Myopic Loss Aversion and the Cross-Section of U.S. Stock Returns: Empirical Evidence

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Abstract:

We empirically analyze the contribution of myopic loss aversion towards explaining the cross-section of U.S. stock returns. We indeed find that the ostensibly anomalous stock returns for different portfolios, ranging from the 25 Fama-French test assets to portfolios formed on size, momentum or value and combinations thereof, seem to be in equilibrium under the prospect-theoretical metric suggested by Benartzi and Thaler (1995). Furthermore, risk as perceived by a loss-averse investor who is subject to myopic loss aversion is a priced factor in a large cross-section of stocks.

Keywords: prospect theory; asset pricing; stock returns; growth stocks; value stocks; momentum returns; contrarian strategy

JEL: G12, G14, G15

February 14, 2007

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I. Introduction

This paper shows that an application of prospect theory to asset pricing helps to explain the cross-section of U.S. stock returns. Of course, there are plenty of models which claim to explain cross-sectional returns, however, the recent study by Lewellen, Nagel and Shanken (2006) has convincingly demonstrated that these models lack generality. All of them explain some cross-sections but none of them is useful in explaining the various kinds of cross-sections of U.S. stock returns as they have been used in recent empirical research. These kinds of cross-sections include the sorting of U.S. stocks according to their book to market ratio, to their prior returns or to their industry classification. Understanding generality of an asset pricing model in this sense, existing models seem to be somewhat specific.

As a contribution towards identifying an asset pricing approach with a higher degree of generality, we rely on Benartzi and Thaler (1995) who apply prospect theory to explain the U.S. equity premium puzzle. Prospect theory assumes that investors are loss averse, i.e. utility functions have a kink at an exogenous reference point. Reference points are set according to particular situations from the viewpoint of individuals. Furthermore, Benartzi and Thaler (1995) use the observation that individual and institutional investors often evaluate portfolios after one-year-periods to introduce myopic behavior.[1] Combining these elements yields myopic loss averse investors who suffer more from losses than from gains of the same size and who pay attention to moments of short horizon returns and not to long horizon properties

[1] Myopia and loss aversion have become widely used tools to describe individual decision making (see Thaler, Tversky, Kahneman, and Schwartz, 1997, Waldfogel, 2005, or Langer and Weber, 2007, for applications and discussions).

of return distributions. Under this modeling device, the utility that investors derive from holding a diversified stock portfolio is not significantly different from earning the risk-free rate.[2] This result motivates to transfer this approach from pricing the market to pricing the cross-sections of returns and we find indeed that a universe of 115 different portfolios – covering the focus of interest of most empirical asset pricing papers – yields the same prospective utility as the broad market portfolio. This is of course a new finding as one approach is helpful in explaining not just one but all relevant cross-sections examined before.

Prospect theory (Kahneman and Tversky, 1979) and its main constituent, loss aversion, have long been a promising way to address asset pricing puzzles. Benartzi and Thaler (1995) give an early application. Barberis and Huang (2001) show how a high mean of stock returns, excess volatility and a value premium in the cross-section of stocks may occur in an economy with loss averse investors. Barberis, Huang and Santos (2001) demonstrate in calibration exercises how loss aversion over financial wealth fluctuations helps explain several aggregate market phenomena such as the equity premium puzzle, the risk-free rate puzzle and predictability in the time-series of stock returns. Most recently, Berkelaar, Kouwenberg and Post (2004) show that loss aversion significantly reduces the share of stock holdings in an optimal portfolio when investors have short planning horizons, Barberis, Huang, and Thaler (2006) apply the prospect-theoretical framework to make sense of the stock market participation puzzle (cf. Mankiw and Zeldes, 1991), and Menkhoff and Schmeling (2006) use prospect utility to explain high momentum returns (Jegadeesh and Titman, 2001).

This paper addresses another important issue which is yet not well understood: is myopic loss aversion helpful in understanding the cross-sectional spread in U.S. stock returns? Motivated by recent advice of Lewellen, Nagel and Shanken (2006) we examine a comprehensive set of portfolios to test the power of this approach in explaining several

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[2] Empirical and experimental evidence suggests that both laymen and professional investors are subject to myopic loss aversion (see for example Haigh and List, 2005).

market anomalies (e.g. value stocks, momentum stocks, contrarian stocks) and standard benchmark portfolios (e.g. the 25 Fama-French portfolios or 30 industry portfolios). We find that several cross-sectional stock return anomalies are well captured under the prospect-theoretical metric. Specifically, the ostensibly anomalous returns of e.g. momentum, value or contrarian portfolios do not outperform the market portfolio from a utility perspective when investors are characterized by myopic loss aversion.

This finding indicates that the way investors assess the utility of portfolios may be important for asset pricing. In a next step, we thus interpret myopic loss aversion itself as a price relevant risk factor and include it into a conventional multi-factor asset pricing approach in the Fama-MacBeth (1973) regression tradition. We show that portfolios with unfavorable distributional properties for loss-averse investors demand a higher premium cross-sectionally. The inclusion of this risk factor robustly generates sensible and insignificant alpha estimates and easily survives the inclusion of a variety of risk factors proposed in the literature.

