stocks in its Fama and French 48 industry. EISKEW is the expected idiosyncratic skewness measure, constructed following Boyer, Mitton and Vorkink (2010). The sample period covers from July 1931 to December 2010, except for EISKEW which is from January 1988.

Panel A. TK

TK	REV		ILLIQ		MAX		IVOL		EISKEW		LT REV		Skew		Industry skew	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Low 1	0.493	0.267	0.626	0.285	0.764	0.281	0.679	0.231	0.511	0.199	0.572	0.295	0.684	0.234	0.690	0.267
	(4.77)	(2.93)	(7.59)	(3.57)	(7.87)	(3.13)	(7.72)	(2.68)	(5.78)	(2.28)	(6.56)	(3.61)	(5.93)	(2.36)	(6.23)	(2.92)
2	0.186	0.261	0.262	0.061	0.201	0.048	0.273	0.047	0.212	0.146	0.249	0.169	0.167	0.119	0.202	0.229
	(3.87)	(3.77)	(5.37)	(1.27)	(4.00)	(0.78)	(5.60)	(0.76)	(4.71)	(2.63)	(5.09)	(3.08)	(3.36)	(1.77)	(4.25)	(3.61)
3	0.154	0.095	0.120	-0.051	0.086	-0.054	0.089	-0.091	0.111	0.045	0.147	0.074	0.100	0.072	0.114	0.114
	(3.75)	(1.92)	(2.99)	(-1.22)	(2.23)	(-1.06)	(2.25)	(-1.73)	(3.02)	(0.94)	(3.84)	(1.52)	(2.60)	(1.45)	(2.77)	(2.23)
4	0.105	0.091	0.049	-0.111	0.002	-0.136	0.025	-0.200	0.106	0.010	0.060	-0.008	0.035	-0.022	0.043	0.058
	(2.60)	(2.33)	(1.14)	(-2.77)	(0.05)	(-2.91)	(0.64)	(-4.29)	(2.71)	(0.23)	(1.60)	(-0.18)	(0.87)	(-0.52)	(1.12)	(1.47)
High 5	-0.007	-0.061	-0.127	-0.345	-0.118	-0.141	-0.135	-0.318	-0.079	-0.166	-0.100	-0.120	-0.056	-0.170	-0.100	-0.059
	(-0.14)	(-1.35)	(-2.59)	(-6.44)	(-2.55)	(-2.83)	(-2.91)	(-5.48)	(-1.75)	(-3.10)	(-2.05)	(-2.53)	(-1.30)	(-4.24)	(-2.10)	(-1.44)
1-5	**0.500**	**0.328**	**0.753**	**0.630**	**0.882**	**0.421**	**0.814**	**0.549**	**0.590**	**0.365**	**0.673**	**0.416**	**0.740**	**0.403**	**0.790**	**0.326**
	(4.34)	(2.94)	(7.94)	(6.23)	(8.15)	(3.79)	(8.34)	(4.83)	(5.91)	(3.25)	(7.02)	(4.11)	(5.77)	(3.47)	(6.38)	(2.95)

Panel B. PW

PW	REV		ILLIQ		MAX		IVOL		EISKEW		LT REV		Skew		Industry skew	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Low 1	0.470	0.286	0.550	0.305	0.508	0.117	0.529	0.140	0.491	0.251	0.551	0.243	0.589	0.229	0.590	0.267
	(6.68)	(4.44)	(8.54)	(4.90)	(7.60)	(1.83)	(8.24)	(1.95)	(7.43)	(3.48)	(8.45)	(4.14)	(7.49)	(3.47)	(8.06)	(4.13)
2	0.304	0.103	0.313	0.132	0.195	-0.023	0.253	-0.026	0.275	0.102	0.240	0.046	0.297	0.024	0.281	0.124
	(6.92)	(2.32)	(6.54)	(2.85)	(4.24)	(-0.48)	(5.44)	(-0.48)	(6.68)	(1.89)	(5.18)	(0.97)	(6.39)	(0.51)	(6.28)	(2.76)
3	0.196	0.021	0.155	-0.027	0.132	-0.109	0.143	-0.156	0.165	-0.031	0.160	-0.044	0.157	-0.084	0.168	-0.040
	(4.81)	(0.44)	(3.44)	(-0.63)	(3.50)	(-2.40)	(3.51)	(-3.23)	(3.99)	(-0.64)	(3.77)	(-0.92)	(3.63)	(-1.72)	(4.28)	(-0.91)
4	0.076	-0.134	0.086	-0.114	0.054	-0.207	0.051	-0.280	0.067	-0.122	0.024	-0.228	0.039	-0.192	0.037	-0.151
	(1.53)	(-2.39)	(1.81)	(-2.48)	(1.23)	(-3.51)	(1.13)	(-4.64)	(1.54)	(-2.16)	(0.49)	(-3.86)	(0.87)	(-3.53)	(0.78)	(-2.79)
High 5	-0.113	-0.287	-0.175	-0.481	0.462	-0.334	-0.047	-0.396	-0.137	-0.315	-0.046	-0.261	-0.151	-0.291	-0.131	-0.355
	(-1.44)	(-3.35)	(-2.47)	(-6.21)	(5.26)	(-4.31)	(-0.73)	(-4.96)	(-2.08)	(-4.25)	(-0.53)	(-2.95)	(-2.36)	(-4.15)	(-1.51)	(-4.16)
1-5	**0.583**	**0.573**	**0.725**	**0.786**	**0.354**	**0.451**	**0.576**	**0.537**	**0.629**	**0.565**	**0.597**	**0.504**	**0.739**	**0.520**	**0.721**	**0.621**
	(5.58)	(4.60)	(7.57)	(7.38)	(3.19)	(4.01)	(6.67)	(4.46)	(6.83)	(4.82)	(5.22)	(4.12)	(7.15)	(4.64)	(6.25)	(4.98)

Table 7. Limits to Arbitrage

All the stocks are first sorted into two groups based on Size, ILLIQ or IVOL. Size is defined as the market capitalization at the end of last month. ILLIQ is defined following Amihud (2002). IVOL is the idiosyncratic volatility measure, defined following Ang, Hodrick, Xing and Zhang (2006). For Size, we use the median of NYSE listed firms as the breakpoint but for ILLIQ and IVOL, we use the sample median as the breakpoint. Within each of the Size/ILLIQ/IVOL portfolios, the stocks are sorted into deciles based on TK/PW. We report the excess return, Carhart 4-factor alpha, and the 5-fator (Carhart 4-factor+Pastor and Stambaugh liquidity factor) alpha, in addition to the DGTW-adjusted return. DGTW-adjusted return is size, Book-to-Market and Momentum adjusted, following DGTW (1997).

		Size				ILLIQ				IVOL			
		Small		Large		Illiquid		Liquid		High		Low	
		EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
TK	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**
		(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-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**
		(7.35)	(3.70)	(4.12)	(3.93)	(7.83)	(3.59)	(4.84)	(4.04)	(8.23)	(3.75)	(2.87)	(3.02)
	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**
		(5.74)	(2.72)	(2.75)	(2.35)	(6.19)	(2.04)	(3.25)	(2.52)	(6.61)	(2.58)	(1.40)	(1.89)
	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**
		(7.70)	(2.98)	(1.70)	(2.57)	(8.17)	(3.47)	(2.41)	(2.60)	(8.57)	(3.34)	(1.77)	(2.65)
PW	Excess return	**0.642**	**0.575**	0.117	-0.023	**0.888**	**0.901**	0.177	0.01	**0.808**	**0.586**	-0.119	-0.162
		(3.39)	(2.77)	(0.62)	(-0.12)	(4.58)	(3.92)	(1.02)	-0.05	(4.05)	(2.14)	(-0.84)	(-0.88)
	4-factor	**1.131**	**1.113**	**0.756**	**0.588**	**1.31**	**1.265**	**0.798**	**0.642**	**1.249**	**1.209**	**0.379**	**0.396**
		(6.70)	(6.43)	(5.11)	(3.83)	(7.30)	(6.49)	(6.09)	(4.26)	(6.80)	(5.00)	(3.15)	(2.54)
	5-factor	**0.973**	**0.814**	**0.319**	0.027	**1.267**	**1.058**	**0.434**	0.151	**1.303**	**1.083**	-0.011	-0.114
		(4.96)	(3.92)	(1.73)	(0.14)	(5.58)	(4.27)	(2.83)	(0.75)	(5.71)	(3.29)	(-0.09)	(-0.55)
	DGTW	**0.511**	**0.474**	**0.194**	0.051	**0.673**	**0.724**	**0.183**	0.071	**0.694**	**0.553**	**-0.063**	-0.059
		(3.80)	(2.99)	(1.80)	(0.50)	(4.67)	(4.18)	(1.88)	(0.69)	(4.88)	(2.92)	(-0.73)	(-0.57)

