DISCUSSION PAPER SERIES

DP17935

THE PROSPECT CAPITAL ASSET PRICING MODEL: THEORY AND EMPIRICS

Xiang Gao, Kees Koedijk, Maurizio Montone and Zhan Wang

ASSET PRICING

CEPR

THE PROSPECT CAPITAL ASSET PRICING MODEL: THEORY AND EMPIRICS

Xiang Gao, Kees Koedijk, Maurizio Montone and Zhan Wang

This Discussion Paper is issued under the auspices of the Centre's research programmes:

- Asset Pricing

Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

THE PROSPECT CAPITAL ASSET PRICING MODEL: THEORY AND EMPIRICS

Abstract

We propose a Capital Asset Pricing Model where investors exhibit prospect preferences. In equilibrium, we find that agents seek an optimal trade-off between expected returns, variance, and skewness. All assets in the economy are then priced by a three-factor model, which augments the security market line with two factors that respectively capture positive and negative coskewness with the market portfolio. Using U.S. stock market data, we find evidence consistent with these predictions. In additional tests, we find that the results are stronger among stocks traded by less sophisticated investors. Overall, prospect preferences have a substantial effect on stock prices.

Xiang Gao - gaoxiang@sbs.edu.cn
Shanghai Business School

Kees Koedijk - keeskoedijk@gmail.com
Utrecht University and CEPR

Maurizio Montone - m.montone@uu.nl
Utrecht

Zhan Wang - zhanwang@sbs.edu.cn
Shanghai Business School

The Prospect Capital Asset Pricing Model: Theory and Empirics

Xiang Gao[a], Kees Koedijk[b,c,*], Maurizio Montone[b], Zhan Wang[a]

[a]*Shanghai Business School*
[b]*Utrecht University*
[c]*CEPR*

Abstract

We propose a Capital Asset Pricing Model where investors exhibit prospect preferences. In equilibrium, we find that agents seek an optimal trade-off between expected returns, variance, and skewness. All assets in the economy are then priced by a three-factor model, which augments the security market line with two factors that respectively capture positive and negative coskewness with the market portfolio. Using U.S. stock market data, we find evidence consistent with these predictions. In additional tests, we find that the results are stronger among stocks traded by less sophisticated investors. Overall, prospect preferences have a substantial effect on stock prices.

JEL classification: G11; G12; G14; G41.

Keywords: Prospect theory; Stock returns; Beta pricing; Skewness.

This draft: December 2022.

*Corresponding author. Address: P.O. Box 80125, 3508 TC Utrecht, Netherlands. Email address: c.g.koedijk@uu.nl.

1. Introduction

In their ground-breaking prospect theory, Kahneman and Tversky (1979) show that the way individuals evaluate risk in laboratory experiments differs substantially from the predictions of neoclassical models. They think in terms of gains and losses rather than wealth levels, and encode choices based on deviations from some predetermined reference point. A key element of the theory is that individuals dislike losses more than gains of the same absolute value, a phenomenon referred to as loss aversion. Notably, individuals become risk-seeking in an attempt to avoid a loss. In recent years, a growing body of evidence shows that prospect theory also characterizes real-world economic behavior (see Barberis (2013) for an excellent review).

In finance, prospect theory is a promising avenue of research. Numerous studies find that investors tend to be risk-averse with respect to gains, but risk-seeking when facing losses (Tversky and Kahneman, 1991; Benartzi and Thaler, 1995; Genesove and Mayer, 2001). Abdellaoui, Bleichrodt, and Kammoun (2013) find strong empirical support for prospect preferences in a sample of private bankers and fund managers. Prospect theory then seems to provide a more accurate description of decision-making under risk than the traditional expected-utility paradigm. The drawback of this approach, however, is that it is positive rather than normative, and then does not provide an ex-ante optimum that might guide portfolio formation.

In this paper, we propose a novel solution to this issue. We develop a Capital Asset Pricing Model (CAPM) where investors exhibit prospect preferences as in Kőszegi and Rabin (2006; 2007; 2009). In particular, we incorporate two key elements of their setup. First, investors use past beliefs as their reference point. Second, the utility function has two components. One is reference-independent as in classical models, while the other is reference-dependent as in prospect theory. To the best of our knowledge, this is the first paper that applies these features to the CAPM.

In equilibrium, investors find an optimal trade-off between the mean, variance, and skewness of portfolio returns. All assets in the economy are then priced by a three-factor model, which augments the canonical security market line with two risk factors that respectively capture positive and negative coskewness with the market portfolio. The intuition is as follows. Assets with positive coskewness increase risk in the region of gains, where investors are risk-averse, whereas assets with negative coskewness reduce risk in the region of losses, where investors are risk-seeking. Such assets are then unattractive to investors with prospect preferences, and correspondingly yield two additional risk premia on top of canonical covariance risk.

In the second part of the paper, we take these predictions to the data. We collect monthly U.S. stock data from the Center for Research in Security Prices (CRSP) equity database, which covers all firms incorporated in the United States and listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ). We exclude return information before 1970 to minimize survivorship bias, and end our analysis in December 2020. Finally, we complement the data set with canonical factor portfolios from the Kenneth French's Database and Wharton Research Data Services.

We construct the two coskewness factors as follows. Each month, we calculate the return coskewness

of each stock in the sample with the market portfolio using daily data, and categorize individual stocks into those that respectively exhibit positive and negative coskewness. Within each group, we calculate the coskewness beta for each individual stock, and rank all stocks in quintiles depending on their coskewness beta. Finally, we construct the two coskewness factors as the difference in monthly returns between the top and the bottom coskewness quintiles within each group.

Both coskewness factors exhibit high Sharpe ratios, which suggests that they indeed capture relevant risk dimensions. Their average monthly returns are 1.1% and 1.3%, respectively. These averages also translate into positive abnormal returns, as they are not explained by canonical measures of systematic risk. Interestingly, stocks that exhibit high coskewness in absolute value have some common characteristics, such as a higher market beta, lower market capitalization, and a lower book-to-market ratio. As shown in previous research, these stocks are indeed characterized by a more skewed return distribution (see, e.g., Conrad, Kapadia, and Xing, 2014; Frazzini and Pedersen, 2014).

Next, we turn to the analysis of individual stock returns through Fama-MacBeth regressions. Consistent with the model predictions, we find that both coskewness factors command a positive and highly significant risk premium on top of the market factor. The results are robust to the inclusion of additional factor-mimicking portfolios for size, book-to-market, profitability, and investment (Fama and French, 2015), momentum (Carhart, 1997), and liquidity (Pástor and Stambaugh, 2003). The coskewness factor loadings also exhibit similar magnitude to the loadings from these other factors.

Previous research shows that prospect preferences, and loss aversion in particular, are inversely related to the degree of sophistication of the investor (see, e.g., Bodnaruk and Simonov, 2016). Highly sophisticated investors, such as international or hedge fund managers, tend to exhibit low loss aversion. In light of these findings, we expect our results to be stronger among stocks that are characterized by a larger proportion of less sophisticated traders.

