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Option Implied Volatility, Skewness, and Kurtosis and the Cross-Section of Expected Stock Returns

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Option Implied Volatility, Skewness, and Kurtosis and the Cross Section of Expected Stock Returns *

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Abstract

We develop an ex-ante measure of expected stock returns based on analyst price targets. We then show that ex-ante measures of volatility, skewness, and kurtosis implied from stock option prices are positively related to the cross section of ex-ante expected stock returns. While expected returns are related to both the systematic and unsystematic components of volatility, only the unsystematic components of skewness and kurtosis are related to the cross section of expected stock returns after controlling for other variables known to be related to the cross section of expected stock returns or analyst forecast bias.

Keywords: Risk-Neutral Moments, Option-Implied Risk, Ex-Ante Expected Stock Returns, Price Targets

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Asset pricing models, by their nature, describe relations between the ex-ante (i.e. forward-looking) risk of a security and the ex-ante expectation of the security's future return. Most empirical research, however, focuses on analyses of historical risk and future realized returns. Our objective in this paper is to develop a forward-looking measure of a stock's expected return and use this measure to examine cross-sectional relations between risk and expected returns using forward-looking measures of both.

We begin by creating a simple measure of forward-looking expected return derived from analyst price targets. The measure takes the average price target as the expected one-year-ahead stock price, and infers the expected return by dividing the expected future price by the stock's current market price. Our price target-based expected return has a positive cross-sectional relation with estimates of expected returns calculated from historical data. In the short sample period for which price targets are available, the measure has an economically strong but statistically weak positive relation with future realized returns.

We then examine the cross-sectional relations between price target-based expected returns and forward-looking measures of risk calculated from option prices. Specifically, we examine the relations between expected returns and the volatility, skewness, and kurtosis of the distributions of future returns. Our results indicate that all three measures of risk are strongly positively related to the cross section of price target-based expected returns. We then decompose the risk measures into systematic and unsystematic components and examine which components drive these relations. The results indicate that the systematic component of variance is the most important driver of the cross section of expected stock returns, followed by the unsystematic components of variance, skewness, and kurtosis. These relations remain strong after controlling for variables previously known to be determinants of the cross section of expected stock returns or bias in analyst forecasts. The systematic component of skewness is positively related to expected stock returns, but this relation is explained by the control variables. We find no evidence that stocks' systematic kurtosis is related to the cross section of expected stock returns.

Our work contributes to two broad lines of research. First, we add to the large body of work examining the cross section of expected stock returns. While the number of papers in this line of literature is very large, our paper is distinct from all previous studies in that, to our knowledge, we are the first to study cross-sectional relations between risk and expected returns using forward-looking measures of both. The positive cross-sectional relation between systematic variance and expected returns supports the main cross-sectional prediction of the CAPM (Sharpe (1964), Lintner (1965), Mossin (1966)). This result distinguishes our paper, and the price target-based expected return, from a long line of work that has found little evidence of a cross-sectional relation between beta and future realized returns (e.g. Black et al. (1972), Blume and Friend (1973), Fama and French (1992, 1993, 2004), Frazzini and Pedersen (2014), and Bali, Brown, Murray, and Tang (2017)). Our finding of a positive relation between the unsystematic component of variance and the cross section of expected returns lends support to theoretical models based on imperfect markets in which unsystematic volatility risk is positively priced (Levy (1978) and Merton (1987)). Once again, this result differs from previous empirical work on this topic, which finds evidence of a negative relation between idiosyncratic volatility and future stock returns (Ang, Hodrick, Xing, and Zhang (2006)). The positive relation between skewness and expected stock returns is inconsistent with the theoretically predicted negative tradeoff between expected stock returns and skewness (Kraus and Litzenberger (1976), Harvey and Siddique (2000), Mitton and Vorkink (2007)), but consistent with demand-based option pricing models (Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009)), suggesting that our skewness results are more indicative of the effect on option prices of price pressure from informed traders than a tradeoff between risk and expected return. This is the conclusion drawn by many previous studies that find positive relation between future realized stock returns and risk-neutral skewness or similar measures (Pan and Poteshman (2006), Bali and Hovakimian (2009), Xing, Zhang, and Zhao (2010), Rehman and Vilkov (2012), DeMiguel, Plyakha, Uppal, and Vilkov (2013), An, Ang, Bali, and Cakici (2014)).[1] Our results add to this work by demonstrating that the positive relation between option-implied skewness and expected stock returns is driven by firm-specific information, since only the unsystematic component of skewness is robustly related to expected stock returns. The positive relation between unsystematic option-implied skewness is contrary to the findings of Boyer, Mitton, and Vorkink (2010). However, our paper is quite different from Boyer et al. (2010) in that we measure holding period return skewness implied from option prices and use forward-looking expected returns, whereas Boyer et al. (2010) examine the ability of the idiosyncratic skewness of daily returns to predict future realized returns. The lack of a robust relation between the systematic component of skewness and expected stock returns is supported by Chabi-Yo (2012), who finds that the sign and price of systematic skewness risk are restricted by investor preferences. Finally, to our knowledge, ours is the first paper to detect a positive cross-sectional relation between kurtosis and expected stock returns, a finding that is consistent with theoretical predictions (Kimball (1993), Dittmar (2002)). However, these theories predict that the systematic component of kurtosis should be positively related to expected stock returns, but we find that it is the unsystematic component of kurtosis that drives this relation.