Table 8. International Equity Returns: Average returns and alphas on the long-short portfolios, country-wise

All common stocks listed on the major exchange(s) in each country are included. For Brazil, the preferred stocks are also included, as they are the most popular stock type in Brazil. Cross listed stocks are only included in its home country sample. If a stock has multiple share class, only the primary class is included in the sample. For example, we only include A-shares in the Chinese stock market and the bearer-shares in the Swiss stock market. All the active stocks and dead stocks are included to alleviate survivorship bias. To filter out suspicious stock returns, following the literature, we set the returns that are larger (less) than 100% (-95%) equal to 100% (-95%). To be included into the sample, we require that one stock to have no missing monthly return in the past 5 years. We use the value weighted market return as the reference. The results are quite similar if we use cash as reference or U.S. one month treasury rate as the reference for all countries/regions. In order to have enough stocks for each country, we also require that for a given month, the number of stocks with valid TK/PW measure to be not less than 50. The last procedure ensures that for each quintile portfolio, we have at least 10 stocks in it. The global factor model and the international factor model are constructed following Hou, Karolyi and Kho (2011). The global factor model is analogous to the Carhart four-factor model in U.S., but is constructed using the universe of stocks available in all countries we look at. The value factor is constructed based on price to cash flow ratio instead of price to book ratio. The international factor model contains the global four factors and the local four factors. The positive and significant (p-value<10%) cases are highlighted in bold (red).

		long short				global factor adjustment				international factor adjustment				local factor adjustment			
Country/Region	# of Months	TK		PW		TK		PW		TK		PW		TK		PW	
		EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Argentina	148	**1.796**	1.078	**1.291**	0.029	**1.703**	1.337	**0.919**	0.162	**1.870**	**1.869**	**0.904**	0.406	**1.970**	**1.687**	**1.277**	0.350
		(3.07)	(1.09)	**(2.60)**	(0.03)	**(2.81)**	(1.29)	**(1.87)**	(0.15)	**(3.19)**	**(2.14)**	**(1.88)**	(0.39)	**(3.44)**	**(1.99)**	**(2.63)**	(0.35)
Australia	300	**1.312**	-0.929	0.379	-0.141	**1.741**	-0.507	0.364	-0.165	**2.298**	-0.221	0.442	-0.233	**2.240**	-0.344	0.448	-0.270
		(3.42)	(-1.86)	(1.09)	(-0.32)	**(4.44)**	(-0.98)	(1.01)	(-0.37)	**(6.94)**	(-0.44)	(1.34)	(-0.53)	**(6.86)**	(-0.70)	(1.40)	(-0.62)
Austria	204	0.141	-0.200	**0.802**	0.256	0.337	0.354	**1.006**	0.567	0.476	0.703	**1.182**	0.549	0.474	0.473	**1.169**	0.474
		(0.36)	(-0.34)	**(2.09)**	(0.50)	(0.83)	(0.60)	**(2.51)**	(1.07)	(1.29)	(1.25)	**(3.11)**	(1.05)	(1.34)	(0.87)	**(3.19)**	(0.94)
Bangladesh	167	**1.620**	1.415	**1.216**	**1.561**	**1.710**	**1.797**	**1.249**	**1.920**	**3.180**	0.507	2.207	1.298	**3.059**	2.409	2.806	3.246
		(2.01)	(1.49)	**(1.71)**	**(1.69)**	**(2.00)**	**(1.79)**	**(1.66)**	**(1.96)**	**(2.59)**	(0.14)	(1.04)	(0.77)	**(2.45)**	(0.77)	(1.37)	(1.27)
Belgium	239	0.028	0.049	0.045	0.155	0.415	0.441	0.285	0.382	**0.786**	0.668	0.379	0.423	**0.725**	0.619	0.353	0.477
		(0.09)	(0.10)	(0.16)	(0.32)	(1.38)	(0.99)	(1.07)	(0.79)	**(2.85)**	(1.53)	(1.46)	(0.90)	**(2.65)**	(1.40)	(1.38)	(1.03)
Brazil	109	-0.014	-1.044	-0.002	-0.809	0.351	-0.771	0.182	-0.805	0.903	0.204	0.428	-0.521	0.664	0.162	0.348	-0.506
		(-0.02)	(-1.03)	(0.00)	(-1.17)	(0.40)	(-0.70)	(0.24)	(-1.08)	(0.99)	(0.19)	(0.54)	(-0.68)	(0.78)	(0.16)	(0.47)	(-0.71)
Canada	300	**1.514**	-0.039	-0.088	0.415	**1.991**	0.484	-0.047	0.328	**2.088**	0.523	0.192	**0.693**	**1.961**	0.369	0.199	**0.791**
		(4.35)	(-0.09)	(-0.28)	(0.96)	**(5.66)**	(1.14)	(-0.14)	(0.75)	**(6.63)**	(1.31)	(0.70)	**(1.89)**	**(6.35)**	(0.94)	(0.75)	**(2.17)**
Chile	197	-0.075	0.357	-0.442	-0.400	0.167	0.636	-0.385	-0.068	**0.451**	0.721	-0.082	0.121	0.193	0.447	-0.150	-0.255
		(-0.29)	(0.56)	(-1.75)	(-0.92)	(0.62)	(0.93)	(-1.44)	(-0.15)	**(1.71)**	(1.07)	(-0.30)	(0.26)	(0.75)	(0.71)	(-0.59)	(-0.57)
China	156	**1.138**	**1.001**	**0.915**	**1.009**	**1.144**	**1.093**	**0.897**	**1.058**	**1.318**	**1.178**	**1.017**	**1.126**	**1.460**	**1.283**	**1.122**	**1.221**
		(2.27)	**(1.82)**	**(2.51)**	**(2.14)**	**(2.16)**	**(1.88)**	**(2.34)**	**(2.12)**	**(2.89)**	**(2.66)**	**(2.86)**	**(2.69)**	**(3.37)**	**(3.05)**	**(3.33)**	**(3.08)**
Cyprus	67	**3.778**	0.024	**2.975**	**3.643**	**3.690**	-1.092	**2.849**	**3.417**	**6.067**	-0.126	**2.303**	**2.702**	**5.298**	1.847	**2.503**	**3.114**
		(3.69)	(0.02)	**(3.74)**	**(2.90)**	**(3.42)**	(-0.81)	**(3.49)**	**(2.96)**	**(3.59)**	(-0.10)	**(2.12)**	**(2.00)**	**(4.00)**	(1.57)	**(2.90)**	**(2.56)**
Czech Republic	75	**1.545**	1.017	0.308	**2.886**	**1.477**	0.860	0.406	**2.909**	1.072	1.403	0.415	**3.619**	1.034	1.482	0.388	**3.845**
		(2.08)	(0.86)	(0.38)	**(2.25)**	**(1.78)**	(0.68)	(0.46)	**(2.05)**	(1.26)	(1.33)	(0.50)	**(2.82)**	(1.30)	(1.48)	(0.48)	**(3.05)**