To test this hypothesis, we perform two additional analyses. First, we acknowledge that the presence of sophisticated investors is inversely related to market capitalization (see, e.g., Nagel, 2005; Baker and Wurgler, 2006, 2007), and the book-to-market ratio (see, e.g., D'Avolio, 2002; Jones and Lamont, 2002; Geczy, Musto, and Reed, 2002). Therefore, the coskewness factors from our model should primarily explain returns on these stocks. We find strong evidence for this prediction, as the estimates are more pronounced among small stocks and growth stocks.

Second, less sophisticated investors face short-sales constraints (see, e.g., Chen, Hong, and Stein, 2002; Hong and Sraer, 2013). As a result, we expect the abnormal returns on the two coskewness portfolios to be mostly driven by the short leg (see, e.g., Stambaugh, Yuan, and Yu, 2012). The intuition is as follows. If unsophisticated investors have stronger prespect preferences than sophisticated ones, they should evaluate return coskewness relatively less favorably. Hence, they should buy low-coskewness stocks and shun (rather than short) stocks with high coskewness. Consistent with this prediction, we find that abnormal returns on both coskewness portfolios are almost entirely explained by the short leg.

Our findings make several contributions to the literature. The present work primarily speaks to the CAPM, arguably the most influential model in modern finance theory. Early empirical studies show that the real-world security market line should have a higher intercept and a lower slope to match its theoretical counterpart (Friend and Blume, 1970; Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973; Blume and Friend, 1973). Later studies question whether the main prediction of the CAPM is verified at all, as market beta has limited explanatory power (see, e.g., Fama and French, 1993), or even exhibits a negative relation with returns (Frazzini and Pedersen, 2014).

To overcome these issues, the asset pricing literature modified the CAPM in a number of ways. Merton (1973) introduced the intertemporal CAPM (ICAPM) to extend the original setup to multiple periods with additional state variables. Based on the ICAPM, Fama and French (1993) augmented the security market line with a size and a book-to-market factor, arguing that such variables capture the latent state variables from Merton's (1973) model. Subsequent studies proposed additional factors, such as momentum (Carhart, 1997), or liquidity (Pástor and Veronesi, 2003). In a more recent paper, Fama and French (2015) augment their original three-factor model with investment and profitability factors.

While these models are empirically successful, they face the issue that neither the state variables nor the factors are defined ex-ante by the ICAPM. The choice of which factors to include is more based on in-sample correlations than conceptual grounds, which is more in line with the statistical approach of Ross's (1976) Arbitrage Pricing Theory (APT) than the ICAPM (see, e.g., Fama and French (2004) for an excellent discussion). This blurred boundary is an issue for asset pricing research, because it constitutes a potential "fishing license" for researchers to look for variables that describe stock returns ex-post, rather than ex-ante, thus lacking clear economic guidance (see, e.g., Fama, 1991; Harvey, Liu, and Zhu, 2016).

In our paper, we overcome this limitation. Our three factors emerge endogenously from the theoretical model we propose. In addition to the canonical market beta, we show that agents require two additional risk premia for sources of coskewness risk in the gains and the losses domain. The results indicate that covariance risk alone does not entirely capture the risk premium required by the marginal investor, thereby providing novel insights on why the empirical security market line has limited explanatory power.

Other extensions of the CAPM include higher moments of the return distribution (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Dittmar, 2002), or a dynamic price movement process (Merton, 1976; Todorov and Bollerslev, 2010; Bollerslev, Li, and Todorov, 2016). These studies, like ours, highlight the importance of skewness in asset pricing. In doing so, however, they work with higher-order derivatives of the utility function. By contrast, we propose a more parsimonious approach where we only need twice-differentiable utility.

Another related strand of research studies the asset pricing implications of prospect theory. Barberis, Huang, and Santos (2001) show that loss aversion over the value of financial wealth helps explain the high average returns, excess volatility, and predictability of stock returns found in empirical studies. Barberis and Huang (2008) propose a similar setup, and show that loss aversion can lead to the overpricing

of positively-skewed securities. Barberis, Mukherjee, and Wang (2016) extend these results by applying prospect preferences to individual stocks, rather than the whole portfolio. More recently, Barberis, Jin, and Wang (2021) show that prospect preferences help explain a number of asset pricing anomalies.

Despite their success, the drawback of these models is that they require relatively strict conditions. The return-generating process is typically based on an exponential value function, which makes the results dependent on specific parameter values. In this paper, we propose a different approach that relaxes these assumptions. We obtain a return-generating process through a classical utility-maximization procedure, where we just impose a reference-dependent utility component to incorporate prospect preferences.

In a related paper, Harvey and Siddique (2000) show that nonincreasing absolute risk aversion in a standard asset pricing model implies a preference for skewness. They show that adding an asset with negative coskewness to a portfolio reduces its total skewness, and therefore commands a risk premium. Using U.S. stock market data, they find empirical support for this prediction. Our paper extends their analysis to the case of prospect preferences. We find that a preference for skewness varies across the gains and losses domain, which leads to two separate risk premia for coskewness instead of just one. We also show that this prediction holds in the data through an analysis of U.S. stock returns.

More generally, our model speaks to recent research on reference-dependent preferences (Abeler, Falk, and Goette, 2011; Ericson and Fuster, 2011; Ingersoll and Jin, 2013; Yao and Li, 2013; Sprenger, 2015; Masatlioglu and Raymond, 2016; Wang, Yan, and Yu, 2017; Pagel, 2019), and their effect on trading behavior (Kaustia, 2010; Henderson, 2012; Li and Yang, 2013; Liu, Zhang, and Zhao, 2018). We show that incorporating these elements into a traditional asset pricing model provides novel testable implications for portfolio analysis, and ultimately a better understanding of the determinants of stock returns.

The rest of the paper is organized as follows. In Section 2, we introduce the model. In Section 3, we present the empirical analysis. In Section 4, we offer some concluding remarks.

2. Model

We propose a Prospect Capital Asset Pricing Model (PCAPM), where investors exhibit two key features of prospect preferences from Kőszegi and Rabin (2006; 2007; 2009). First, they form their reference points using past (rational) beliefs. Hence, the reference point is fixed when the choice is made. Second, the utility function has two components. One captures standard reference-independent utility as in classical models, whereas the other is a reference-dependent utility part as in prospect theory. In particular, this function is concave above the reference point, indicating risk aversion, and convex below, denoting risk-seeking behavior.