The rest of the paper proceeds as follows. Section II describes the data used in the empirical analysis, Section III details the methodology and results. We perform several robustness checks in Section IV and conclude in Section V.

II. Data

In the empirical analysis we fully rely on data of stock portfolios that have been used extensively in earlier research. Thus, our contribution with respect to data is not that we would have new data but rather that we use—inspired by Lewellen, Nagel and Shanken (2006)—a broad set of portfolio data compared to earlier studies in this line of literature.

Specifically, we include the following portfolios in our empirical analysis:[3]

(a) 10 portfolios formed on book-to-market (BE/ME)

[3] All portfolio return data is obtained from Prof. Kenneth French's web site.

(b) 10 portfolios sorted on the dividend-price ration (D/P)

(c) 10 portfolios sorted on size (ME)

(d) 25 Fama-French portfolios (FF)

(e) 10 portfolios sorted on short-term performance, i.e. the return over the prior month (Prior 1-0)

(f) 10 portfolios sorted on momentum, i.e. the return over the prior 12 months (Prior 12-2)

(g) 10 portfolio sorted in long-term reversals, i.e. the return over the prior five years (Prior 60-13)

(h) 30 industry portfolios (30 Industries),

which gives a total of 8 portfolio cross sections and 115 portfolios under consideration which will be examined jointly and separately. Returns are monthly and the sample period is January 1936 to December 2005. We also employ CPI inflation data obtained from Prof. Robert Shiller's web page and returns on the market portfolio, the HML and SMB factors which are again collected from Prof. French's web site.

We will provide only short descriptions of these portfolios because they are subject to a large amount of previous research and are described in detail on the website of Prof. French. First of all, the portfolios sorted on BE/ME and D/P are a means to look at the return spread of glamour (low BE/ME, D/P) versus value stocks (high BE/ME, D/P) (cf. Fama and French, 1998). The portfolios sorted on size (ME) have been constructed to investigate the so-called size premium (cf. Fama and French, 1992). The 25 Fama-French portfolios (FF) have become the benchmark each asset-pricing model has to surmount (Fama and French, 1993). The following three sets of portfolios are formed on past prices. The Prior 1-0 portfolios are formed on short-term performance and were studied in Jegadeesh (1990). There it is found, that past short-term losers (over the last month) earn higher returns than past winners subsequently. The ten momentum portfolios (Prior 12-2) were analyzed in Jegadeesh and Titman (1993, 2001). Portfolios are formed on prior 12 months performance. Past winners continue to outperform past losers. The long-term reversal portfolios (Prior 60-13) come from the studies of DeBondt and Thaler (1985) who show that past long-term losers outperform past long-term winners by a substantial amount. Finally, the 30 industry portfolios are common in empirically testing asset-pricing models (cf. Lewellen, Nagel and Shanken, 2006) since they are based on a somewhat more natural sorting procedure that does not include past security prices. So we also include these industry portfolios here.

Descriptive statistics can be found in Table 1 and reveal the usual pattern observed in the spread of returns for these portfolios. For example, value stocks (high BE/ME) earn higher returns than growth stocks (low BE/ME), small stocks (Low ME) command a larger return than large stocks (high ME), and past winners (high prior 12-2 return) outperform past losers (low prior 12-2) by a significant amount. Large differences of up to 0.65% p.m. can be observed even among the industry portfolios.

However, apart from the first moments, there is also considerable spread in higher order moments. For example, small stocks (low ME) have a much higher kurtosis than large stocks (high ME) which is quite unattractive to a loss averse investor and might (partially) compensate for the higher returns of small stocks. The same is true for portfolios sorted on BE/ME. Value stocks have a kurtosis that is higher by a factor of about three compared to growth stocks which might make the higher returns of value stocks less attractive. For the prior 12-2 (momentum) portfolios we observe that past winners have not only higher returns than past winners but also a much lower skewness, a feature being unattractive to loss averse investors.

That said, the ultimate goal of the next sections is to cast this informal discussion of cross-sectional moments into a fully developed utility framework. This serves to analyze whether stock returns are in equilibrium when looking at them from the perspective of myopically loss averse investors.

III. Empirical approach and results

A. Methodology

We closely follow the methodology employed by Benartzi and Thaler (1995) in their seminal paper to ensure comparability of results. Their intuition is to apply the prospect theory to investment decisions because prospect theory is a positive theory of decision making with a very robust empirical foundation. So, we assume that investors assess stock portfolios relative to the total stock market by effectively showing shorter-term evaluation horizons, loss aversion and miscalibrated probability judgments (cf. recently Barberis, Huang and Thaler, 2006).

Therefore, we employ cumulative prospective utility in the sense of Kahneman and Tversky (1979) and Tversky and Kahneman (1992) which has a value function v(·)

$$v(\chi) = \begin{cases} \chi^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-\chi)^{\beta} & \text{if } x < 0 \end{cases} \tag{1}$$

where χ denotes returns, α and β are curvature parameters and λ is the coefficient of loss aversion. Tversky and Kahneman (1992) estimate α and β to be 0.88 yielding risk averse (risk seeking) behavior in the domain of gains (losses). They also estimate λ to be 2.25 which leads to the result that a loss causes a (more than) twofold reduction in the value of a return compared to the value increase for a gain of the same absolute size.