Denmark	212	0.234	0.505	**0.737**	**0.832**	0.539	0.830	**0.797**	**0.812**	**0.904**	**1.250**	**1.056**	**1.094**	**0.847**	**1.110**	**1.116**	**1.234**
		(0.63)	(1.01)	**(2.64)**	**(1.83)**	(1.45)	(1.63)	**(2.73)**	**(1.76)**	**(2.85)**	**(2.71)**	**(3.78)**	**(2.41)**	**(2.75)**	**(2.46)**	**(4.10)**	**(2.74)**
Egypt	111	**1.647**	0.799	**1.115**	0.948	**1.698**	1.237	**1.473**	1.307	**1.837**	1.426	**1.888**	**1.982**	**1.847**	1.110	**1.714**	**1.785**
		(2.62)	(0.97)	**(1.75)**	(1.13)	**(2.53)**	(1.43)	**(2.25)**	(1.49)	**(2.94)**	(1.64)	**(3.07)**	**(2.32)**	**(3.11)**	(1.34)	**(2.85)**	**(2.17)**
Finland	139	0.356	0.518	0.459	0.281	0.677	-0.359	0.241	-0.856	**0.750**	-0.160	0.143	-0.836	0.657	-0.324	0.124	-0.861
		(0.76)	(0.56)	(1.03)	(0.27)	(1.51)	(-0.42)	(0.55)	(-0.86)	**(1.66)**	(-0.29)	(0.33)	(-0.99)	(1.48)	(-0.58)	(0.29)	(-1.04)
France	300	**0.866**	0.476	**0.421**	**1.019**	**1.107**	**0.950**	**0.575**	**0.987**	**1.280**	**0.918**	**0.605**	**1.089**	**1.275**	0.698	**0.650**	**1.220**
		(3.54)	(1.05)	**(1.86)**	**(2.77)**	**(4.49)**	**(2.08)**	**(2.50)**	**(2.60)**	**(5.91)**	**(2.06)**	**(2.74)**	**(2.97)**	**(6.02)**	(1.60)	**(3.02)**	**(3.39)**
Germany	300	0.003	-0.270	**0.619**	0.568	0.300	0.091	**0.744**	**0.864**	0.415	0.174	**0.792**	**0.929**	0.376	0.044	**0.780**	**0.812**
		(0.01)	(-0.70)	**(3.32)**	(1.19)	(1.11)	(0.23)	**(3.84)**	**(1.76)**	(1.61)	(0.46)	**(4.13)**	**(1.87)**	(1.51)	(0.12)	**(4.19)**	**(1.65)**
Greece	215	**1.687**	**1.335**	**1.359**	**1.550**	**2.016**	**1.492**	**1.412**	**1.524**	**1.649**	**1.126**	**1.356**	**1.282**	**1.516**	**1.133**	**1.369**	**1.392**
		(2.98)	**(2.01)**	**(3.20)**	**(3.27)**	**(3.40)**	**(2.13)**	**(3.15)**	**(3.06)**	**(3.63)**	**(1.94)**	**(3.31)**	**(2.69)**	**(3.47)**	**(2.04)**	**(3.48)**	**(3.03)**
Hong Kong	300	**1.090**	-0.277	**1.026**	**1.039**	**1.215**	-0.220	**0.989**	**0.752**	**1.969**	**0.787**	**0.958**	**0.733**	**1.858**	**0.722**	**0.951**	**0.927**
		(2.96)	(-0.64)	**(3.59)**	**(2.45)**	**(3.13)**	(-0.48)	**(3.33)**	**(1.74)**	**(5.84)**	**(2.04)**	**(3.72)**	**(1.88)**	**(5.83)**	**(1.98)**	**(3.89)**	**(2.50)**
India	191	**1.661**	0.111	0.585	0.291	**1.630**	-0.353	0.261	-0.582	**1.988**	0.215	**0.784**	0.379	**1.782**	0.549	**0.978**	0.820
		(2.90)	(0.19)	(1.43)	(0.39)	**(2.67)**	(-0.57)	(0.63)	(-0.76)	**(3.81)**	(0.41)	**(2.36)**	(0.64)	**(3.59)**	(1.10)	**(2.98)**	(1.44)
Indonesia	188	**3.308**	**3.921**	**0.953**	0.468	**3.156**	**2.963**	**1.000**	0.287	**3.045**	1.856	**1.024**	0.839	**3.171**	**2.918**	0.717	0.275
		(4.72)	**(3.31)**	**(1.72)**	(0.40)	**(4.07)**	**(2.32)**	**(1.67)**	(0.23)	**(3.89)**	(1.50)	**(1.84)**	(0.69)	**(4.54)**	**(2.55)**	(1.38)	(0.25)
Ireland	82	0.988	-0.353	0.314	0.726	1.284	0.036	-0.108	0.988	**1.751**	0.589	0.148	1.061	**1.816**	0.528	0.540	0.980
		(1.24)	(-0.27)	(0.38)	(0.75)	(1.46)	(0.02)	(-0.12)	(0.93)	**(2.12)**	(0.43)	(0.16)	(1.02)	**(2.28)**	(0.40)	(0.61)	(0.98)
Israel	239	**0.998**	-0.113	**0.919**	1.048	**1.188**	0.163	**1.091**	1.278	**1.325**	0.469	**0.920**	0.448	**1.323**	0.335	**0.948**	0.622
		(3.28)	(-0.13)	**(3.48)**	(1.21)	**(3.76)**	(0.17)	**(3.99)**	(1.40)	**(4.68)**	(0.52)	**(3.96)**	(0.52)	**(4.86)**	(0.39)	**(4.27)**	(0.76)
Italy	300	0.206	0.034	**0.434**	-0.005	0.329	0.223	**0.446**	-0.010	**0.580**	0.340	**0.620**	0.274	**0.616**	0.353	**0.706**	0.359
		(0.78)	(0.10)	**(1.89)**	(-0.01)	(1.19)	(0.62)	**(1.85)**	(-0.03)	**(2.50)**	(1.01)	**(2.81)**	(0.76)	**(2.75)**	(1.06)	**(3.31)**	(1.03)
Japan	300	**1.142**	**0.813**	**1.123**	**1.022**	**1.574**	**1.287**	**1.087**	**1.149**	**0.942**	0.483	**1.067**	**0.809**	**0.900**	0.466	**1.066**	**0.778**
		(4.11)	**(2.05)**	**(6.23)**	**(2.93)**	**(5.80)**	**(3.27)**	**(5.86)**	**(3.27)**	**(4.94)**	(1.50)	**(6.59)**	**(2.56)**	**(4.99)**	(1.53)	**(6.99)**	**(2.63)**
Malaysia	239	0.669	0.362	**1.110**	**0.874**	**1.093**	**0.935**	**0.817**	**0.661**	**0.880**	0.583	**0.973**	**0.753**	**0.801**	0.385	**1.186**	**0.925**
		(1.60)	(0.68)	**(3.81)**	**(2.42)**	**(2.57)**	**(1.74)**	**(2.75)**	**(1.78)**	**(2.72)**	(1.32)	**(3.54)**	**(2.12)**	**(2.60)**	(0.90)	**(4.47)**	**(2.71)**
Mexico	174	-0.820	-0.554	-0.579	-0.331	-0.587	-0.638	-0.294	-0.275	-0.313	-0.362	-0.055	0.174	-0.548	-0.277	-0.300	0.148
		(-1.95)	(-0.83)	(-1.52)	(-0.50)	(-1.39)	(-0.91)	(-0.75)	(-0.40)	(-0.78)	(-0.52)	(-0.15)	(0.27)	(-1.37)	(-0.42)	(-0.86)	(0.24)
Netherlands	300	-0.782	0.335	-0.559	0.212	-0.367	**1.127**	-0.403	0.327	-0.078	**1.487**	-0.134	0.734	-0.045	**1.332**	-0.060	0.794
		(-2.30)	(0.70)	(-2.11)	(0.44)	(-1.05)	**(2.36)**	(-1.46)	(0.64)	(-0.25)	**(3.24)**	(-0.50)	(1.42)	(-0.15)	**(2.94)**	(-0.23)	(1.55)
New Zealand	215	0.191	-0.282	**1.088**	-0.079	0.505	-0.169	**1.002**	0.304	0.716	0.399	**1.086**	0.636	0.515	0.277	**1.070**	0.292
		(0.36)	(-0.47)	**(2.20)**	(-0.10)	(0.92)	(-0.27)	**(1.93)**	(0.39)	(1.30)	(0.65)	**(2.10)**	(0.80)	(0.97)	(0.46)	**(2.13)**	(0.37)
Norway	275	0.688	0.527	0.373	0.224	**1.377**	**1.400**	0.497	0.403	**1.369**	**1.353**	**0.665**	0.659	**1.099**	**0.891**	**0.694**	0.556
		(1.63)	(1.03)	(0.98)	(0.52)	**(3.26)**	**(2.77)**	(1.25)	(0.88)	**(3.57)**	**(2.78)**	**(1.67)**	(1.45)	**(2.95)**	**(1.85)**	**(1.81)**	(1.27)
Pakistan	161	**2.060**	**1.203**	**1.103**	**1.445**	**2.268**	**1.466**	**1.107**	**1.625**	**2.499**	**1.682**	**1.076**	**1.819**	**2.207**	**1.341**	**1.116**	**1.631**
		(3.85)	**(1.88)**	**(2.62)**	**(2.52)**	**(4.04)**	**(2.18)**	**(2.47)**	**(2.68)**	**(4.46)**	**(2.60)**	**(2.55)**	**(3.15)**	**(4.12)**	**(2.19)**	**(2.83)**	**(3.02)**
Peru	165	**1.174**	-0.574	-0.054	-0.096	**1.289**	-0.821	0.124	0.435	**1.485**	-0.739	0.483	0.895	**1.401**	-0.433	0.299	0.374
		(2.16)	(-0.45)	(-0.09)	(-0.11)	**(2.27)**	(-0.61)	(0.20)	(0.50)	**(2.81)**	(-0.61)	(0.85)	(1.05)	**(2.76)**	(-0.38)	(0.55)	(0.45)
Philippines	192	**2.727**	**1.217**	**1.347**	**1.063**	**3.076**	**1.692**	**1.208**	**1.379**	**3.071**	**1.835**	**1.401**	**1.384**	**2.751**	**1.531**	**1.398**	**1.219**
		(5.37)	**(1.85)**	**(2.54)**	**(1.72)**	**(5.81)**	**(2.45)**	**(2.14)**	**(2.10)**	**(5.68)**	**(2.69)**	**(2.54)**	**(2.12)**	**(5.30)**	**(2.38)**	**(2.70)**	**(1.99)**
Poland	81	**3.246**	**4.796**	**2.595**	**2.871**	**3.283**	**4.313**	**2.287**	**3.333**	**2.180**	**3.646**	**2.305**	**3.774**	**2.305**	**3.920**	**2.684**	**3.575**
		(2.90)	**(3.15)**	**(2.49)**	**(2.09)**	**(2.73)**	**(2.66)**	**(2.03)**	**(2.24)**	**(1.83)**	**(2.13)**	**(1.95)**	**(2.40)**	**(2.04)**	**(2.41)**	**(2.39)**	**(2.42)**
Portugal	202	**2.806**	0.860	**1.107**	0.694	**2.608**	0.868	**1.368**	0.592	**2.918**	0.984	**1.322**	0.564	**3.085**	1.013	**1.302**	1.014
		(4.14)	(1.06)	**(1.92)**	(0.96)	**(3.64)**	(1.01)	**(2.29)**	(0.79)	**(4.17)**	(1.16)	**(2.29)**	(0.83)	**(4.58)**	(1.24)	**(2.33)**	(1.53)
Romania	95	-0.019	0.600	-0.335	-0.585	1.032	1.905	0.500	0.113	**1.887**	3.168	0.625	1.149	1.469	2.496	0.383	0.792
		(-0.02)	(0.42)	(-0.46)	(-0.45)	(1.21)	(1.32)	(0.72)	(0.09)	**(1.86)**	(1.45)	(0.72)	(0.72)	(1.32)	(1.15)	(0.37)	(0.47)