Let $U_i(R)$ be investor i's utility over asset returns R, and z_i a reference point indicating a particular level or returns. We express the investor's total utility as the sum of the two aforementioned components:

$$U_i(R) = U_i^Q(R) + dU_i(R), \tag{1}$$

where the first one represents a traditional quadratic utility function, expressed as a Taylor expansion around the reference point:

$$U_i^Q(R) = U_i(z_i) + U_i'(z_i)(R - z_i) + \frac{U_i''(z_i)}{2}(R - z_i)^2, \tag{2}$$

with $U_i'(z_i) > 0$ and $U_i''(z_i) \leq 0$, whereas the second component is:

$$dU_i(R) = \gamma Cov\{(R - z_i)^2, (R - z_i)\}, \tag{3}$$

where $\gamma \leq 0$ is a parameter that represents attitude towards risk, and satisfies the property that a prospect investor prefers low risk in the area of gains and high risk in the area of losses. Specifically, an increase in risk implies that $dU_i(R)$ is negative when the return is above the reference point ($R \in R^+$), and positive otherwise ($R \in R^-$). If $\gamma = 0$, the agent exhibits canonical risk-averse preferences.

Next, we derive a generalized aggregate utility function $U^G(R)$ for the entire market:

$$U^G(R) = U^Q(R) + dU(R), \tag{4}$$

where the two components $U^Q(R)$ and $dU(R)$ are respectively the sum of Eq. (2) and Eq. (3) over all investors, and the aggregate reference point is equal to μ. Since $dU_i(R)$ is monotonically decreasing, so is its aggregate counterpart $dU(R)$. This implies that there exist unique lower and upper bounds to the distribution of reference points across investors, which we denote by z_{min} and z_{max}, respectively.

If the return falls below the lower bound ($R < z_{min}$), the aggregate utility function is convex because every investor will be in the loss domain. This implies $dU(R) > 0$, and correspondingly $U^G(R) > U^Q(R)$, i.e., the aggregate utility function lies above its quadratic component – which serves as a benchmark for the case of simple risk-averse preferences. Conversely, a return above the upper bound ($R > z_{max}$) implies $dU(R) < 0$, and then $U^G(R) < U^Q(R)$. In this case, the aggregate utility function lies below its quadratic component, and therefore exhibits a higher degree of concavity. In the middle range between reference points, there exists a value of returns such that $dU(R) = 0$, and aggregate utility exactly coincides with quadratic utility. These three parts are depicted in Figure 1.

[Figure 1 here]

Expected utility can be expressed as follows:

$$EU^G(R) = U(\mu) + \frac{U''(\mu)}{2}E(R - \mu)^2 + \gamma Cov\{(R - \mu)^2, (R - \mu)\}, \tag{5}$$

where the covariance term represents the aggregate reference-dependent component. Using unconditional expectations and rational beliefs ($\mu = E(R)$), it is easy to see that this term captures the third moment of the return distribution:

$$Cov\{(R - \mu)^2, (R - \mu)\} \equiv E(R - \mu)^3 - E(R - \mu)^2 \underbrace{E(R - \mu)}_{=0} \equiv E(R - \mu)^3. \tag{6}$$

With reference-dependent utility, however, the expectation differs depending on whether returns are in the

area of gains or losses. As a result, we can decompose skewness into a separate component for each domain:

$$E(R - \mu)^3 \equiv E(R - \mu)^3 \times I_{R \in R^+} + E(R - \mu)^3 \times I_{R \in R^-} \equiv S^+ + S^-, \tag{7}$$

where $I_{R \in R^+}$ and $I_{R \in R^-}$ are indicator variables that take on value one when returns are above and below the reference point, respectively; correspondingly, S^+ and S^- represent positive and negative skewness. Note that utility over skewness is symmetric. Larger absolute values of S^+ make the distribution of returns more positively skewed in the gains domain, where the agent is risk-averse, thus reducing expected utility. Similarly, larger absolute values of S^- make the distribution of returns more negatively skewed in the losses domain, where the agent is risk-seeking, also reducing expected utility. In the reference-independent part, on the other hand, expected utility increases with expected returns and decreases with their variance, as in canonical risk-averse preferences.

Having derived an expected utility function, we can now solve a canonical utility maximization problem to find the optimal portfolio p^*. To this end, we consider an economy with n risky securities and one risk-free asset. Let L be the following Lagrange function:

$$L = EU\left(\mu_{p^*}, \sigma^2_{p^*}, S^+_{p^*}, S^-_{p^*}\right) - \lambda\left(1 - \sum_{i=1}^{n} w_i - f\right), \tag{8}$$

where the four arguments of expected utility are the mean (μ_{p^*}), variance ($\sigma^2_{p^*}$), positive skewness ($S^+_{p^*}$), and negative skewness ($S^-_{p^*}$) of portfolio returns. In the constraint, w_i is the weight of security i in the optimal portfolio, and f is the weight assigned to the risk-free asset. The first-order conditions are as follows:

$$\frac{\partial L}{\partial w_i} = \frac{\partial EU}{\partial \mu_{p^*}}\frac{\partial \mu_{p^*}}{\partial w_i} + \frac{\partial EU}{\partial \sigma^2_{p^*}}\frac{\partial \sigma^2_{p^*}}{\partial w_i} + \frac{\partial EU}{\partial S^+_{p^*}}\frac{\partial S^+_{p^*}}{\partial w_i} + \frac{\partial EU}{\partial S^-_{p^*}}\frac{\partial S^-_{p^*}}{\partial w_i} + \lambda = 0 \tag{9}$$

for all i, and:

$$\frac{\partial L}{\partial f} = \frac{\partial EU}{\partial \mu_{p^*}}\frac{\partial \mu_{p^*}}{\partial f} + \lambda = 0, \tag{10}$$

for the risk-free asset. Combining the two first-order conditions, and defining the following as:

$$\left(\frac{\partial \mu_{p^*}}{\partial w_i} - \frac{\partial \mu_{p^*}}{\partial f}\right) \equiv E(R^e_i), \tag{11}$$

$$\frac{\partial \sigma^2_{p^*}}{\partial w_i} \equiv Cov_{i,p^*}, \tag{12}$$

$$\frac{\partial S^+_{p^*}}{\partial w_i} = 3E\left((R_{p^*} - \mu_{p^*})^2(R_i - \mu_i) \times I_{R \in R^+}\right) \equiv Coskew^{R^+}_{i,p^*}, \tag{13}$$

$$\frac{\partial S^-_{p^*}}{\partial w_i} = 3E\left((R_{p^*} - \mu_{p^*})^2(R_i - \mu_i) \times I_{R \in R^-}\right) \equiv Coskew^{R^-}_{i,p^*}, \tag{14}$$

we can express expected excess returns on security i as:

$$E(R^e_i) = -\frac{\frac{\partial EU}{\partial \sigma^2_{p^*}}}{\frac{\partial EU}{\partial \mu_{p^*}}}Cov_{i,p^*} - \frac{\frac{\partial EU}{\partial S^+_{p^*}}}{\frac{\partial EU}{\partial \mu_{p^*}}}Coskew^{R^+}_{i,p^*} - \frac{\frac{\partial EU}{\partial S^-_{p^*}}}{\frac{\partial EU}{\partial \mu_{p^*}}}Coskew^{R^-}_{i,p^*}$$

$$\equiv \beta_1 Cov_{i,p^*} + \beta_2 Coskew^{R^+}_{i,p^*} + \beta_3 Coskew^{R^-}_{i,p^*} \tag{15}$$

which indicates that the risk premium is a linear combination of standard covariance risk and two measures of coskewness risk, one in the gains domain and the other in the losses domain. The arguments above imply

$\beta_1 > 0$, $\beta_2 > 0$, and $\beta_3 < 0$.