Furthermore, under cumulative prospect utility investors also have miscalibrated probability judgements in the sense of an overweighting of very unlikely outcomes and on underweighting of highly probable outcomes. Tversky and Kahneman (1992) employ the following parametrization for the perceived probability π_i and outcome *i* which is adopted by Benartzi and Thaler (1995):

$$\pi_i = w(P_i) - w(P_i^*) \tag{2}$$

where π_i is the weighted probability of obtaining outcome *i*, P_i is the actual probability of outcome *i* and P_i^* is the probability of realizing an outcome as least as good as *i*. The weighting of probabilities is obtained via the following weighting function:

$$w(p) = \frac{p^{\gamma}}{\left(p^{\gamma} + \left(1 - p^{\gamma}\right)\right)^{\frac{1}{\gamma}}}. \tag{3}$$

From (2) it can be seen that the perceived probability of event *i* does not only depend on that event's probability but also on the probabilities of the other outcomes. The parameter γ in (3) is estimated to be 0.61 (0.69) for the domain of gains (losses). Assembling the pieces in (1)-(3), the cumulative prospect utility (henceforth CPT) of a gamble G, V(G), is computed in the standard way by summing over the probability weighted values, i.e.

$$V(G) = \sum_{i} \pi_i v\left(\chi_i\right). \tag{4}$$

In order to empirically calculate the CPT of a given portfolio it is necessary to calculate π_i which in turn depends on the "true" probabilities P_i. Benartzi and Thaler (1995) obtain the P_i's by bootstrapping and discretizing the return distribution which is also the method we employ here. For a given evaluation horizon *n*, e.g. *n* = 12 months for an annual horizon, one draws with replacement 1,000,000 *n*-months returns from the return history and ranks them in descending order. One hundred intervals of 10,000 *n*-months (beginning with the highest returns) are formed and then the mean return for each interval is computed. This yields one hundred pairs of (χ_i, P_i) where P_i=1/100 for all *i*. With these pairs in hand it is straightforward to compute the CPT in (4) for a desired return series and sample period.

B. Portfolio performance under cumulative prospect utility

The prospect utility of all 115 portfolios under consideration is not significantly different from the market portfolio's utility, although many of these portfolios have positive excess returns above the market return which cannot be easily explained by standard asset pricing models (cf. Cochrane, 2006).

In order to provide an easily accessible graphical presentation of the portfolio performances under consideration here, we compute CPT's for all portfolios over rolling 60 months periods with a 12 months skipping. That means we compute the first CPT for portfolio *k* over the period January 1936 to December 1940, the second CPT for portfolio *k* over the period January 1937 to December 1941 and so on. This yields a total of 66 CPT's for each of the 115 portfolios. Following Benartzi and Thaler (1995) we compare the CPT of a portfolio to a benchmark. Whereas they use the bond return as a natural benchmark to compare the aggregate stock market return, we rely on the latter to compare our portfolios with since the aggregate market seems to be the natural benchmark when evaluating the performance of a specific stock portfolio.[4] Therefore, we also compute the CPT of the aggregate U.S. stock market return over the 66 five year samples and report the difference between a portfolio's CPT and the market's CPT in Figure 1. Shown are the median as well as 10 and 90 percent point of these CPT's for each portfolio *k*. All calculations are CPI deflated.

As can be seen from Figure 1, all portfolios have median (and mean, though not shown) CPT's near zero. Although some (median) utilities are higher than the utility from holding the market portfolio, the distribution of CPT's around the median – as indicated by the 90% confidence interval shown in these graphs – does not indicate that the utility from any portfolio is significantly better than that of the aggregate market: all portfolios fail to systematically yield positive utility compared to the aggregate real market returns over the last 80 years.

We conclude that, assuming myopic loss aversion correctly describes the utility which investors receive from holding certain portfolios, the returns of various kinds of portfolios seem to be consistent with the notion of market equilibrium in such a kind of economy.

[4] Descriptive statistics for the market (excess) return can be found in Appendix 1.

C. Cross-sectional analysis: Fama-MacBeth regressions

This section examines a core implication of the above analysis by showing that the assessment of portfolios via prospective utility can be regarded as a pricing factor, similar to other pricing factors. We find that prospective utility robustly explains cross-sectional returns in the presence of other pricing factors and that its relative contribution is remarkable.

In this section we run cross-sectional regressions of portfolio returns on risk factors (such as HML or SMB) and characteristics (such as firm size) and on a pricing measure based on cumulative prospect theory. This CPT-based factor measures how much return a loss averse investor demands for holding a certain stock or portfolio with given risk characteristics. The construction of this measure proceeds as follows. We calculate the prospective utility given (as shown in (4)) for the real market return (call it V^M). Then, for a given portfolio *k* we first demean the time series of returns to obtain a mean zero return series $\tilde{r}_t^k$ and numerically solve for the return θ^k that makes the prospective utility of the return series equal to the prospective utility of the market portfolio. This means that we solve for the θ^k that satisfies the following equality

$$V\left(\tilde{r}_t^k + \theta^k\right) = V^M . \tag{5}$$

Since we are still employing (monthly overlapping) annual returns, θ^k directly gives the annual return that a myopic loss averse investor demands to hold portfolio *k* with all its other moments, e.g. variance, skewness, kurtosis, being unchanged. Therefore, portfolios with second or higher order return moments that are unfavorable for a loss averse investor, most importantly a large variance, negative skewness or high kurtosis, should demand a higher return θ^k and vice versa. We would therefore expect to see cross-sectionally that at a given point in time, *t*, θ_t^k is a priced factor.