Singapore	311	**1.017**	0.678	**0.783**	0.160	**1.120**	**0.758**	**0.600**	-0.290	**1.028**	**0.732**	**0.943**	-0.065	**1.144**	**0.898**	**1.146**	0.476
		(2.56)	(1.53)	**(2.61)**	(0.35)	**(2.71)**	**(1.67)**	**(1.93)**	(-0.62)	**(2.69)**	**(1.79)**	**(3.31)**	(-0.14)	**(3.16)**	**(2.30)**	**(4.19)**	(1.09)
South Africa	300	**1.563**	0.735	**1.135**	**0.852**	**1.740**	**1.021**	**1.453**	**1.172**	**2.275**	**1.667**	**1.598**	**1.654**	**2.222**	**1.537**	**1.410**	**1.556**
		(4.31)	(1.48)	**(3.43)**	**(1.83)**	**(4.55)**	**(1.96)**	**(4.20)**	**(2.41)**	**(6.26)**	**(3.47)**	**(4.59)**	**(3.44)**	**(6.37)**	**(3.32)**	**(4.19)**	**(3.37)**
South Korea	257	**1.039**	0.016	**1.692**	0.391	**1.227**	0.426	**1.531**	0.314	**0.985**	0.480	**1.370**	0.163	**1.126**	0.129	**1.678**	0.338
		(2.24)	(0.02)	**(4.71)**	(0.71)	**(2.53)**	(0.60)	**(4.07)**	(0.54)	**(2.77)**	(0.70)	**(3.83)**	(0.32)	**(3.39)**	(0.20)	**(4.97)**	(0.71)
Spain	225	0.336	0.265	**0.503**	**0.874**	**0.754**	0.636	**0.602**	**1.161**	**0.741**	**0.807**	**0.605**	**0.991**	**0.564**	0.603	**0.611**	**0.895**
		(0.94)	(0.57)	**(1.81)**	**(1.70)**	**(2.11)**	(1.35)	**(2.10)**	**(2.24)**	**(2.41)**	**(1.92)**	**(2.12)**	**(1.92)**	**(1.88)**	(1.48)	**(2.21)**	**(1.79)**
Sri Lanka	222	**1.922**	**1.359**	**1.090**	**1.104**	**2.032**	**1.624**	**1.047**	**1.181**	**1.869**	0.226	**1.296**	**1.963**	**1.928**	-0.001	**1.404**	**2.120**
		(5.88)	**(3.06)**	**(3.90)**	**(2.63)**	**(5.96)**	**(3.54)**	**(3.56)**	**(2.69)**	**(2.96)**	(0.25)	**(2.18)**	**(2.03)**	**(2.96)**	(0.00)	**(2.49)**	**(2.31)**
Sweden	242	-0.979	-0.533	-0.004	0.150	-0.731	-0.264	-0.114	-0.032	-0.416	0.123	-0.116	-0.044	-0.290	0.232	-0.075	0.029
		(-2.10)	(-0.76)	(-0.01)	(0.28)	(-1.51)	(-0.37)	(-0.27)	(-0.06)	(-0.95)	(0.19)	(-0.31)	(-0.08)	(-0.70)	(0.37)	(-0.21)	(0.06)
Switzerland	300	-0.065	-0.026	0.040	-0.175	0.305	0.573	0.056	0.048	**0.743**	**0.855**	**0.430**	0.435	**0.659**	0.649	**0.564**	0.486
		(-0.24)	(-0.05)	(0.18)	(-0.46)	(1.18)	(1.22)	(0.25)	(0.12)	**(3.39)**	**(1.89)**	**(1.97)**	(1.12)	**(3.07)**	(1.46)	**(2.63)**	(1.28)
Taiwan	209	0.309	0.282	0.531	0.242	-0.032	-0.129	0.334	-0.224	**0.841**	**0.879**	**0.761**	0.558	**1.116**	**1.164**	**0.903**	**0.857**
		(0.58)	(0.49)	(1.33)	(0.45)	(-0.06)	(-0.22)	(0.80)	(-0.41)	**(1.85)**	**(1.93)**	**(2.13)**	(1.24)	**(2.58)**	**(2.69)**	**(2.69)**	**(2.02)**
Thailand	263	**0.880**	0.053	**1.133**	0.615	**1.171**	0.135	**1.099**	0.425	**1.417**	0.377	**1.212**	0.531	**1.195**	0.352	**1.225**	0.737
		(2.19)	(0.09)	**(2.56)**	(1.12)	**(2.81)**	(0.23)	**(2.38)**	(0.74)	**(3.67)**	(0.69)	**(2.87)**	(0.97)	**(3.22)**	(0.67)	**(3.05)**	(1.41)
Turkey	215	**2.020**	1.164	**2.241**	**1.631**	**2.059**	**1.343**	**2.363**	**1.680**	**1.795**	**1.744**	**1.961**	**1.688**	**1.704**	**1.367**	**1.854**	**1.479**
		(3.67)	(1.56)	**(5.31)**	**(2.20)**	**(3.55)**	**(1.70)**	**(5.32)**	**(2.15)**	**(4.25)**	**(2.79)**	**(4.87)**	**(2.37)**	**(4.27)**	**(2.31)**	**(4.90)**	**(2.21)**
UK	300	-0.146	-0.009	0.268	0.538	0.252	0.665	0.320	0.559	**0.820**	**1.545**	**0.494**	**0.891**	**0.793**	**1.552**	**0.530**	**1.030**
		(-0.67)	(-0.02)	(1.40)	(1.42)	(1.20)	(1.49)	(1.63)	(1.43)	**(4.83)**	**(3.98)**	**(2.84)**	**(2.37)**	**(4.72)**	**(4.01)**	**(3.07)**	**(2.74)**

Positive and significant	**26**	**8**	**28**	**17**	**29**	**16**	**28**	**18**	**38**	**18**	**32**	**20**	**35**	**16**	**31**	**21**
Positive and insignificant	**12**	**24**	**10**	**20**	**13**	**19**	**12**	**18**	**5**	**23**	**10**	**21**	**8**	**23**	**11**	**21**
Negative and significant	**3**	**1**	**2**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Negative and insignificant	**5**	**13**	**6**	**9**	**4**	**11**	**6**	**10**	**3**	**5**	**4**	**5**	**3**	**7**	**4**	**4**
Percent correct sign	**83%**	**70%**	**83%**	**80%**	**91%**	**76%**	**87%**	**78%**	**93%**	**89%**	**91%**	**89%**	**93%**	**85%**	**91%**	**91%**

Table 9. Can TK/PW help explain the value or size premium? Conditional double sorts

This table reports the results of using TK/PW to explain the value premium (Panel A) and size premium (Panel B). The first sub-panel reports the portfolio returns of single sort analysis of size or value, with the requirement that TK/PW is available. The second sub-panel reports the portfolio returns of single sort analysis of size or value, without the requirement that TK/PW is available. The third and fourth sub-panel reports the portfolio returns of double sort analysis, by TK and PW, respectively. In the third (fourth) sub-panel, we first sort stocks into TK (PW) quintiles, and then within each TK (PW) quintile, we sort all stocks into quintiles based on size (BM). We report the long short TK/PW strategy portfolio excess return, three factor adjusted alphas (mktrf, umd, and smb for Panel A, and mktrf, umd, and hml for Panel B), Carhart four-factor alpha, characteristics adjusted abnormal returns. DGTW benchmark returns are constructed following DGTW (1997). We adjust the raw return by assigning stocks based on BM and momentum (Panel A) or size, momentum (Panel B). Besides, we also report the size, momentum and BM adjusted excess returns. The sample period covers from July 1931 to December 2010.

