The Prospect Capital Asset Pricing Model: Theory and Empirics

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Abstract:

EWe propose a capital asset pricing model in which investors exhibit prospect preferences. In equilibrium, we predict that agents seek an optimal trade-off between expected returns, variance, and skewness. Specifically, assets with positive coskewness increase risk in the region of gains (investors are risk-averse), whereas assets with negative coskewness reduce risk in the region of losses (investors are risk-loving). Using U.S. stock market data, we find evidence consistent with the above theoretical predictions. A 1% rise in positive coskewness factor loading leads to 0.42% more stock returns. The negative coskewness coefficients are also positive and significant. The empirics indicate a 0.53% return increase for each 1% increase in the negative coskewness factor loading. In additional tests, we find that the results become stronger among stocks traded by less sophisticated investors. Overall, the implication is that there is a pervasive impact of prospect utility in financial markets..

Keywords:

prospect theory; stock returns; beta pricing; skewness

JEL classification: G11; G12; G14; G41.

1. Introduction:

Prospect theory finds that investors are loss averse (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991; Benartzi and Thaler, 1995; Genesove and Mayer, 2001; Abdellaoui, Bleichrodt, and Kammoun, 2013; Barberis, 2013). However, this finding is positive instead of normative, less useful for deriving the ex-ante optimum that might guide portfolio formation. This paper hence proposes a Capital Asset Pricing Model (CAPM) where investors exhibit prospect preferences as in Kőszegi and Rabin (2006; 2007; 2009). 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.

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 the predicted coskewness-risk relation 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. 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. Considering 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). 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 prospect 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 several 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 Stambaugh, 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.

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 that only requires 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 few 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 difference between the findings of this paper and previous literature is threefold. First, the model in this paper lies in the generality of the utility function, which releases the strict utility assumption in previous theoretical research. Second, this study builds the explicit separation of gain/loss domain skewness effects, which is consistent with the reference-dependence utility framework, and this setting is different from most existing literature. Third, this study combines the classical utility maximization model with the insights of behavioral finance and shows the derivation of pricing factors under a normative behavioral framework.

The rest of the paper is organized as follows. In Section 2, we introduce the modelling setup and equilibrium. 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. 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 components:

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

where the first component U_i^Q (R) represents a traditional quadratic utility function, expressed as a Taylor expansion around the reference point:

$$_i(z_i) + U_i'(z_i)(R - z_i) + \frac{U_i''(z_i)}{2}(R - z_i)^2, \qquad \textbf{(2)}$$

with U_i^' (z_i)>0 and U_i^'' (z_i) ≤0, , whereas the second component dU_i (R) is:

$$\mathbf{d}U_i(R) = \gamma^+ \mathrm{Cov}\{(R - z_i)^2, (R - z_i)\} \times I_{R\in R^+} + \gamma^- \mathrm{Cov}\{(R - z_i)^2, (R - z_i)\} \times I_{R\in R^-}, \qquad \textbf{(3)}$$

where and are indicator variables that take on value one when returns are above and here $I_{(R\in R^+)}$ and $I_{(R\in R^-)}$ are indicator variables that take on value one when returns are above and below the reference point, respectively. $\gamma^+\geq 0$ and $\gamma^-\leq 0$ are parameters that represent attitude towards risk, and satisfies the property that a prospect investor prefers low risk in the region of gains and high risk in the region of losses. It merits a note that the following theoretical derivation does not depend on the exact value of γ, and there are no extant studies have attempted to calibrate its value to real investors since it is a new parameter proposed by this paper. Moreover, since utility declines more steeply for losses than it increases for equivalent gains, $\gamma^+<\gamma^-$ in Equation (3). 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:

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

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. Prospect and standard utility functions

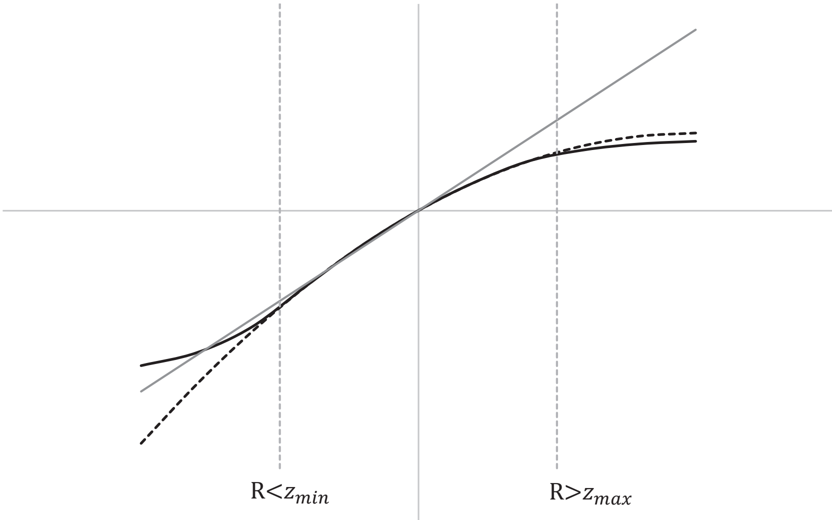

Figure 1. Prospect and standard utility functions

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 risk-neutral utility U^N (R) is also provided for reference. 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.