Moreover, this required return (derived from prospective utility) has an intuitive meaning. A one percent increase in this factor should lead to a one percent increase in returns. Therefore, when cumulative prospect utility as calibrated by Tversky and Kahneman (1992) is the correct utility function for investors, we should find a one to one relation between our estimate of the factor θ^k and returns r^k.

For the Fama-MacBeth regressions we calculate the required return θ^k for periods of 60 months that have an overlapping structure of twelve months. This means for example, that we estimate the required return for January 1936 to December 1940 to obtain an estimate of θ^k for January 1940 to December 1940 and then shift the estimation window to January 1937 to December 1941 which yields the estimated return for January 1941 to December 1941 and so forth. Therefore, our sample effectively starts in January 1940. In the cross-sectional regressions we regress returns on the estimated risk factor θ^k and other factors from the earlier literature, e.g. HML, SMB or firm size.[5]

Results from the regressions for all 115 portfolios jointly are shown in Table 2. The first specification (1) just includes the estimated required return as defined above ($\hat{\theta}$) and shows that the coefficient on $\hat{\theta}$ is significantly positive, albeit smaller than one.

It is noteworthy, however, that this factor is powerful for pricing the large cross-section of portfolios and that the estimated intercept is not significantly different from zero. Furthermore, following Lewellen, Nagel and Shanken (2006) we take serious the size of the estimated intercept. The value of 0.11% p.m. corresponds to a real risk-free rate of roughly 1.3% p.a. which seems to be a much more reasonable number than the implied risk-free rates from traditional asset pricing models (cf. Lewellen, Nagel and Shanken, 2006).

The next columns (2) to (7) include further cross-sectional pricing factors in the Fama-MacBeth regressions as they were employed in earlier papers. Specifically, the second

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[5] Descriptive statistics for the three Fama-French risk factors can be found in Appendix 1.

specification picks up the core ingredient of consumption based asset pricing models and thus adds log real consumption growth (cf. Cochrane, 2004). Interestingly, it does not enter significantly and does not change the general conclusion for the intercept and slope obtained from specification (1). Column (3) adds HML and SMB as the most prominent pricing factors in the literature. Again, the alpha from this regression is small and the coefficient on $\hat{\theta}$ is highly significant although HML enters significantly. For comparison, we also show results for the Fama-French (1996) three factor model in column (4). For this large cross-section of returns the estimated alpha is highly significant and much too large to represent a reasonable risk free rate ($0.62 \times 12 \approx 7.4\%$) whereas the estimated risk premium on the beta factor is not significant and much too small, implying an annual equity risk premium of only $0.09 \times 12 \approx 1.1\%$. However, we know that this risk premium is above 6% p.a. from the early paper of Mehra and Prescott (1985) and the annual market excess return is indeed about 7.5% in our sample.

Column (5) adds firm size which enters significantly negative as can be expected from earlier studies which show that the characteristic itself is priced although the corresponding risk factor (here SMB) is included in the cross-sectional regression (Daniel and Titman, 1997).

Finally, we add other measures of non-linear risk in column (6), namely downside and upside betas as well as coskewness and cokurtosis. This serves to investigate whether the use of our CPT risk premium θ^k is dominated by these variables that also proxy for non-linear risk. Downside betas (β^-) and upside betas (β^+) are computed as in Ang, Chen and Xing (2006):

$$\beta^- = \frac{\mathrm{cov}\left(r^k, r^m \mid r^m < \mu^m\right)}{\mathrm{var}\left(r^m \mid r^m < \mu^m\right)} \tag{6}$$

$$\beta^{+} = \frac{\operatorname{cov}\left(r^{k}, r^{m} \mid r^{m} > \mu^{m}\right)}{\operatorname{var}\left(r^{m} \mid r^{m} > \mu^{m}\right)} \tag{7}$$

where μ^m denotes the mean return. Intuitively, upside and downside betas measure how much covariation an asset has with the market in good and bad times. Therefore, portfolios with higher upside betas (downside betas) should command lower (higher) mean returns.

Coskewness (coskew) and cokurtosis (cokurt) are computed as follows (see Ang, Chen and Xing, 2006):

$$\text{coskew} = \frac{E\left[\left(r^{k} - \mu^{k}\right)\left(r^{m} - \mu^{m}\right)^{2}\right]}{\sqrt{\operatorname{var}\left(r^{k}\right)} \operatorname{var}\left(r^{m}\right)} \tag{8}$$

$$\text{cokurt} = \frac{E\left[\left(r^{k} - \mu^{k}\right)\left(r^{m} - \mu^{m}\right)^{3}\right]}{\sqrt{\operatorname{var}\left(r^{k}\right)} \operatorname{var}\left(r^{m}\right)^{3/2}} \tag{9}$$

Harvey and Siddique (2000) predict that lower coskewness should be associated with higher expected returns since portfolios that have low returns when the market realizes more extreme returns are riskier. Similarly, assets with higher cokurtosis (cf. Dittmar, 2002) should show higher returns in order to compensate for the risk of obtaining unfavorable returns when market returns are negatively skewed.