Panel A. Double sorts: The Value Premium

	Excess return		Beta+MOM+Size alpha		4 factor alpha		Size, MOM adjusted		DGTW	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Panel 1. Single sort										
	1.103	0.484	1.452	0.731	0.882	0.058	0.792	0.234	0.464	0.111
	(6.00)	(2.50)	(8.86)	(4.30)	(7.00)	(0.50)	(5.96)	(1.69)	(4.92)	(1.27)
Panel 2. Single sort: without requiring the availability of PW/TK										
	1.368	0.498	1.827	0.791	1.261	0.091	0.986	0.228	0.614	0.072
	(6.97)	(2.61)	(10.56)	(4.69)	(9.08)	(0.85)	(6.60)	(1.70)	(5.67)	(0.89)
Panel 3: double sort by TK										
	0.719	0.255	0.970	0.442	0.487	-0.159	0.483	0.063	0.167	-0.059
	(5.22)	(1.65)	(7.63)	(2.97)	(5.39)	(-1.62)	(4.15)	(0.49)	(2.34)	(-0.76)
Panel 4: double sort by PW										
	0.946	0.507	1.123	0.653	0.693	0.058	0.654	0.274	0.348	0.140
	(5.77)	(2.84)	(7.76)	(4.23)	(5.66)	(0.54)	(5.95)	(2.20)	(4.06)	(1.67)

Panel B. Double sorts: The Size Premium

	Excess return		Beta+MOM+BM alpha		4 factor alpha		BM, MOM adjusted		DGTW	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Panel 1. Single sort										
	0.631	0.502	0.659	0.414	0.332	0.088	0.512	0.354	0.226	0.078
	(3.26)	(2.79)	(3.39)	(2.35)	(3.37)	(1.61)	(3.50)	(2.75)	(4.13)	(3.22)
Panel 2. Single sort: without requiring the availability of PW/TK										
	0.502	0.307	0.613	0.304	0.299	-0.022	0.476	0.268	0.205	0.003
	(2.55)	(1.68)	(3.09)	(1.69)	(2.58)	(-0.32)	(3.05)	(1.98)	(3.29)	(0.15)
Panel 3: double sort by TK										
	0.451	0.345	0.417	0.243	0.175	-0.006	0.343	0.228	0.096	-0.027
	(3.00)	(2.42)	(2.65)	(1.64)	(1.81)	(-0.09)	(2.60)	(1.99)	(1.43)	(-0.51)
Panel 4: double sort by PW										
	0.696	0.522	0.730	0.482	0.442	0.194	0.588	0.394	0.337	0.132
	(3.86)	(3.15)	(4.04)	(2.96)	(4.24)	(2.82)	(4.22)	(3.27)	(5.12)	(2.92)

Table 10. Can TK/PW help explain the value or size premium? Fama-MacBeth regressions

This table shows the results of Fama-MacBeth regressions analysis on whether PW/TK can help explain the size effect and value effect. Panel A looks at TK and Panel B looks at PW, respectively, to capture the preferences of prospect theory-utility investors. The details of their construction can be found in the text. Beta is calculated from past five years' monthly return, following Fama and French (1992). Size is the natural log of firm market capitalization at the end of last month. BM is the natural log of book-to-market ratio. When the book value of equity is missing in Compustat, we use the data from Davis, Fama and French (2002). The cases with negative book value are deleted. MOM is momentum which is defined as the cumulative return from month t-12 to t-1. ILLIQ is the Amihud (2002) illiquidity measure. REV is the short term reversal measure which is the lagged monthly return. LT REV is the long term reversal measure which is the cumulative return from month t-60 to t-13. IVOL is the standard deviation of the idiosyncratic return, calculated following Ang, Hodrick, Xing and Zhang (2006). MAX and MIN are the maximum and minimum daily return in month t-1, defined following Bali, Cakici and Whitelaw (2011). Skew is skewness of monthly return from month t-60 to t-1. The sample period covers from July 1931 to December 2010. All the t-statistics are Newey-West adjusted with 12 lags.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
TK		**-0.1076**			**-0.1006**			**-0.05**			**-0.0431**			**-0.0434**	
		(-4.94)			(-4.58)			(-2.6)			(-2.16)			(-2.18)	
PW			**-0.1138**			**-0.12**			**-0.059**			**-0.0361**			**-0.0381**
			(-6.54)			(-6.77)			(-4.02)			(-2.16)			(-2.29)
Size	**-0.0018**	**-0.0013**	**-0.0022**	**-0.0013**	**-0.0009**	**-0.0018**	**-0.001**	**-0.0008**	**-0.0012**	**-0.0011**	**-0.001**	**-0.0012**	**-0.001**	**-0.0009**	**-0.0012**
	(-4.52)	(-4.07)	(-5.39)	(-3.64)	(-3.11)	(-4.56)	(-2.62)	(-2.44)	(-3.27)	(-3.5)	(-3.38)	(-3.98)	(-3.41)	(-3.24)	(-3.88)
BM	**0.0025**	**0.0015**	**0.0016**	**0.0022**	**0.0013**	**0.0012**	**0.0023**	**0.0018**	**0.0017**	**0.0015**	**0.0013**	**0.0013**	**0.0015**	**0.0013**	**0.0013**
	(4.37)	(2.67)	(2.85)	(4.01)	(3.29)	(2.31)	(3.90)	(3.06)	(2.96)	(2.65)	(2.26)	(2.26)	(2.66)	(2.29)	(2.28)
Beta	0.0005	0.0013	**0.0024**	0.0006	0.0015	**0.0028**	0.0014	0.0019	**0.0025**	**0.002**	**0.0024**	**0.0026**	**0.0021**	**0.0024**	**0.0027**
	(0.49)	(1.14)	(2.18)	(0.61)	(1.28)	(2.44)	(1.11)	(1.40)	(1.88)	(1.79)	(1.99)	(2.19)	(1.88)	(2.07)	(2.32)
MOM	**0.0079**	**0.01**	**0.0101**	**0.0083**	**0.0102**	**0.0105**	**0.0081**	**0.0088**	**0.0091**	**0.0075**	**0.0085**	**0.0082**	**0.0076**	**0.0085**	**0.0084**
	(5.55)	(7.99)	(7.36)	(5.83)	(8.26)	(7.75)	(5.41)	(6.73)	(6.05)	(4.94)	(6.39)	(5.17)	(4.99)	(6.47)	(5.35)
ILLIQ				180.37	146.83	**233.31**	**297.41**	**285.53**	**329.84**	**586.72**	**596.83**	**594.02**	**612.04**	**621.95**	**622.26**
				(1.51)	(1.22)	(1.98)	(2.41)	(2.37)	(2.69)	(4.76)	(4.90)	(4.8)	(4.93)	(5.08)	(4.99)
REV							**-0.0794**	**-0.0793**	**-0.0787**	**-0.079**	**-0.0785**	**-0.0789**	**-0.0816**	**-0.0812**	**-0.0814**
							(-16.05)	(-16.28)	(-15.84)	(-15.02)	(-15.2)	(-14.76)	(-16.36)	(-16.47)	(-16.08)
LT REV										**-0.0012**	**-0.0004**	**-0.0009**	**-0.0012**	**-0.0004**	**-0.0009**
										(-2.59)	(-1.40)	(-2.24)	(-2.56)	(-1.31)	(-2.16)
IVOL										**-0.129**	**-0.1384**	**-0.122**	**0.0737**	**0.068**	**0.086**
										(-3.7)	(-4.27)	(-3.53)	(1.48)	(1.43)	(1.73)
MAX													**-0.0359**	**-0.0364**	**-0.0374**
													(-3.39)	(-3.45)	(-3.57)
MIN													**0.056**	**0.0585**	**0.0568**
													(4.30)	(4.50)	(4.35)
N	954	954	954	954	954	954	954	954	954	954	954	954	954	954	954

Table 11. Characteristics of PW/TK portfolios

This table presents the results on decile portfolios sorted based on TK (Panel A) and PW (Panel B). For each month, all the stocks are sorted into deciles based on PW/TK. Reported are the average value of firm characteristics for each decile. STD is the standard deviation of the past five years' monthly returns. Definitions of other variables can be found in the Appendix A5 or Table 1. The sample covers July 1931 to December 2010.