The risk premia are then as follows. Assets with high covariance are less preferable, much like in the standard CAPM, because they increase the variance of portfolio returns. Hence, they command a canonical risk premium. In addition, assets with positive coskewness command a risk premium in the gains domain, because they increase the skewness of portfolio returns when the investor is risk-averse. Conversely, assets with negative coskewness command a risk premium in the losses domain, as they reduce the skewness of portfolio returns when the investor is risk-seeking.

In the empirical analysis below, we take these predictions to the data.

3. Empirical analysis

We present our empirical results as follows. First, we perform a portfolio analysis. Second, we estimate Fama-MacBeth regressions. Third, we analyze cross-sectional effects to shed light on the mechanism underlying our findings. Finally, we perform an analysis of abnormal returns.

3.1. Portfolio analysis

We consider U.S. stock market data from the CRSP database, which cover all firms incorporated in the United States and listed on the NYSE, AMEX, and NASDAQ. To minimize survivorship bias, we exclude return information before 1970. The ending month of our sample period is December 2020. To address the potential concern that illiquidity may affect our estimates, we only include stocks that are traded for a minimum of 17 trading days within any given month during the sample period. We complement the data with returns on risk factors from the Kenneth French Database and Wharton Research Data Services.

We construct the mimicking portfolios for the two coskewness factors as follows. At the end of each formation month $t-1$, we compute the coskewness between the daily returns on each individual stock in the sample and the daily returns on the market portfolio. To identify coskewness in the gains and the losses domain, we follow the model's guidance and divide stocks into two groups depending on whether they exhibit positive or negative coskewness.

Next, we estimate the beta of each individual stock with respect to its corresponding coskewness portfolio using daily returns in the holding month t. To remove the potential influence of outliers, we winsorize the beta distribution at the 5% tails. Then for each of the two coskewness groups, we sort stocks into five beta quintiles and calculate equal-weighted returns. The difference in returns between the top and bottom quintiles represents the returns on our factor-mimicking portfolios for positive and negative coskewness, respectively.

[Table 1 here]

Table 1 reports some summary statistics. Among the positive coskewness portfolios, monthly returns are 0.50% for the bottom quintile, and 1.59% for the top quintile. As a result, the monthly returns on the

long-minus-short portfolio are 1.09% and highly significant (t-stat 4.60). We find similar estimates for the negative coskewness portfolios. The monthly returns on the bottom and top quintiles are 0.50% and 1.78%, respectively, and their 1.28% difference is highly significant (t-stat 5.37). For both sets of portfolios, returns monotonically increase with beta.

In Table 2, we report the Sharpe ratios of the factor-mimicking portfolios in the sample. The market portfolio and the two coskewness portfolios stand out, with estimates of 0.13, 0.15, and 0.17, respectively. The momentum factor exhibits the next best Sharpe ratio with 0.06. The substantial Sharpe ratios of our three portfolios of interest suggest that they indeed capture relevant risk dimensions.

[Table 2 here]

In Table 3, we estimate a correlation matrix between factors. Among the coefficients of interest, we find that the positive and negative coskewness factors exhibit positive and highly significant correlation with the market factor (0.69 and 0.71, respectively), and the size factor (0.57 and 0.62, respectively), and negative correlation with the book-to-market factor (-0.23 for both). High-coskewness stocks then seem to be particularly sensitive to market fluctuations, and tend to be small growth stocks. These stock categories are usually indeed characterized by higher skewness. Finally, the two coskewness factors exhibit positive, large, and highly significant correlation with each other (0.89). We take this potential confounding effect into account in the regression analysis that follows.

[Table 3 here]

3.2. Fama-MacBeth regressions

Following the model's guidance, we expect to find a positive relation between stock returns and factor loadings on the market portfolio and the two coskewness factors. To test this prediction, we estimate Fama-MacBeth regressions. We regress the monthly returns on each individual stock in our sample on the above factors in non-overlapping three-year subperiods, controlling for the canonical factors introduced above, and then report the average coefficients across periods.

Given the high correlation between the positive and negative coskewness factors, we begin the analysis by introducing them separately. In doing so, we alternatively consider the subsamples of stocks that exhibit positive and negative coskewness, respectively, in a given month. We also acknowledge the high correlation across the other factors, and therefore first estimate models without controls.

[Table 4 here]

The results, reported in Table 4, lend support to our theoretical predictions. In column (1), we estimate a simple model that only includes the market portfolio and the positive coskewness factor as explanatory

variables. The coefficients are positive, highly significant, and of similar magnitude (0.41 and 0.42, respectively). In column (2), we replace the positive coskewness factor with its negative counterpart. Again, the estimates are similar (0.50 and 0.53). In column (3), we include all three main explanatory variables jointly, and therefore consider the full sample. Attesting to the high correlation between the positive and negative coskewness factors, the magnitude of their coefficients decreases (0.27 and 0.31). However, statistical significance is virtually unaffected. The factor loading of the market portfolio remains large (0.48).

In columns (4) to (6), we repeat the analysis using the entire battery of controls. Due to the high correlation across factors, the magnitude of the factor loadings for the positive and negative coskewness portfolios decreases further (0.11 and 0.09), but both coefficients remain highly significant. The coefficient of the market portfolio, on the other hand, increases further in magnitude (0.76). Among the controls, we find a size premium (0.62) and a book-to-market premium (0.11), which is consistent with previous research (see, e.g., Fama and French, 1993). In unreported analyses, we obtain similar estimates when considering subperiods of five years instead of three. The results are also similar when re-estimating the regressions without subperiods, although statistical significance is lower due to the relatively wide time variation of factor loadings over time.

Overall, then, the results lend support to model prediction that positive and negative coskewness should command separate and positive risk-premia.

3.3. Cross-sectional effects

In additional tests, we look further into the mechanism underlying our results. To this end, we acknowledge that prospect preferences seem to characterize the trading behavior of less sophisticated traders (see, e.g., Bodnaruk and Simonov, 2016). Conversely, highly sophisticated investors tend to exhibit low loss aversion, and correspondingly exhibit stronger performances. In light of these findings, we expect prospect preferences to have a stronger effect on stocks traded by less sophisticated investors. Our three-factor model should then exhibit higher explanatory power for these stocks.