Second, we contribute to the line of work that uses analyst forecasts to create forward-looking measures of expected return. While there is a large literature that uses analyst earnings and growth forecasts to generate measures of firms' cost of equity capital (e.g. Gebhardt, Lee, and Swaminathan (2001) and Hughes, Liu, and Liu (2009)), only a small number of papers (Bradshaw (2002), Brav and Lehavy (2003), Brav, Lehavy, and Michaely (2005)) have used price targets for this purpose, and of these, only Brav et al. (2005) perform cross-sectional asset pricing tests using such a measure. Our price target-based measure of expected return differs from that used in previous work by using a market price taken after, instead of before or contemporaneous with, the release of the price target. As such, our

[1] Conrad, Dittmar, and Ghysels (2013) and Bali and Murray (2013) empirically detect a negative relation between skewness and future asset returns.

measure is designed to capture the rate of return required by the marginal investor in the stock, not a rate determined by analysts. An obvious caveat with using analyst price targets to calculate expected stock returns is the well-documented bias in analyst forecasts. This bias has been shown to be related to earnings (Abarbanell and Lehavy (2003)), growth (Jegadeesh et al. (2004)), investment banking relations (Ljungqvist et al. (2006), Lin and McNichols (1998), Michaely and Womack (1999)), mispricing (Jegadeesh et al. (2004)), past stock returns (De Bondt and Thaler (1990), Jegadeesh et al. (2004)), and liquidity (Jegadeesh et al. (2004)). Conrad et al. (2006), Bernhardt et al. (2016), and Linnainmaa et al. (2016) show that analyst forecasts are sticky. Ivković and Jegadeesh (2004) find that the timing of analyst forecasts relative to earnings announcement dates is related to the informativeness of the forecasts.[2] While the list of variables known to be related to biases in analyst forecasts is long, for these biases to impact our cross-sectional tests, the analyst bias would also need to manifest itself in our option-implied measures of risk, which seems unlikely. Nonetheless, in our empirical tests, we absorb analyst bias-related cross-sectional variation in the price target-based expected return by including several variables known to be related to bias as controls. Despite these biases, numerous papers have demonstrated that analyst reports play an important role in price formation (Jegadeesh and Kim (2006), Womack (1996)) and are informative about future expected stock returns (Frankel and Lee (1998), Barber et al. (2001), Boni and Womack (2006), Jegadeesh et al. (2004)).

The remainder of this paper proceeds as follows. Section 1 compares the price target-based measure of expected returns to other measures of expected return. Section 2 explains the calculation of the risk variables used in our empirical examinations and describes the construction of our sample. Section 3 investigates the relations between total risk-neutral moments and expected returns. Section 4 analyzes the relations between expected returns and the systematic and unsystematic components of risk-neutral moments. Section 5 con-

[2] See Womack (1996), Rajan and Servaes (1997), Bradshaw (2002), Brav and Lehavy (2003), Brav et al. (2005), Asquith et al. (2005), and Bonini, Zanetti, Bianchini, and Salvi (2010) for additional discussions of the biases in analyst forecasts.

cludes.

1 Ex-Ante Expected Returns

In this section, we present our rationale for choosing the price target-based expected return as our ex-ante expected return measure. Our choice is informed by conceptual analysis, a review of previous research, and an empirical investigation comparing the price target-based measure to an alternative ex-ante measure of expected return, the implied cost of capital.

1.1 Price Target Expected Returns

The price target-based measure of expected stock return is calculated by dividing analyst price targets by the stock's market price. Analyst price target data come from the Institutional Brokers Estimate System (I/B/E/S) unadjusted Detail History database. We use the unadjusted database because the price targets in this database are not adjusted for corporate actions. Therefore, when we merge the I/B/E/S data with databases that contain stock and stock option data (CRSP and OptionMetrics), the price target can be appropriately compared to the market price. We take all price targets for U.S. firms with a target horizon of 12 months where both the firm's base currency and the currency of the estimate are USD. The price target data cover the period from March 1999 through December 2012.