Panel A. TK

Portfolios	TK	Beta	Size	BM	MOM	REV	AMIHUD	LT REV	IVOL	MAX	MIN	Skew	EISKEW	Industry Skew	STD
Low TK	-0.124	1.274	9.783	0.133	-0.122	-0.017	15.122	-0.408	0.047	0.122	-0.098	0.554	0.980	0.007	0.175
2	-0.093	1.221	10.600	-0.087	0.025	0.004	5.039	-0.069	0.033	0.088	-0.071	0.571	0.741	0.011	0.153
3	-0.079	1.156	11.029	-0.193	0.081	0.009	3.000	0.161	0.028	0.075	-0.061	0.570	0.637	0.014	0.140
4	-0.069	1.098	11.373	-0.275	0.113	0.012	2.044	0.370	0.025	0.066	-0.054	0.551	0.550	0.014	0.129
5	-0.060	1.049	11.653	-0.347	0.139	0.014	1.425	0.572	0.022	0.060	-0.049	0.545	0.488	0.014	0.120
6	-0.053	1.008	11.901	-0.402	0.166	0.016	1.050	0.769	0.020	0.055	-0.045	0.537	0.438	0.015	0.113
7	-0.046	0.979	12.131	-0.473	0.190	0.017	0.878	0.983	0.019	0.052	-0.042	0.536	0.392	0.016	0.107
8	-0.039	0.969	12.343	-0.553	0.223	0.020	0.775	1.238	0.018	0.049	-0.040	0.571	0.356	0.016	0.103
9	-0.030	0.987	12.491	-0.655	0.276	0.024	0.750	1.634	0.018	0.049	-0.040	0.665	0.346	0.016	0.105
High TK	-0.008	1.218	12.321	-0.926	0.470	0.039	2.015	3.196	0.023	0.065	-0.049	1.315	0.496	0.019	0.159

Panel B. PW

Portfolios	PW	Beta	Size	BM	MOM	REV	AMIHUD	LT REV	IVOL	MAX	MIN	Skew	EISKEW	Industry Skew	STD
Low PW	-0.011	0.907	11.317	0.061	-0.108	-0.018	4.506	-0.202	0.029	0.073	-0.064	0.004	0.553	0.006	0.105
2	-0.002	0.875	12.002	-0.191	0.020	0.000	1.759	0.129	0.020	0.053	-0.046	0.154	0.392	0.010	0.092
3	0.003	0.889	12.135	-0.274	0.069	0.006	1.353	0.337	0.019	0.050	-0.043	0.233	0.369	0.012	0.092
4	0.007	0.931	12.108	-0.321	0.101	0.010	1.496	0.503	0.019	0.051	-0.044	0.318	0.380	0.013	0.096
5	0.011	0.980	12.006	-0.370	0.132	0.013	1.739	0.672	0.020	0.054	-0.045	0.401	0.406	0.014	0.103
6	0.015	1.040	11.856	-0.417	0.165	0.016	1.879	0.845	0.022	0.059	-0.048	0.517	0.450	0.015	0.113
7	0.021	1.134	11.590	-0.457	0.198	0.019	2.562	1.027	0.024	0.065	-0.053	0.656	0.520	0.016	0.127
8	0.028	1.242	11.315	-0.534	0.241	0.022	3.320	1.293	0.027	0.074	-0.058	0.848	0.604	0.017	0.145
9	0.041	1.379	10.949	-0.599	0.297	0.027	4.486	1.616	0.032	0.087	-0.066	1.161	0.729	0.018	0.174
High PW	0.089	1.580	10.347	-0.723	0.445	0.042	8.983	2.224	0.041	0.114	-0.081	2.125	1.023	0.020	0.258

Table 12. Fama-Macbeth regressions for different TK components

This table reports the Fama-MacBeth regression results of different component of the cumulative prospect theory. The definitions of each component and the other variables can be found in the text. The sample covers July 1931 to December 2010. All the t-statistics are Newey-West adjusted with 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LA	PW	CC	LACC	LAPW	CCPW	TK
TK components	**-0.2217**	**-0.1290**	**-0.1497**	**-0.1622**	**-0.1501**	**-0.1287**	**-0.1607**
	(-1.90)	**(-2.16)**	**(-1.59)**	**(-1.46)**	**(-2.16)**	**(-2.26)**	**(-2.16)**
Beta	0.1210	0.1776	0.1850	0.1133	0.1611	0.1829	0.1621
	(1.69)	(2.19)	(2.15)	(1.68)	(1.99)	(2.23)	(1.99)
Size	-0.1856	-0.2718	-0.2490	-0.1956	-0.2143	-0.2722	-0.2115
	(-3.24)	(-3.98)	(-3.59)	(-3.42)	(-3.39)	(-3.94)	(-3.38)
BM	0.1056	0.1193	0.0958	0.1095	0.1247	0.1170	0.1202
	(1.99)	(2.26)	(1.81)	(2.08)	(2.35)	(2.21)	(2.26)
MOM	0.5345	0.5339	0.5734	0.5068	0.5420	0.5475	0.5497
	(6.03)	(5.17)	(6.7)	(5.59)	(6.13)	(5.54)	(6.39)
ILLIQ	2.9784	2.9206	3.0063	2.9867	2.9206	2.9293	2.9344
	(5.04)	(4.8)	(4.92)	(5.06)	(4.86)	(4.81)	(4.89)
REV	-1.2222	-1.2326	-1.2271	-1.2311	-1.2267	-1.2293	-1.2253
	(-15.29)	(-14.76)	(-15.53)	(-15.27)	(-15.12)	(-14.84)	(-15.19)
LT REV	-0.0230	-0.2047	-0.0376	-0.1002	-0.1183	-0.1765	-0.0901
	(-0.31)	(-2.24)	(-0.41)	(-1.44)	(-1.73)	(-2.11)	(-1.40)
IVOL	-0.3666	-0.3036	-0.3440	-0.35112	-0.3407	-0.3074	-0.3435
	(-5.17)	(-3.53)	(-4.13)	(-5.01)	(-4.17)	(-3.56)	(-4.27)
N	954	954	954	954	954	954	954

Table 13. Varying the Probability weighting parameters

This table reports Fama-MacBeth regression results for different values of deltas. In order to compare between different specifications, we standardize all the independent variables to have mean 0 and standard deviation to 1. Then the coefficient of each independent variable can be explained as the change of expected stock return when the independent variable increases by one standard deviation. The sample period is from July 1931 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Gamma/Delta	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	1.41/1.49	1.51/1.59	1.61/1.69
TK	**-0.0661**	**-0.0875**	**-0.1185**	**-0.1607**	**-0.1986**	**-0.2073**	**-0.1881**	**-0.1465**	**-0.1347**	**-0.1142**	**-0.0981**	**-0.0855**	**-0.0755**	**-0.0674**
	(-1.73)	**(-2.00)**	**(-2.14)**	**(-2.16)**	**(-2.07)**	**(-1.90)**	**(-1.69)**	**(-1.37)**	**(-1.32)**	**(-1.17)**	**(-1.06)**	**(-0.96)**	**(-0.88)**	**(-0.81)**
Beta	0.1581	0.1625	0.1646	0.1621	0.1518	0.1370	0.1261	0.1175	0.1204	0.1211	0.1222	0.1236	0.1248	0.1260
	(1.99)	(2.01)	(2.01)	(1.99)	(1.91)	(1.81)	(1.75)	(1.72)	(1.75)	(1.77)	(1.79)	(1.81)	(1.82)	(1.84)
Size	-0.2356	-0.2337	-0.2258	-0.2115	-0.1967	-0.1908	-0.1942	-0.2035	-0.2082	-0.2140	-0.2186	-0.2223	-0.2253	-0.2277
	(-3.52)	(-3.51)	-(3.46)	(-3.38)	(-3.29)	(-3.27)	(-3.35)	(-3.52)	(-3.57)	(-3.66)	(-3.72)	(-3.77)	(-3.80)	(-3.83)
BM	0.1357	0.1328	0.1280	0.1202	0.1115	0.1067	0.1066	0.1094	0.1108	0.1130	0.1148	0.1162	0.1175	0.1185
	(2.57)	(2.51)	(2.41)	(2.26)	(2.10)	(2.01)	(2.01)	(2.08)	(2.11)	(2.16)	(2.20)	(2.23)	(2.25)	(2.28)
MOM	0.5117	0.5223	0.5360	0.5497	0.5538	0.5441	0.5286	0.5060	0.5045	0.4972	0.4922	0.4886	0.4860	0.4842
	(5.52)	(5.72)	(6.04)	(6.39)	(6.48)	(6.28)	(6.01)	(5.60)	(5.57)	(5.44)	(5.34)	(5.27)	(5.22)	(5.18)
ILLIQ	2.8982	2.9032	2.9153	2.9344	2.9564	2.9748	2.9882	2.9993	3.0055	3.0112	3.0154	3.0186	3.0211	3.0229
	(4.78)	(4.79)	(4.83)	(4.90)	(4.97)	(5.02)	(5.04)	(5.06)	(5.06)	(5.06)	(5.06)	(5.05)	(5.05)	(5.05)
REV	-1.2367	-1.2345	-1.2304	-1.2253	-1.2221	-1.2232	-1.2272	-1.2334	-1.2346	-1.2370	-1.2388	-1.2401	-1.2410	-1.2417
	(-15.00)	(-15.01)	(-15.09)	(-15.20)	(-15.30)	(-15.35)	(-15.35)	(-15.31)	(-15.33)	(-15.32)	(-15.31)	(-15.30)	(-15.29)	(-15.29)
LT REV	-0.2335	-0.2056	-0.1573	-0.0901	-0.0322	-0.0185	-0.0426	-0.1019	-0.1071	-0.1310	-0.1493	-0.1636	-0.1748	-0.1838
	(-2.50)	(-2.40)	(-2.13)	(-1.40)	(-0.48)	(-0.25)	(-0.57)	(-1.43)	(-1.49)	(-1.85)	(-2.11)	(-2.30)	(-2.44)	(-2.55)
IVOL	-0.3213	-0.3241	-0.3315	-0.3435	-0.3557	-0.3604	-0.3566	-0.3464	-0.3431	-0.3378	-0.3339	-0.3309	-0.3286	-0.3269
	(-3.74)	(-3.79)	(-3.96)	(-4.27)	(-4.67)	(-4.93)	(-4.96)	(-4.86)	(-4.75)	(-4.64)	(-4.55)	(-4.47)	(-4.41)	(-4.37)
N	954	954	954	954	954	954	954	954	954	954	954	954	954	954