As can be seen from column 6 in Table 2, the down- and upside risk measures as well as the higher-order co-moments are not helpful in pricing this large cross-section of returns. This is different from the significant the findings of Ang, Chen and Xing (2006) but may be explained by the fact that we use portfolio returns and not individual stocks as in their study. Portfolio returns are different from individual stock returns, since portfolio characteristics are much more stable than characteristics of individual firms (cf. Cochrane, 2004).

The last column in Table 2 shows results when we include the CPT-based factor and all other factors considered above jointly in the regressions. The CPT factor seems to dominate all other variables which is evident from the large t-statistic of more than six and which dwarfes the significance of all other variables. Therefore, it seems unlikely, that risk, as perceived by myopically loss averse investors, is well proxied for by linear and non-linear pricing factors employed in earlier work.

IV. Robustness tests

A. Randomization of test assets and test periods

As a first robustness check we randomize over the test assets used in the Fama-MacBeth regressions, i.e. we run 5,000 Fama-MacBeth regressions with the premium θ^k, HML and SMB as explanatory variables where in each run, only 60 portfolios are randomly selected as test assets.

The first column of Table 4, Panel A, reports the mean of the 5,000 estimated coefficient vectors along with empirical 95% confidence intervals in curly brackets. As is evident from this exercise, the results shown in Table 2 are not sensitive to the specific choice of which test assets are used. The estimated α is still around 0.2 per month and insignificant while the CPT risk premium factor θ^k still is significantly priced with a mean coefficient of around 0.6 and tight confidence intervals.

Secondly, we investigate whether the specific test periods used are critical to our results. Therefore, we run 5,000 repetitions of the Fama-MacBeth procedure with the same risk factors as above, where in each repetition we randomly select 396 out of the available 792 months as the test period. The months selected need not be consecutive. Mean coefficient vectors and empirical confidence intervals can be found in the second column of Table 4, Panel A. The results are highly similar to the results obtained above so we conclude that the specific choice of test period does not seem to be drive our results.

Finally, column three of the same table and panel shows results when we jointly randomize over test assets and test periods as described above. Again, the results remain unchanged.

B. Randomization of explanatory variables

As an alternative robustness check we test whether our results are spurious in the sense, that the CPT risk premia used in the Fama-MacBeth regressions have unfavorable statistical properties of some (unknown) form that spuriously generates the results documented above.

Therefore, we proceed as follows. We randomly match each asset return series with the estimated factor risk premia (θ^k, HML, SMB) of another series (drawing with replacement), apply the Fama-MacBeth procedure, save the estimated coefficients and repeat this procedure 5,000 times. This procedure allows us to test, whether our coefficient estimates, obtained from the original cross-sectional regressions are spurious.

Table 4, Panel b, shows the original coefficient estimates in the second column and the mean coefficient estimates from the bootstrap procedure in the third column. These show that our the estimates slope coefficients are uniformly zero on average, i.e. unbiased. The fourth and fifth column of the same table and panel shows the standard deviation of estimated slope coefficients and bootstrap t-test statistics, respectively. It can be seen, that the coefficient on the CPT risk premium is significantly different from zero and that HML also adds some statistically significant explanatory power.

V. Conclusions

Prospect theory is an established and empirically robust positive theory of decisions under risk (Kahneman and Tversky, 1979). We follow the method introduced by Benartzi and

Thaler (1995) to apply prospect theory in order to investigate the cross-section of U.S. stock returns. We find that myopic loss aversion helps to explain the returns of a large universe of portfolios to a degree that could make it an interesting ingredient for asset pricing models in general.

Indeed, under the prospect-theoretical metric, portfolios' return distributions deliver near zero utility when compared to the market portfolio and the perceived riskiness of return distributions under myopic loss aversion is a systematically priced factor in the cross-section of returns that tends to dominate other popular measures of risk. Furthermore, the inclusion of this perceived risk for a myopic loss averse investor yields empirically plausible estimates of the real risk-free rate, a point recently reinforced by Lewellen, Nagel and Shanken (2006).

We are aware that the approach chosen here is not derived from a theoretically sound pricing model. However, some earlier applications – in particular Benartzi and Thaler (1995) – have motivated to apply the approach of myopic loss aversion to another big open question that is the cross-sectional pricing of U.S. stock returns. Findings are quite supportive to this approach and may stimulate further research to better integrate myopic loss aversion into a more general understanding of asset pricing.