To test this hypothesis, we identify stocks characterized by a lower proportion of sophisticated traders as those with weaker arbitrage forces (see, e.g., Baker and Wurgler, 2006, 2007). Previous research shows that limits to arbitrage are inversely related to market capitalization (see, e.g., Nagel, 2005; Baker and Wurgler, 2006, 2007), and the book-to-market ratio (see, e.g., D'Avolio, 2002; Jones and Lamont, 2002; Geczy, Musto, and Reed, 2002). Therefore, we expect our results to be stronger for small and growth stocks.

We test this prediction by re-estimating the Fama-MacBeth regressions separately for stocks that respectively exhibit an above- or below-median market capitalization and a top or bottom book-to-market ratio at the end of the previous year. The results are in Tables 5 and 6. Consistent with our conjecture, we find that the coefficients of the two coskewness factors decrease with both size and the book-to-market ratio. The results from the full sample then hide important cross-sectional effects, indicating that prospect investors seem predominantly less sophisticated.

10

[Table 5 here]

[Table 6 here]

3.4. Abnormal returns

The Fama-MacBeth regressions show that the coskewness factors have explanatory power over individual stock returns, and the results are unaffected by the inclusion of canonical measures of systematic risk. In our last empirical exercise, we perform an analysis at the portfolio level. We analyze whether the returns on the coskewness portfolios are also not explained by the canonical risk factors introduced above, and therefore represent abnormal returns.

For the sake of comparability with the previous results, we leave the construction of the portfolios unaltered. For each of the two coskewness groups, the dependent variable is the monthly equal-weighted return on a portfolio that takes on a long position in stocks that belong in the top coskewness quintile and a short position in stocks from the bottom coskewness quintile. We rebalance these portfolios monthly.

[Table 7 here]

The results are in Table 7, columns (1) and (4). We find that both coskewness factors exhibit positive and highly significant abnormal returns. The estimates are respectively 2.23% and 2.26% for positive and negative coskewness. The results indicate that the returns on these coskewness-based investment strategies are not explained by canonical measures of risk.

The analysis of abnormal returns also allows us to shed further light on the mechanism underlying our findings. Previous research shows that less sophisticated investors face short-sales constraints (see, e.g., Chen, Hong, and Stein, 2002; Hong and Sraer, 2013). If our results are driven by such investors, the abnormal returns on the two coskewness portfolios should be mostly driven by the short leg (see, e.g., Stambaugh, Yuan, and Yu, 2012). The intuition is that relative to more sophisticated investors, prospect investors should find low-coskewness stocks more attractive and high-coskewness stocks less attractive. Therefore, they should buy the former and shun (rather than short) the latter.

We test this prediction for both coskeweness factors. The results for the positive coskewness factor are in Table 7, columns (2) and (3). We find strong evidence for the hypothesized mechanism. The abnormal returns are equal to 0.19% for the long leg, and -2.04% for the short leg. Therefore, the latter accounts almost entirely for the abnormal returns on the long-minus-short portfolio. The estimates are similar for the negative coskewness factor, in columns (5) and (6), and respectively equal to 0.19% and -2.06%. Overall, these additional results indicate that prospect investors indeed tend to be less sophisticated.

4. Conclusion

Prospect theory is a promising avenue of research for finance. A growing body of evidence shows that real-world investors make decision based on prospect preferences, rather than the traditional expected-utility framework. Despite its success, however, prospect theory lacks an ex-ante optimum because it is not normative in nature. Therefore, it is unclear how it might guide portfolio formation.

In this paper, we address this issue by developing a standard asset pricing model where investors exhibit prospect preferences. They rationally use past beliefs as a reference point, and their utility function includes a reference-dependent component. In so doing, we derive a Prospect Capital Asset Pricing Model. In this economy, all assets are then priced by a three-factor model that on top of market beta also includes two factors that respectively capture positive and negative coskewness with the market portfolio. Using data on U.S. stocks, we find strong evidence for the model predictions.

Our findings support the view that skewness matters in asset pricing. We show that a preference for skewness varies across the gains and losses domains, which leads to two separate risk premia for return coskewness. This is a novel insight for portfolio formation and our understanding of the determinants of stock returns. It is important to note that we obtain this result without using a value function or higher-order derivatives of the utility function. The advantage of this approach is that it is more parsimonious and does not depend on specific parameter values.

More generally, our three-factor model constitutes an attempt to derive risk factors directly from the theoretical analysis. In so doing, we address the issue of modern empirical asset pricing that risk factors are typically found on the basis of in-sample correlations rather than ex-ante economic guidance. Our two coskewness factors extend the security market line, thus providing novel insights as to why market beta alone has limited explanatory power on stock returns. In additional tests, we show that our model is especially well-suited to explain returns on stocks traded by less sophisticated investors.

Overall, the results suggest that the effect of prospect preferences on financial markets is more pervasive than previously thought. These findings have potential implications for other fields of finance outside of asset pricing. For example, it would be interesting to assess the effect of coskewness risk on firms' investment decisions or analyst recommendations. We leave these tasks to future research.

References

Abdellaoui, M., Bleichrodt, H, and Kammoun, H. Do financial professionals behave according to prospect theory? An experimental study. Theory and Decision 74 (2013): 411-429.

Abeler, J., Falk, A., Goette, L., and Huffman, D. Reference points and effort provision. American Economic Review 101, no. 2 (2011): 470-492.

Baker, M., and Wurgler, J. Investor sentiment and the cross-section of stock returns. The Journal of Finance 61, no. 4 (2006): 1645-1680.

Baker, M., and Wurgler, J. Investor sentiment in the stock market. Journal of Economic Perspectives 21, no. 2 (2007): 129-151.

Barberis, N. Thirty years of prospect theory in economics: A review and assessment. Journal of Economic Perspectives 27, no. 1 (2013): 173-196

Barberis, N., Huang, M., and Santos, T., Prospect theory and asset prices. The Quarterly Journal of Economics 116, no. 1 (2001): 1-53.

Barberis, N., and Huang, M. Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98, no. 5 (2008): 2066-2100.

Barberis, N., Jin, L. J., and Wang, B. Prospect theory and stock market anomalies. The Journal of Finance 76, no. 5 (2021): 2639-2687.

Barberis, N., Mukherjee, A., and Wang, B. Prospect theory and stock returns: An empirical test. The Review of Financial Studies 29, no. 11 (2016): 3068-3107.

Benartzi, S., and Thaler, R. Myopic loss aversion and the equity premium puzzle. The Quarterly Journal of Economics 110, no. 1 (1995): 73-92.

Black, F., Jensen, M., and Scholes, M. The capital asset pricing model: Some empirical tests. In Studies in the Theory of Capital Markets, edited by M. C. Jensen. New York: Praeger (1972): 79-121.

Blume, M., and Friend, I. A new look at the capital asset pricing model. The Journal of Finance 28, no. 1 (1973): 19-34.

Bodnaruk, A., and Simonov, A. Loss-averse preferences, performance, and career success of institutional investors. The Review of Financial Studies 29, no. 11 (2016): 3140-3176.

Bollerslev, T., Li, S., and Todorov, V. Roughing up beta: Continuous versus discontinuous betas and the cross section of expected stock returns. Journal of Financial Economics 120, no. 3 (2016): 464-490.