Table 14. Varying the LA parameter

This table reports the Fama-MacBeth regression results when we vary the loss aversion parameter used to construct the TK measure. The definitions of each component and the other variables can be found in the text. In order to compare between different specifications, we standardize all the independent variables to have mean 0 and standard deviation to 1. Then the coefficient of each independent variable can be explained as the change of expected stock return when the independent variable increases by one standard deviation. The sample covers July 1931 to December 2010. All the t-statistics are Newey-West adjusted with 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LA parameter	0.5	1	1.5	2	2.25	2.5	3	3.5	4
TK	**-0.0961**	**-0.1287**	**-0.1462**	**-0.1565**	**-0.1607**	**-0.1636**	**-0.1646**	**-0.1611**	**-0.1557**
	(-1.44)	**(-2.26)**	**(-2.53)**	**(-2.29)**	**(-2.16)**	**(-2.05)**	**(-1.86)**	**(-1.71)**	**(-1.60)**
Beta	0.1678	0.1829	0.1841	0.1709	0.1621	0.1534	0.1387	0.1283	0.1212
	(2.21)	(2.23)	(2.15)	(2.04)	(1.99)	(1.94)	(1.86)	(1.79)	(1.75)
Size	-0.2765	-0.2722	-0.2497	-0.2224	-0.2115	-0.2032	-0.1931	-0.1888	-0.1874
	(-4.21)	(-3.95)	(-3.63)	(-3.44)	(-3.38)	(-3.34)	(-3.30)	(-3.29)	(-3.30)
BM	0.1166	0.1170	0.1188	0.1200	0.1202	0.1202	0.1203	0.1203	0.1204
	(2.24)	(2.22)	(2.23)	(2.25)	(2.26)	(2.27)	(2.29)	(2.31)	(2.32)
MOM	0.5164	0.5475	0.5648	0.5578	0.5497	0.5411	0.5252	0.5131	0.5042
	(4.87)	(5.55)	(6.28)	(6.47)	(6.39)	(6.26)	(5.98)	(5.74)	(5.56)
ILLIQ	2.9422	2.9293	2.9240	2.9310	2.9344	2.9371	2.9406	2.9427	2.9441
	(4.90)	(4.81)	(4.80)	(4.87)	(4.90)	(4.92)	(4.96)	(4.98)	(5.00)
REV	-1.2337	-1.2293	-1.2259	-1.2252	-1.2253	-1.2256	-1.2265	-1.2276	-1.2285
	(-14.78)	(-14.85)	(-15.01)	(-15.16)	(-15.20)	(-15.22)	(-15.24)	(-15.24)	(-15.22)
LT REV	-0.2471	-0.1765	-0.1099	-0.0874	-0.0901	-0.0980	-0.1200	-0.1419	-0.1602
	(-2.45)	(-2.11)	(-1.60)	(-1.36)	(-1.40)	(-1.51)	(-1.76)	(-1.97)	(-2.12)
IVOL	-0.3001	-0.3074	-0.3237	-0.3383	-0.3435	-0.3473	-0.3514	-0.3525	-0.3522
	(-3.64)	(-3.56)	(-3.73)	(-4.09)	(-4.27)	(-4.44)	(-4.79)	(-4.86)	(-4.95)
N	954	954	954	954	954	954	954	954	954

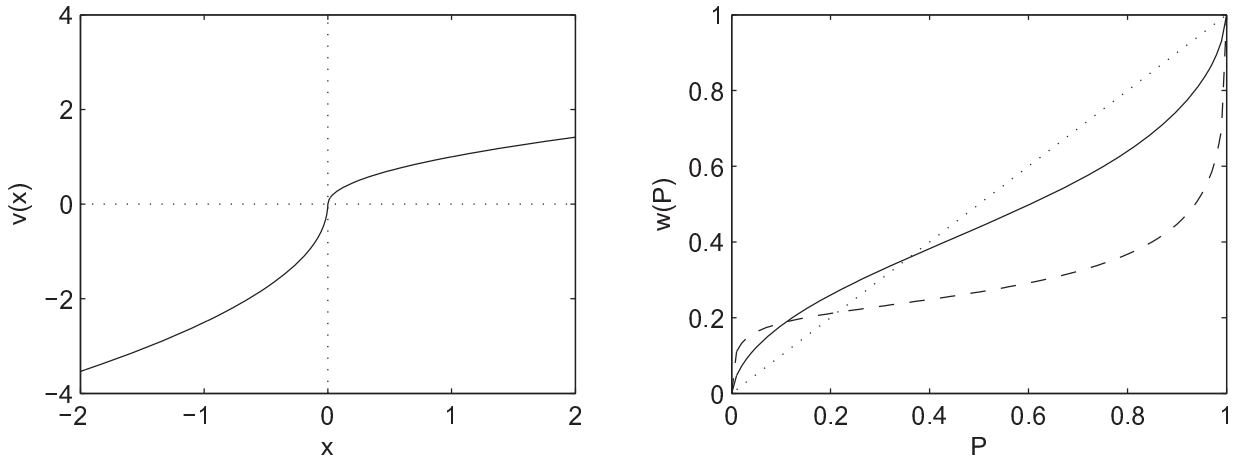

Figure 1. The left panel plots the value function proposed by Tversky and Kahneman (1992) as part of their cumulative prospect theory, namely $v(x) = x^{\alpha}$ for $x \geq 0$ and $v(x) = -\lambda(-x)^{\alpha}$ for $x < 0$, for $\alpha = 0.5$ and $\lambda = 2.5$. The right panel plots the probability 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 $\delta = 1$.

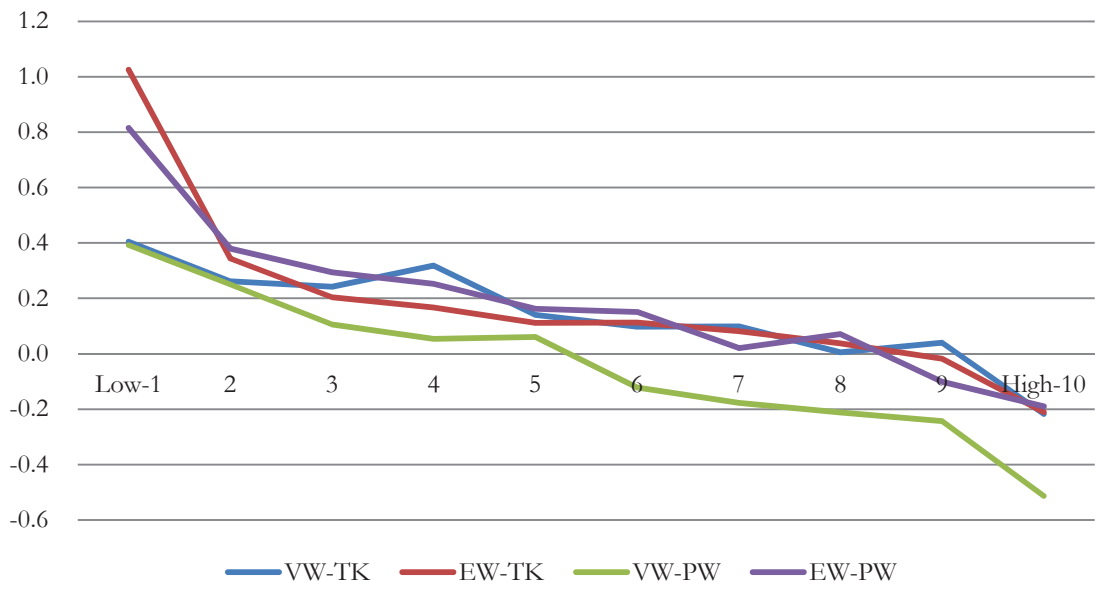

Figure 2. Decile Portfolio Performance- PW & TK

This figure shows the average Carhart 4-factor adjusted alphas for four groups of decile portfolios. VW-TK, EW-TK, VW-PW, and EW-PW represent value weighted TK portfolios, equal weighted TK portfolios, value weighted PW portfolios and equal weighted PW portfolios. The y-axis is the alpha (in precent) for each decile portfolio and the x-axis is the decile portfolio from low PW/TK to high PW/TK.