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Table 1. Descriptive statistics

	mean	std	skew	Kurt
BE/ME				
Low	0.87	5.03	-0.24	5.20
2	0.96	4.83	-0.42	6.31
3	0.96	4.73	-0.47	6.67
4	0.96	4.74	-0.35	7.04
5	1.10	4.40	-0.47	6.45
6	1.14	4.62	-0.54	6.51
7	1.14	4.93	0.07	8.09
8	1.29	4.98	-0.21	7.32
9	1.32	5.80	0.41	12.86
High	1.41	7.23	0.70	17.85
D/P				
Low	0.98	5.70	-0.36	5.60
2	0.97	5.06	-0.35	5.89
3	0.97	4.86	-0.27	6.94
4	1.03	4.52	-0.39	5.22
5	0.95	4.45	-0.36	6.13
6	1.01	4.45	-0.35	5.58
7	1.08	4.45	-0.43	5.30
8	1.18	4.55	-0.28	6.89
9	1.16	4.43	-0.25	5.70
High	1.07	4.71	0.23	9.59
ME				
Low	1.42	8.10	2.05	26.39
2	1.28	7.07	0.57	12.95
3	1.26	6.34	-0.22	6.94
4	1.24	6.11	-0.12	7.80
5	1.22	5.84	-0.36	7.15
6	1.16	5.51	-0.39	6.67
7	1.17	5.43	-0.39	7.34
8	1.09	5.11	-0.46	5.87
9	1.05	4.78	-0.37	6.33
High	0.91	4.32	-0.40	6.20

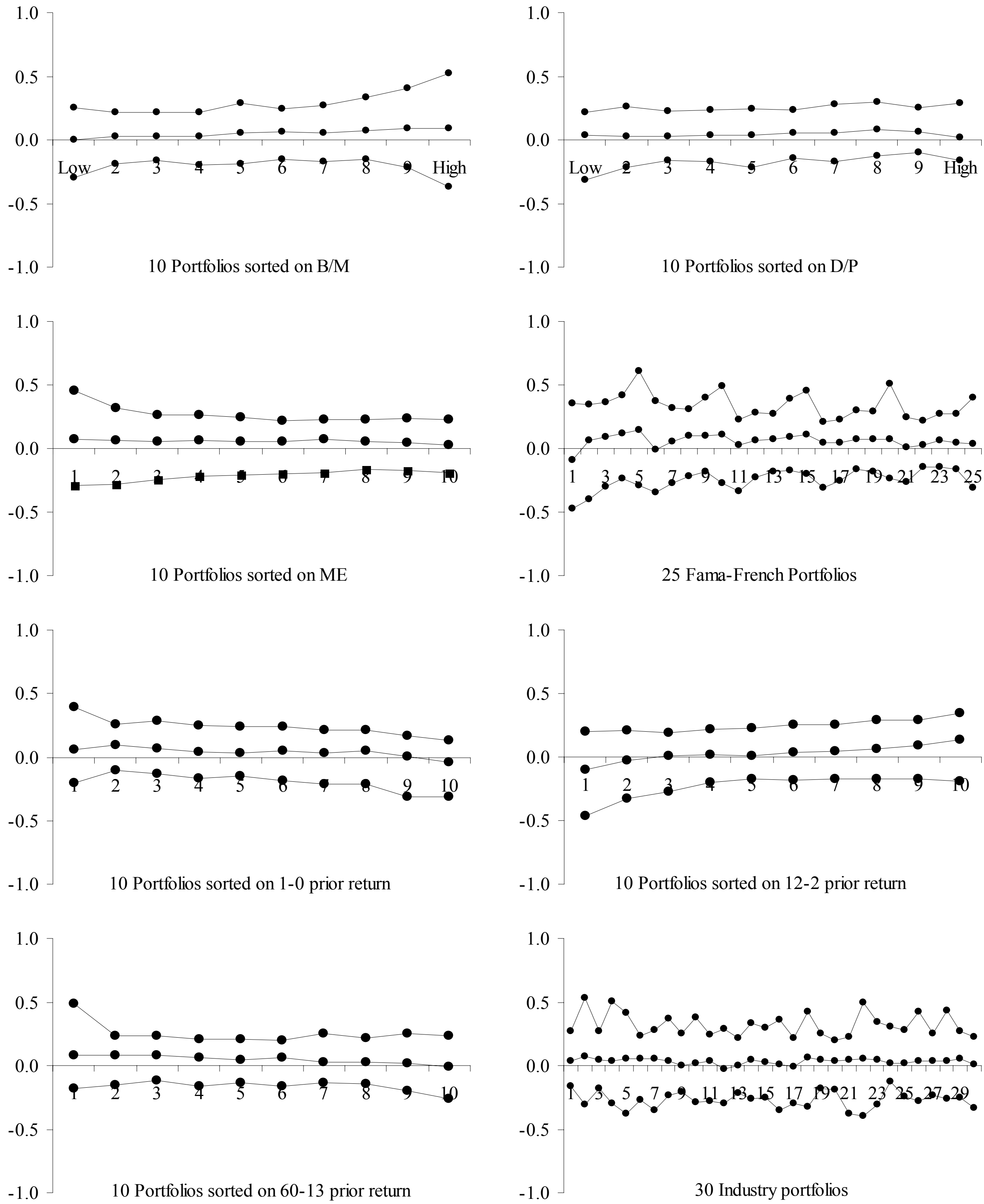
	mean	std	skew	kurt
FF25				
Small - Low	0.72	9.14	0.36	7.14
2	1.16	7.76	0.37	9.01
3	1.33	7.18	0.87	15.15
4	1.49	6.48	0.28	10.77
Small - High	1.67	7.52	1.77	27.12
2 - Low	0.94	7.39	0.18	8.00
2	1.20	6.29	-0.07	8.32
3	1.32	5.69	-0.21	7.83
4	1.40	5.81	-0.21	8.08
2 - High	1.56	6.84	0.21	10.53
3 - Low	0.95	6.49	-0.24	5.78
2	1.20	5.62	-0.47	7.00
3	1.24	5.37	-0.39	7.92
4	1.34	5.22	-0.25	6.53
3 - High	1.48	6.48	0.07	9.24
4 - Low	0.99	5.68	-0.29	5.34
2	1.01	5.22	-0.50	7.22
3	1.25	5.09	-0.58	6.72
4	1.27	5.32	-0.16	7.21
4 - High	1.43	6.59	0.22	9.98
Big - Low	0.90	4.75	-0.27	5.73
2	0.93	4.55	-0.32	6.47
3	1.06	4.32	-0.37	6.10
4	1.11	4.88	0.05	7.80
Big - High	1.17	6.18	0.49	13.95