Carhart, M. On persistence in mutual fund performance. The Journal of Finance 52, no. 1 (1997): 57-82.

Chen, J., Harrison, H., and Stein, J. Breadth of ownership and stock returns. Journal of Financial Economics 66, no. 2-3 (2022), 171-205.

Conrad, J., Kapadia, N., and Xing, Y. Death and jackpot: Why do individual investors hold overpriced stocks? Journal of Financial Economics 113, issue 3 (2014): 455-475.

D'Avolio, G. The market for borrowing stock. Journal of Financial Economics 66, no. 2-3 (2002), 271-306.

Dittmar, R. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. The Journal of Finance 57, no. 1 (2002): 369-403.

Ericson, K. M. M., and Fuster, A. Expectations as endowments: Evidence on reference-dependent preferences from exchange and valuation experiments. The Quarterly Journal of Economics 126, no. 4 (2011): 1879-1907.

Fama, E. Efficient capital markets. The Journal of Finance 46, no. 5 (1991), 1575-1617.

Fama, E., and French, K. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, no. 1 (1993): 3-56.

Fama, E., and French, K. The capital asset pricing model: Theory and evidence. The Journal of Economic Perspectives 18, no. 3 (2004): 25-46.

Fama, E., and French, K. A five-factor asset pricing model. Journal of Financial Economics 116, no. 1 (2015): 1-22.

Fama, E., and MacBeth, J. Risk, return, and equilibrium: Empirical tests. The Journal of Political Economy 81, no. 3 (1973): 607-636.

Frazzini, A., and Pedersen, L. H.. Betting Against Beta. Journal of Financial Economics 111, no. 1 (2014): 1-25.

Friend, I., and Blume, M. Measurement of portfolio performance under uncertainty. The American Economic Review 60, no. 4 (1970): 561-575.

Geczy, C., Musto D.K., and Reed, A. Stocks are special too: An analysis of the equity lending market. Journal of Financial Economics 66, no. 2-3 (2002), 241-269.

Genesove, D., and Mayer, C. Loss aversion and seller behavior: Evidence from the housing market. The Quarterly Journal of Economics 116, no. 4 (2001): 1233-1260.

Harvey, C., Liu, Y., and Zhu, H. ... and the cross-section of expected returns. The Review of Financial Studies 29, no. 1 (2016), 5-68.

Harvey, C., and Siddique, A. Conditional skewness in asset pricing tests. The Journal of Finance 55, no. 3 (2000): 1263-1295.

Henderson, V. Prospect theory, liquidation, and the disposition effect. Management Science 58, no. 2 (2012): 445-460.

Hong, H., and Sraer, D. Quiet bubbles. Journal of Financial Economics 110, no. 3 (2013): 596-606.

Ingersoll, J. E., and Jin, L. J. Realization utility with reference-dependent preferences. The Review of Financial Studies 26, no. 3 (2013): 723-767.

Jones, C.M., and Lamont, O.A. Short-sale constraints and stock returns. Journal of Financial Economics 66, no. 2-3 (2002), 207-239.

Kahneman, D., and Tversky, A. Prospect theory: An analysis of decision under risk. Econometrica 47, no. 2 (1979): 263-292.

Kaustia, M. Prospect theory and the disposition effect. The Journal of Financial and Quantitative Analysis 45, no. 3 (2010): 791-812.

Kőszegi, B., and Rabin, M. A model of reference-dependent preferences. The Quarterly Journal of Economics 121, no. 4 (2006): 1133-1165.

Kőszegi, B., and Rabin, M. Reference-dependent risk attitudes. The American Economic Review 97, no. 4 (2007): 1047-1073.

Kőszegi, B., and Rabin, M. Reference-dependent consumption plans. The American Economic Review 99, no. 3 (2009): 909-936.

Kraus, A., and Litzenberger, R. Skewness preference and the valuation of risk assets. The Journal of Finance 31, no. 4 (1976): 1085-1100.

Li, Y., and Yang, L. Prospect theory, the disposition effect, and asset prices. Journal of Financial Economics 107, no. 3 (2013): 715-739.

Liu, X., Zhang, H., and Zhao, S. Can prospect theory explain the disposition effect? An analysis based on value function. China Financial Review International 8, no. 3 (2018): 235-255.

Masatlioglu, Y., and Raymond, C. A behavioral analysis of stochastic reference dependence. The American Economic Review 106, no. 9 (2016): 2760-2782.

Merton, R. C. An intertemporal asset pricing model. Econometrica 41 (1973): 867-887.

Merton, R. C. Option pricing when underlying stock returns are discontinuous. Journal of Financial Economics 3, no. 1-2 (1976): 125-144.

Nagel, S. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, no. 2 (2005), 277-309.

Pagel, M. Prospective gain-loss utility: Ordered versus separated comparison. Journal of Economic Behavior & Organization 168 (2019): 62-75.

Pástor, L., and Stambaugh, R. Liquidity risk and expected stock returns. Journal of Political Economy 111, no. 3 (2003), 642-685.

Ross, S. The arbitrage theory of capital asset pricing. Journal of Economic Theory 13, no. 3 (1976): 341-360.

Sprenger, C. An endowment effect for risk: Experimental tests of stochastic reference points. Journal of Political Economy 123, no. 6 (2015): 1456-1499.

Stambaugh, R.F., Yu, J., and Yuan, Y. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, no. 2 (2012): 288-302.

Todorov, V., and Bollerslev, T. Jumps and betas: A new framework for disentangling and estimating systematic risks. Journal of Econometrics 157, no. 2 (2010): 220-235.

Tversky, A., and Kahneman, D. Loss aversion in riskless choice: A reference-dependent model. The Quarterly Journal of Economics 106, no. 4 (1991): 1039-1061.

Wang, H., Yan, J., and Yu, J. Reference-dependent preferences and the risk-return tradeoff. Journal of Financial Economics 123, no. 2 (2017): 395-414.

Yao, J., and Li, D. Prospect theory and trading patterns. Journal of Banking & Finance 37, no. 8 (2013): 2793-2805.