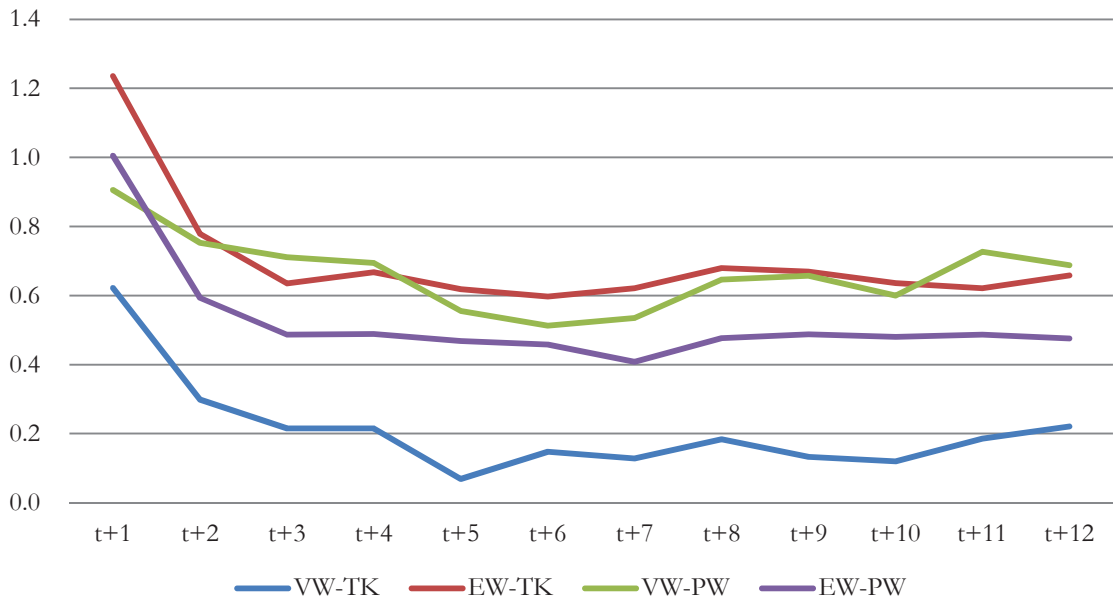

Figure 3. How do Long-Short portfolio returns decline over time?

This figure shows the average Carhart 4-factor adjusted alphas for four long-short portfolios, by different horizons. VW-TK, EW-TK, VW-PW and EW-PW represent value weighted TK portfolios, equal weighted TK portfolios, value weighted PW portfolios and equal weighted TK portfolios. The y-axis is the alpha (in precent) for each decile portfolio and the x-axis is the length of the horizon. The period used to calculate PW/TK ends at month t, t+1 means sorting stocks based on PW/TK calculated at the end of month t and hold them for month t+1.

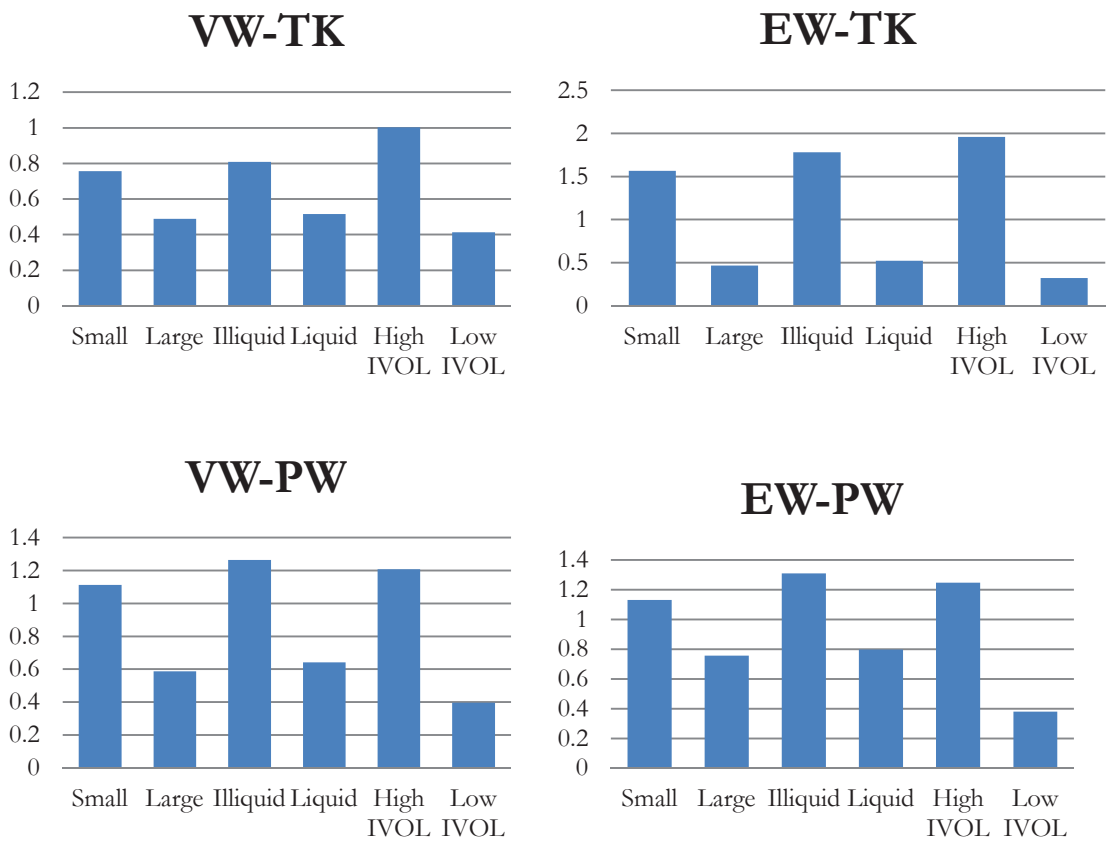

Figure 4. Limits to Arbitrage

This figure shows the results in Table 7 (limit to arbitrage) graphically. For each proxy of limit-to-arbitrage, we sort all the stocks into two portfolios, using the median of all the sample stocks (for firm size, the median firm size is based on NYSE firms). Then within each portfolio, we sort all the stocks by PW/TK into deciles and calculate the 4-factor adjusted alpha for the Lowest PW/TK and Highest PW/TK portfolio. VW-TK, EW-TK, VW-PW and EW-PW represent value weighted TK portfolios, equal weighted TK portfolios, value weighted PW portfolios and equal weighted TK portfolios.

Appendix: Table A1- Definition of variables

Variable	Definition	Formulae
Beta	Beta	Following Fama and French (1992), calculated from monthly return of past 5 years
Size	Market value of equity	ABS(ALTPRC*SHROUT)
BM	Book to market	CEQ/SIZE. Following Fama-French (1992). The negative BM observations are excluded.
MOM	Momentum	cumulative return from month t-12 to month t-2
REV	Short term reversal	return for month t-1
LT REV	Long Term reversal	cumulative return from month t-60 to month t-13
ILLIQ	Amihud Illiquidity	Following Amihud (2002). Calculated using daily data from month t-1
MAX	MAX	the maximum daily return of Bali et al. (2011)
MIN	MIN	The minimum daily return of Bali et al. (2011)
Skew	Skewness	Calculated from using past 5 years monthly returns
Industry skew	Industry skewness	Following Zhang (2006). Firm in each industry (Fama-French 48 industry) is assigned the same industry skewness. Industry skewness is the cross sectional skewness of stocks within a given industry.
EISKEW	Expected idiosyncratic skewness	following Boyer et al. (2011)
IVOL	Idiosyncratic volatility	Calculated from using daily returns in month t-1