Table 1. (continued)

	mean	std	skew	kurt		mean	std	skew	kurt
Prior 1-0					30 Industries				
Low	1.40	7.03	0.29	8.06	Autos	1.01	6.33	-0.08	5.66
2	1.39	5.93	0.66	10.14	Beer	1.16	5.77	0.12	6.82
3	1.32	5.20	0.27	8.68	Books	1.02	6.01	-0.23	6.31
4	1.09	4.98	0.05	7.88	BusEq	1.11	6.37	-0.29	5.19
5	1.05	4.83	0.27	10.49	Carry	1.17	6.78	0.17	7.54
6	1.03	4.62	-0.21	7.26	Chems	0.94	5.23	0.01	6.03
7	0.90	4.55	-0.39	7.11	Clths	1.11	6.31	-0.09	6.05
8	0.91	4.59	-0.65	5.75	Cnstr	1.02	5.93	-0.12	7.51
9	0.67	4.81	-0.77	6.59	Coal	1.45	8.67	1.32	12.12
High	0.53	5.72	-0.31	7.15	ElcEq	1.16	6.19	-0.15	5.25
Prior 12-2					FabPr	1.01	5.96	-0.13	6.82
Low	0.32	7.48	0.56	9.26	Fin	1.10	5.22	-0.33	5.92
2	0.74	6.16	0.46	11.82	Food	1.02	4.28	-0.19	6.08
3	0.84	5.37	0.47	11.92	Games	1.17	7.05	-0.27	5.59
4	0.91	4.99	0.24	11.02	Hlth	1.12	5.01	0.00	5.14
5	0.88	4.79	0.20	12.82	Hshld	1.00	4.76	-0.37	5.12
6	0.98	4.84	-0.19	9.83	Meals	1.24	6.49	-0.26	5.00
7	1.06	4.72	-0.28	7.96	Mines	0.93	6.38	-0.04	5.39
8	1.18	4.73	-0.33	6.45	Oil	1.15	5.37	0.02	5.46
9	1.26	5.08	-0.68	6.08	Other	0.80	5.80	-0.36	6.28
High	1.62	6.15	-0.55	5.18	Paper	1.02	5.16	-0.19	5.78
Prior 60-13					Rtail	1.07	5.33	-0.24	5.66
Low	1.33	6.88	0.59	7.89	Servs	1.17	7.04	-0.11	5.76
2	1.17	5.36	-0.05	8.21	Smoke	1.15	5.71	-0.05	5.92
3	1.18	4.96	-0.27	7.86	Steel	0.95	7.03	0.23	7.33
4	1.02	4.49	-0.47	6.63	Telcm	0.83	4.21	-0.13	5.20
5	1.05	4.51	-0.53	7.01	Trans	1.00	6.11	0.00	7.39
6	1.01	4.41	-0.65	6.79	Txtls	1.03	6.47	-0.26	6.53
7	1.05	4.67	-0.28	7.24	Util	0.89	4.46	0.01	5.60
8	1.00	4.87	-0.21	8.12	Whlsl	1.06	5.93	-0.36	6.33
9	0.97	5.19	-0.23	7.86					
High	0.93	6.00	-0.39	5.84					

Note: This table shows descriptive statistics, namely the monthly mean, standard deviation (std), skewness (skew) and kurtosis (kurt) for each of the 115 equity portfolios.

Figure 1. Prospective utilities of 115 simulated portfolios in excess of the market



Note: Simulated cumulative prospective utilities for the 115 portfolios under consideration minus the cumulative prospective utility of the market. The middle line shows medians, the upper and lower line shows the simulated 90% confidence interval.