Figure 1. Prospect and standard utility functions

Plot of the generalized utility function of the representative agent in the Prospect Capital Asset Pricing Model (PCAPM), denoted by $U^G(R)$, and a standard quadratic utility function, denoted by $U^Q(R)$. The horizontal axis represents asset returns (R), where z_{min} and z_{max} are respectively the lower and upper bounds of the distribution of reference points across investors.
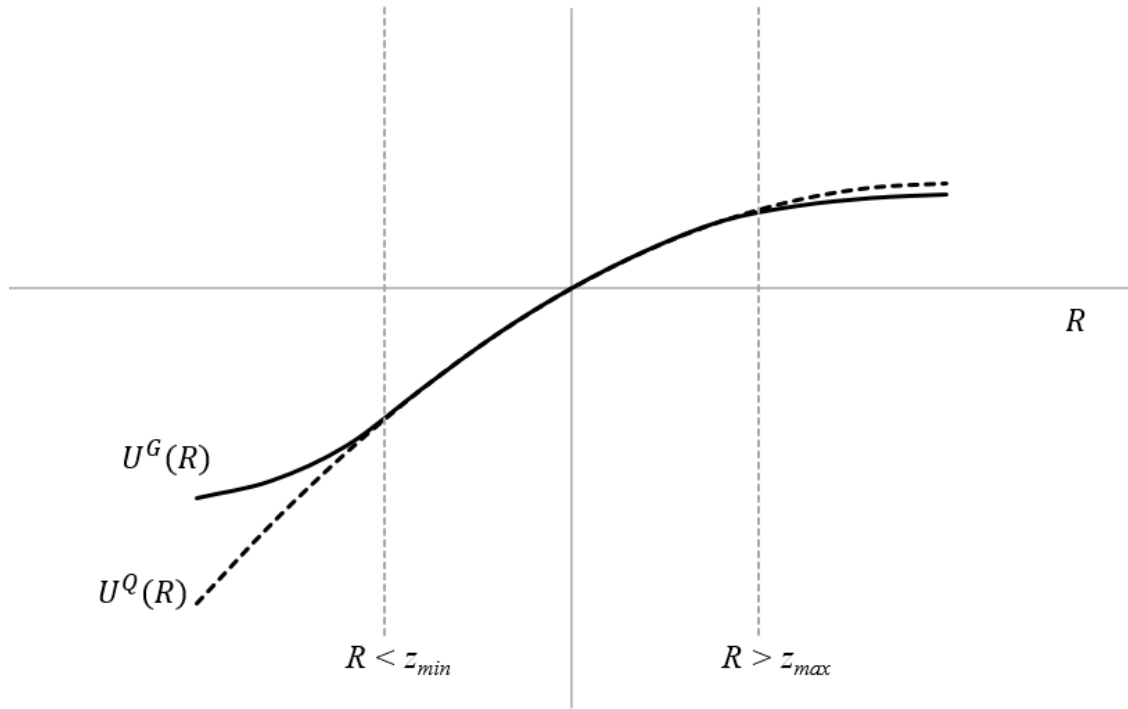
Table 1. Summary statistics: Coskewness portfolios and stock returns

Summary statistics for the average betas and monthly returns on the coskewness portfolios. At the end of each formation month $t-1$, we compute the coskewness between the returns on each individual stock in the sample and the returns on the market portfolio. Then we divide stocks into two groups, depending on whether they exhibit positive or negative coskewness. Next, we estimate the beta of each individual stock with respect to its corresponding coskewness portfolio using daily returns in the holding month t. To remove the potential influence of outliers, we winsorize the beta distribution at the 5% tails. Then for each of the two coskewness groups, we sort stocks into five quintiles and calculate equal-weighted portfolio returns. The difference in returns between the top and bottom quintiles represents the returns on our factor-mimicking portfolios for positive and negative coskewness, respectively. Returns are expressed in percentage points. The numbers in parentheses are t statistics, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period is from January 1970 to December 2020.

	Positive Coskewness		Negative Coskewness	
Quintile	Beta	Return	Beta	Return
1	0.250	0.496	0.249	0.496
2	0.732	0.646	0.718	0.679
3	1.222	0.798	1.194	0.836
4	1.840	1.007	1.794	1.082
5	2.958	1.591	2.867	1.779
5-1		1.095***		1.282***
		(4.60)		(5.37)

Table 2. Summary statistics: Return distribution and Sharpe ratios

Summary statistics for the distribution of monthly stock returns in our sample. The statistics include mean, standard deviation (SD), median, first quartile (P25), third quartile (P75), and the Sharpe ratio (SR). All returns are expressed in percentage points. The variables are individual stock returns (IR), the risk-free rate (RF), and factor-mimicking portfolios for market (MKT), positive coskewness (PC), negative coskewness (NC), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), momentum (UMD), and liquidity (IML). The coskewness portfolios are constructed as in Table 1. The other factor-mimicking portfolios are defined as in Fama and French (2015), Carhart (1997), and Pástor and Veronesi (2003). The sample period is from January 1970 to December 2020.

Variable	Mean	SD	Median	P25	P75	SR
IR	1.171	1.815	0	-6.832	7.316	
RF	0.373	0.280	0.390	0.130	0.530	
MKT	0.970	4.574	1.290	-1.750	3.930	0.131
PC	1.095	5.878	0.886	-1.934	3.914	0.123
NC	1.282	5.899	1.097	-1.602	4.172	0.154
SMB	0.142	3.032	0.080	-1.600	1.920	-0.076
HML	0.264	2.949	0.220	-1.420	1.730	-0.037
RMW	0.278	2.240	0.260	-0.760	1.290	-0.042
CMA	0.300	1.949	0.110	-0.980	1.480	-0.037
UMD	0.627	4.358	0.660	-0.960	2.910	0.058
IML	0.358	3.494	0.286	1.688	2.549	-0.004

Table 3. Summary statistics: Correlation matrix

Correlation matrix between the factor-mimicking portfolios in our sample, including factors for market (MKT), positive coskewness (PC), negative coskewness (NC), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), momentum (UMD), and liquidity (IML). The coskewness portfolios are constructed as in Table 1. The other factor-mimicking portfolios are defined as in Fama and French (2015), Carhart (1997), and Pástor and Veronesi (2003). The numbers in parentheses are p-values. The sample period is from January 1970 to December 2020.

	PC	NC	SMB	HML	RMW	CMA	IML	UMD
MKT	0.687	0.705	0.273	-0.217	-0.219	-0.377	0.041	-0.175
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.31)	(0.00)
PC		0.890	0.573	-0.227	-0.465	-0.318	-0.020	-0.259
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.62)	(0.00)
NC			0.624	-0.228	-0.476	-0.316	0.021	-0.227
			(0.00)	(0.00)	(0.00)	(0.00)	(0.61)	(0.00)
SMB				-0.029	-0.359	-0.073	0.022	-0.089
				(0.47)	(0.00)	(0.07)	(0.58)	(0.03)
HML					0.113	0.675	0.029	-0.217
					(0.01)	(0.00)	(0.48)	(0.00)
RMW						0.014	0.026	0.088
						(0.73)	(0.52)	(0.03)
CMA							-0.019	-0.009
							(0.63)	(0.83)
IML								0.020
								(0.62)

Table 4. Fama-MacBeth regressions

Fama-MacBeth regressions of individual stock returns on factor-mimicking portfolios for market (MKT), positive coskewness (PC), and negative coskewness (NC). The vector of controls includes the size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) factors from Fama and French (2015), the momentum factor (UMD) from Carhart (1997), and the liquidity factor (IML) from Pástor and Stambaugh (2003). The coskewness portfolios are constructed as in Table 1. We regress the monthly returns on each individual stock in our sample on the above factors in non-overlapping three-year subperiods, and then report the average coefficients. The numbers in parentheses are t statistics. The sample period is from January 1970 to December 2020.