Plot of the generalized utility function of the representative agent in the Prospect Capital Asset Pricing Model (PCAPM), denoted by , and a standard quadratic utility function, denoted by . The risk-neutral utility is also provided for reference. The horizontal axis represents asset returns (), where and are respectively the lower and upper bounds of the distribution of reference points across investors.

Expected utility can be expressed as follows:

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

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

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

With reference-dependent utility, however, the expectation differs depending on whether returns are in the region of gains or losses. As a result, we can decompose skewness into a separate component for each domain:

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

where 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 gain's 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 loss's 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:

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

where the four arguments of expected utility are the mea (μ_{p*}), varianc (σ^2_{p*}), positive skewnes (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:

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

for all and:

$$\frac{\partial L}{\partial f} = \frac{\partial EU}{\partial \mu_{p*}}\frac{\partial \mu_{p*}}{\partial f} - \lambda = 0, \qquad \textbf{(10)}$$

for the risk-free asset. Note that we don't impose any restrictions on $\frac{\partial EU}{\partial S^+_{p*}}$ and $\frac{\partial EU}{\partial S^-_{p*}}$ being constant. So, the relationship between utility and skewness can be non-linear. Combining the two first-order conditions, and defining the following as:

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

$$\frac{\partial \sigma^2_{p*}}{\partial w_i} \equiv CoV_{i,p*}, \qquad \textbf{(12)}$$

$$\frac{\partial S^+_{p*}}{\partial w_i} = 3E\left((R_p - \mu_p)^2 (R_i - \mu_i) \times I_{R\in R^+}\right) \equiv CoSKEW^{R+}_{i,p*}, \qquad \textbf{(13)}$$

$$\frac{\partial S^-_{p*}}{\partial w_i} = 3E\left((R_p - \mu_p)^2 (R_i - \mu_i) \times I_{R\in R^-}\right) \equiv CoSKEW^{R-}_{i,p*}, \qquad \textbf{(14)}$$

we can express expected excess returns on security as:

$$(R^e_i) = -\frac{\frac{\partial EU}{\partial \sigma^2_{p*}}}{\frac{\partial EU}{\partial \mu_{p*}}} CoV_{i,p*} - \frac{\frac{\partial EU}{\partial S^+_{p*}}}{\frac{\partial EU}{\partial \mu_{p*}}} CoSKEW^{R+}_{i,p*} - \frac{\frac{\partial EU}{\partial S^-_{p*}}}{\frac{\partial EU}{\partial \mu_{p*}}} CoSKEW^{R-}_{i,p*} \qquad \textbf{(15)}$$

$$\equiv \beta_1 CoV_{i,p*} - \beta_2 CoSKEW^{R+}_{i,p*} - \beta_3 CoSKEW^{R-}_{i,p*}.$$

Equation (15) indicates that the risk premium is a linear combination of standard covariance risk and two measures of coskewness risk, one in the gain's domain and the other in the loss's domain. The arguments above implyimply $\beta_1>0$, $\beta_2>0$, 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 gain's 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 loss's domain, as they reduce the skewness of portfolio returns when the investor is risk-seeking.

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 , 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 gain's domain and the loss's domain, 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 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. 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 brackets 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 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. 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	09.130	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

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. 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 brackets 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]

3.2 Fama-MacBeth regressions

In this section, 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 one given month. We also acknowledge the high correlation across the other factors, and therefore first estimate models without controls.

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 brackets are t statistics. The sample period is from January 1970 to December 2020.

Table 4. Fama-MacBeth regressions

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
MKT	**0.407*** [21.03]**	**0.504*** [21.77]**	**0.480*** [39.01]**	**0.554*** [25.58]**	**0.730*** [38.14]**	**0.755*** [67.04]**
PC	**0.423*** [26.04]**		**0.273*** [22.90]**	**0.139*** [6.99]**		**0.106*** [9.19]**
NC		**0.534*** [31.58]**	**0.313*** [31.64]**		*****0.186 [10.89]**	**0.088*** [7.21]**

Follow: Table 4. Fama-MacBeth regressions

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
SMB				**0.408*** [15.34]**	**0.759*** [31.39]**	**0.622*** [42.26]**
HML				**-0.012 [-0.36]**	**0.034 [1.05]**	**0.108*** [6.22]**
RMW					**-0.377*** [-9.93]**	**-0.376*** [-18.29]**
CMA				**-0.023 [-0.54]**	**0.191*** [6.13]**	**0.118*** [5.89]**
UMD					**-0.044*** [-2.98]**	**-0.068*** [-7.89]**
IML				**-0.003 [-0.21]**	**0.052*** [5.36]**	**0.005 [0.73]**
Obs.	1,276,676	1,337,133	2,613,809	1,276,676	1,337,133	2,613,809
R-sq.	0.096	0.102	0.113	0.130	0.126	0.127

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). Therefore, the implication of this consistent significance is that, although these two coskewness factors are highly positively correlated (i.e., sharing explanatory power to some extent), they can still provide independent pricing information. The drop of coefficients in the regression containing both coskewness factors represents the impacts of these factors have been diluted.