Table 2. Fama-MacBeth regressions for all portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	0.11 [0.59]	0.13 [0.58]	0.19 [1.14]	0.62 [4.39]	0.21 [1.24]	0.83 [5.05]	0.14 [0.68]
$\hat{\theta}$	0.61 [3.61]	0.41 [2.31]	0.66 [5.09]		0.66 [5.14]		0.86 [6.30]
log Δc		0.03 [0.39]					
Beta				0.09 [0.46]			
HML			0.22 [2.01]	0.26 [2.24]	0.22 [1.98]	0.19 [1.65]	0.18 [1.58]
SMB			0.01 [0.06]	0.14 [1.18]	-0.01 [-0.13]	0.12 [1.10]	-0.00 [-0.05]
firm size					-0.29 [-2.57]		-0.26 [-2.99]
Downside beta						0.06 [0.26]	-0.36 [-1.87]
Upside beta						-0.08 [-0.40]	-0.22 [-1.24]
Coskewness						0.17 [0.24]	0.11 [0.17]
Cokurtosis						0.02 [0.12]	0.18 [1.34]
R^2	0.08	0.15	0.29	0.32	0.29	0.37	0.41

Note: Results from Fama-MacBeth two-step regressions for the whole sample period January 1940 to December 2005 and for all 115 portfolios.

Table 3. Fama-MacBeth regressions for different portfolio groups

	Const.	$\hat{\theta}$	Beta	HML	SMB	R^2
10 BE/ME	0.18 [0.84]	0.62 [2.83]		0.34 [2.68]	-0.08 [-0.32]	0.34
	0.40 [1.36]		0.29 [0.86]	0.38 [3.01]	-0.01 [-0.05]	0.36
10 D/P	0.07 [0.20]	0.62 [2.60]		0.45 [3.05]	-0.11 [-0.45]	0.31
	0.46 [1.75]		0.03 [0.82]	0.30 [1.84]	0.01 [0.02]	0.34
10 ME	-0.01 [-0.02]	0.76 [2.50]		-0.21 [-0.99]	0.01 [0.10]	0.53
	0.46 [1.44]		0.24 [0.71]	0.03 [0.16]	0.22 [1.79]	0.55
25 FF	0.19 [0.91]	0.54 [2.99]		0.32 [2.81]	-0.01 [-0.13]	0.43
	1.06 [5.89]		-0.36 [-1.70]	0.48 [3.85]	0.13 [1.09]	0.45
10 Prior 1-0	0.27 [0.97]	0.88 [2.94]		0.03 [0.11]	0.13 [0.59]	0.27
	0.05 [0.15]		0.61 [1.67]	-0.01 [-0.04]	-0.02 [-0.09]	0.28
10 Prior 12-2	0.33 [1.28]	0.55 [2.06]		-0.57 [-2.26]	-0.62 [-2.74]	0.38
	1.20 [3.31]		-0.46 [-1.14]	-0.54 [-2.36]	-0.36 [-1.60]	0.43
10 Prior 60-13	0.15 [0.63]	0.76 [3.26]		0.33 [1.79]	-0.18 [-0.99]	0.36
	0.78 [2.82]		-0.05 [-0.16]	0.12 [0.70]	-0.04 [-0.22]	0.37
30 Industry portfolios	0.04 [0.22]	0.75 [4.76]		0.06 [0.46]	-0.07 [-0.52]	0.20
	0.56 [3.13]		0.15 [0.65]	0.15 [1.12]	0.11 [0.78]	0.24

Note: Results from Fama-MacBeth two-step regressions for the whole sample period January 1940 to December 2005 and for different subsets from the universe of all portfolios.

Table 4. Robustness checks

PANEL A: RANDOMIZATION OF TEST ASSETS AND TEST PERIODS

	Random portfolios	Random periods	Random portfolios and periods
Const.	0.20 {0.08 ; 0.32}	0.17 {-0.17 ; 0.51}	0.20 {-0.17 ; 0.59}
$\hat{\theta}$	0.58 {0.45 ; 0.72}	0.63 {0.40 ; 0.84}	0.58 {0.30 ; 0.87}
HML	0.20 {0.12 ; 0.28}	0.24 {0.02 ; 0.45}	0.20 {-0.03 ; 0.44}
SMB	0.07 {-0.04 ; 0.18}	0.07 {-0.16 ; 0.28}	0.07 {-0.19 ; 0.33}
R^2	0.31 {0.28 ; 0.33}	0.30 {0.28 ; 0.31}	0.31 {0.28 ; 0.34}

PANEL B: BOOTSTRAP ANALYSIS

	$\hat{\beta}$	$\bar{\hat{\beta}}$	$\sigma\left(\bar{\hat{\beta}}\right)$	$\left(\hat{\beta}-\bar{\hat{\beta}}\right)/\sigma\left(\bar{\hat{\beta}}\right)$
$\hat{\theta}$	0.66	0.00	0.07	9.43
HML	0.22	-0.00	0.06	3.67
SMB	0.01	0.00	0.05	0.21
R^2	0.29	0.00	0.01	

Notes: Panel A shows results from Fama-MacBeth regressions when the test assets and/or test periods are randomized. Panel B shows results from a bootstrap analysis where portfolio returns are matched randomly with risk factors.

Appendix 1. Descriptive statistics for the Fama-French risk factors

	MKTRF	HML	SMB
Mean	0.64	0.45	0.21
Std	4.55	2.93	2.98
Skew	-0.53	0.74	0.76
Kurt	6.28	8.95	9.63

Note: Descriptive statistics for the three Fama-French risk factors, namely the monthly mean, standard deviation (std), skewness (skew) and kurtosis (kurt). MKTRF denotes the market excess return (over the risk-free rate).