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.407***	0.504***	0.480***	0.554***	0.730***	0.755***
	(21.03)	(21.77)	(39.01)	(25.58)	(38.14)	(67.04)
PC	0.423***		0.273***	0.139***		0.106***
	(26.04)		(22.90)	(6.99)		(9.19)
NC		0.534***	0.313***		0.186***	0.088***
		(31.58)	(31.64)		(10.89)	(7.21)
SMB				0.408***	0.759***	0.622***
				(15.34)	(31.39)	(42.26)
HML				-0.012	0.034	0.108***
				(-0.36)	(1.05)	(6.22)
RMW				-0.389***	-0.377***	-0.376***
				(-10.17)	(-9.93)	(-18.29)
CMA				-0.023	0.191***	0.118***
				(-0.54)	(6.13)	(5.89)
UMD				-0.186***	-0.044***	-0.068***
				(-11.17)	(-2.98)	(-7.89)
IML				-0.003	0.052***	0.005
				(-0.21)	(5.36)	(0.73)
Observations	1,276,676	1,337,133	2,613,809	1,276,676	1,337,133	2,613,809
R-squared	0.096	0.102	0.113	0.130	0.126	0.127

Table 5. Fama-MacBeth regressions: Size breakdown

Fama-MacBeth regressions of individual stock returns on factor-mimicking portfolios for market (MKT), positive coskewness (PC), and negative coskewness (NC). The vector of controls includes the size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) factors from Fama and French (2015), the momentum factor (UMD) from Carhart (1997), and the liquidity factor (IML) from Pástor and Stambaugh (2003). The coskewness portfolios are constructed as in Table 1. We regress the monthly returns on each individual stock in our sample on the above factors in non-overlapping three-year subperiods, and then report the average coefficients. Panels A and B respectively include stocks with below- and above-median market capitalization, measured at the end of the previous year. The numbers in parentheses are t statistics. The sample period is from January 1970 to December 2020.

Panel A. Small Stocks

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.428***	0.429***	0.422***	0.439***	0.434***	0.434***
	(25.07)	(24.85)	(25.38)	(24.47)	(24.58)	(24.73)
PC	0.618***		0.579***	0.615***		0.598***
	(24.69)		(24.93)	(25.56)		(26.06)
NC		0.626***	0.616***		0.645***	0.648***
		(25.08)	(25.03)		(25.59)	(25.83)
Controls	N	N	N	Y	Y	Y
Observations	383,002	401,139	784,141	383,002	401,139	784,141
R-squared	0.078	0.080	0.085	0.125	0.126	0.131

Panel B. Large Stocks

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.323***	0.318***	0.314***	0.319***	0.323***	0.317***
	(14.55)	(14.52)	(14.53)	(16.53)	(16.73)	(16.34)
PC	0.306***		0.295***	0.346***		0.343***
	(9.13)		(9.20)	(12.72)		(12.57)
NC		0.328***	0.326***		0.367***	0.363***
		(9.44)	(9.54)		(12.62)	(12.46)
Controls	N	N	N	Y	Y	Y
Observations	510,672	534,855	1,045,527	510,672	534,855	1,045,527
R-squared	0.087	0.091	0.101	0.200	0.203	0.206

Table 6. Fama-MacBeth regressions: Book-to-market breakdown

Fama-MacBeth regressions of individual stock returns on factor-mimicking portfolios for market (MKT), positive coskewness (PC), and negative coskewness (NC). The vector of controls includes the size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) factors from Fama and French (2015), the momentum factor (UMD) from Carhart (1997), and the liquidity factor (IML) from Pástor and Stambaugh (2003). The coskewness portfolios are constructed as in Table 1. We regress the monthly returns on each individual stock in our sample on the above factors in non-overlapping three-year subperiods, and then report the average coefficients. Panels A, B, and C respectively include stocks with a top 30%, middle 40%, and bottom 30% book-to-market ratio, measured at the end of the previous year. The numbers in parentheses are t statistics. The sample period is from January 1970 to December 2020.

Panel A. Top 30% Book-to-Market

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.184***	0.191***	0.187***	0.202***	0.200***	0.199***
	(9.93)	(9.96)	(9.84)	(10.56)	(10.70)	(10.62)
PC	0.163***		0.157***	0.201***		0.197***
	(6.78)		(6.52)	(9.39)		(9.13)
NC		0.153***	0.148***		0.191***	0.190***
		(6.23)	(6.18)		(8.20)	(8.36)
Controls	N	N	N	Y	Y	Y
Observations	383,002	401,139	784,141	383,002	401,139	784,141
R-squared	0.070	0.072	0.084	0.150	0.152	0.160

Panel B. Middle 30% Book-to-Market

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.287***	0.292***	0.293***	0.309***	0.308***	0.311***
	(18.33)	(18.07)	(18.54)	(19.01)	(18.83)	(18.91)
PC	0.258***		0.256***	0.263***		0.261***
	(11.96)		(12.03)	(12.48)		(12.29)
NC		0.257***	0.254***		0.263***	0.264***
		(11.43)	(11.41)		(11.90)	(11.88)
Controls	N	N	N	Y	Y	Y
Observations	510,672	534,855	1,045,527	510,672	534,855	1,045,527
R-squared	0.086	0.086	0.099	0.180	0.182	0.190

Panel C. Bottom 30% Book-to-Market

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.550***	0.549***	0.542***	0.513***	0.525***	0.518***
	(24.62)	(24.80)	(25.17)	(25.60)	(26.31)	(25.75)
PC	0.671***		0.643***	0.630***		0.627***
	(22.40)		(21.71)	(22.78)		(22.33)
NC		0.709***	0.703***		0.668***	0.667***
		(23.33)	(23.56)		(23.38)	(23.25)
Controls	N	N	N	Y	Y	Y
Observations	383,002	401,139	784,141	383,002	401,139	784,141
R-squared	0.096	0.100	0.109	0.194	0.194	0.201

Table 7. Abnormal returns

Abnormal returns on the positive and negative coskewness portfolios, constructed as in Table 1. The estimates are reported separately for the long-minus-short positions (columns (1) and (4)), the long leg (columns (2) and (5)), and the short leg (columns (3) and (6)). The vector of controls includes the market, size, book-to-market, profitability, and investment factors from Fama and French (2015), the momentum factor from Carhart (1997), and the liquidity factor from Pástor and Stambaugh (2003). The numbers in parentheses are t statistics. The sample period is from January 1970 through December 2020.

	Positive Coskewness			Negative Coskewness		
Dep. Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Returns	Long-Short	Long	Short	Long-Short	Long	Short
Alpha	2.23%	0.19%	-2.04%	2.26%	0.19%	-2.06%
	(14.15)	(4.78)	(-13.75)	(14.45)	(4.89)	(-14.02)