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.

We can also estimate the specific effects of the volatility of coskewness factors on individual returns by a worked example. Given that the estimated price of risk for the positive coskewness factor is 0.423 in the first column in Table (4), and the cross-sectional standard deviation of the positive coskewness portfolio is 5.878% in Table (2), then a one-standard-deviation increase in exposure implies an expected return increase of 2.486% per month. Similarly, for the negative coskewness factor, a one-standard-deviation increase in exposure implies an expected return increase of 3.150% per month. Overall, 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. Considering 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.

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 brackets 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*** [25.07]	0.429*** [24.85]	0.422*** [25.38]	0.439*** [24.58]	0.434*** [24.58]	**0.434*** [24.73]**
PC	0.618*** [24.69]		0.579*** [24.93]	0.615*** [25.56]		**0.598*** [26.06]**
NC		0.626*** [25.08]	0.616*** [25.03]		0.645*** [25.59]	**0.648*** [25.83]**

Follow: Panel A. Small Stocks

Dep. Variable: Stock Returns	(1)	(2)	(3)	(4)	(5)	(6)
Controls	N	N	N	Y	Y	Y
.Obs	383,002	401,139	784,141	383,002	401,139	784,141
.R-sq	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*** [14.55]	0.318*** [14.52]	0.314*** [14.53]	0.319*** [16.53]	0.323*** [16.73]	0.317*** [16.34]
PC	0.306*** [9.13]		0.295*** [9.20]	0.346*** [12.72]		0.343*** [12.57]
NC		0.328*** [9.44]	0.326*** [9.54]		0.367*** [12.62]	0.363*** [12.46]
Controls	N	N	N	Y	Y	Y
.Obs	510,672	534,855	1,045,527	510,672	534,855	1,045,527
.R-sq	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 brackets 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 [9.93]	***0.191 [9.96]	***0.187 [9.84]	***0.202 [10.56]	***0.200 [10.70]	***0.199 [10.62]
PC	***0.163 [6.78]		***0.157 [6.52]	***0.201 [9.39]		***0.197 [9.13]
NC		***0.153 [6.23]	***0.148 [6.18]		***0.191 [8.20]	***0.190 [8.36]
Controls	N	N	N	Y	Y	Y
.Obs	383,002	401,139	784,141	383,002	401,139	784,141
.R-sq	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 [18.33]	***0.292 [18.07]	***0.293 [18.54]	***0.309 [19.01]	***0.308 [18.83]	***0.311 [18.91]
PC	***0.258 [11.96]		***0.256 [12.03]	***0.263 [12.48]		***0.261 [12.29]

Panel Panel B. Middle 30% Book-to-Market

NC		***0.257 [11.43]	***0.254 [11.41]		***0.263 [11.90]	***0.264 [11.88]
Controls	N	N	N	Y	Y	Y
.Obs	510,672	534,855	1,045,527	510,672	534,855	1,045,527
.R-sq	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 [24.62]	***0.549 [24.80]	***0.542 [25.17]	***0.513 [25.60]	***0.525 [26.31]	***0.518 [25.75]
PC	***0.671 [22.40]		***0.643 [21.71]	***0.630 [22.78]		***0.627 [22.33]
NC		***0.709 [23.33]	***0.703 [23.56]		***0.668 [23.38]	***0.667 [23.25]
Controls	N	N	N	Y	Y	Y
.Obs	383,002	401,139	784,141	383,002	401,139	784,141
.R-sq	0.096	0.100	0.109	0.194	0.194	0.201

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. 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 brackets are t statistics. The sample period is from January 1970 through December 2020.

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

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. As retail investors are constrained in short selling, if our results are driven by such investors, the abnormal returns on the two coskewness portfolios should be mostly reflected in 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 coskewness 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.

We address this issue by developing a standard asset pricing model in which 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 PCAPM. In this economy, all assets are 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 explanatory power of these two coskewness factors.

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 based on 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 also have potential implications for other fields of research outside of asset pricing, such as corporate finance or macroeconomics. For example, it would be interesting to assess the effect of coskewness risk on firms' investment decisions both at the micro and at the macro level. We leave these tasks to future research.

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