For each price target, we calculate the expected stock return implied by the price target ($PrcTgtER$) to be the price target ($PrcTgt$) divided by the stock's market price at the end of the month during which the price target was announced ($MonthEndPrc$), minus 1. To ensure the validity of the month-end stock price, we remove observations where either the announcement date or month-end stock price in CRSP is missing or non-positive.[3] To ensure that the price target is appropriately compared to the month-end market price, we remove

[3]Non-positive prices in CRSP result from days where there are no trades, in which case the price is reported as the negative of the average of the bid and offer. If neither bid nor offer is available, CRSP reports the price as 0.

observations where there is a stock split or distribution between the announcement date and the last day of the announcement month. To calculate the expected future return for stock i at the end of month t, we take the average of all price target-implied expected returns from price targets announced during month t. Therefore, the expected future return for stock i calculated at the end of month t is:

$$ER_{i,t} = \frac{\sum_{j=1}^{n_{i,t}} PrcTgtER_j}{n_{i,t}} \times 100 \tag{1}$$

where $n_{i,t}$ is the number of analyst price targets for stock i announced during month t, multiplication by 100 is so that the expected return is recorded as a percentage, and

$$PrcTgtER_j = \frac{PrcTgt_j}{MonthEndPrc} - 1. \tag{2}$$

To ensure data quality, we discard values of ER that are less than -50% or greater than 100%. An assumption in this measure is that the price targets used to calculate the expected return is inclusive of dividends expected to be paid on the stock in the next year. Since it is unclear whether price targets are inclusive or exclusive of expected dividends, in Section I and Tables A1 and A2 of the Internet Appendix, we demonstrate that our results hold when using an alternative measure of price target-based expected return that adds expected dividends to the price target.

There price target-based expected return measure has several benefits. First, it has the intuitive appeal of being consistent with the definition of the expected return as the expected future stock price divided by the current price. While the current market price of a stock is easily observable, the expectation of the future price is not. An analyst price target represents an explicit forecast, generated by an informed market observer, of the stock's future price. Second, the price target-based expected return has a time horizon of one year. As such, it is flexible enough to account for term structure variation in the risk and expected return profile of a stock. This contrasts substantially with the implied cost of capital measure, which does not associate a time horizon with the expected return. Third, the price target measure is simple, easily calculated, and largely free from assumptions that afflict alternative measures such as the implied cost of capital. While both measures rely on analyst forecasts, calculating the price target-based expected return requires no assumptions as to the future growth rate of the firm's earnings or the firm's future return on equity, whereas the implied cost of capital is heavily reliant on such assumptions. Finally, because we use the month-end price of the stock, which comes after the announcement of the price target, ER is designed to measure a discount rate determined by the marginal investor, not the analyst, since all information presented in the analyst report is publicly available before the month-end price is known. The sequence of events leading up to the calculation of the price target-based expected return is: 1) the price target is announced, 2) investors process the information in the analyst report (including the price target), 3) based on the information in the report and all other available information, investors determine the required rate of return on the stock, and 4) based on the required rate of return and the expected future price of the stock, the stock price is determined in a manner that equates the stock's expected return to the discount rate required by the marginal investor in the stock. Fourth, since in our main tests we measure risk from month-end option prices, it would be difficult to interpret our results as evidence that analysts use information related to option-implied risk to determine the target price of the stock, since this information is not yet known at the time the price target is announced.

In addition to the conceptual appeal of using price targets to calculate expected returns, there is substantial previous research indicating that price targets are the most informative component of analyst reports. Asquith et al. (2005) conclude that the information in price targets subsumes the information in earnings forecasts and recommendations (the other quantifiable components of analyst reports). Bradshaw (2002) finds that price targets reflect analysts' valuations of securities, and Bradshaw (2004) shows that valuations calculated using residual income models based on analysts' earnings and growth forecasts, such as the implied cost of capital, fail to accurately reflect analysts' assessments of stock value. In addition, Bradshaw (2002) finds that analysts are less likely to issue price targets when they lack confidence in their forecasts, suggesting that our price target-based measure is likely to be more accurate than measures based on other components of analyst reports. Taken together, these results favor the use of price targets over earnings and growth forecasts.

1.2 Implied Cost of Capital

We calculate the implied cost of capital (ICC) following Gebhardt et al. (2001). Conceptually, ICC is found by solving for the discount rate that equates the present value of expected future cash flows to the current stock price. For each stock-month observation in fiscal year y, ICC is calculated by solving:

$$P = B_y + \sum_{i=1}^{11} \frac{FROE_{y+i} - ICC}{(1 + ICC)^i} B_{y+i-1} + \frac{FROE_{y+12} - ICC}{ICC(1 + ICC)^{11}} B_{y+11} \tag{3}$$

where B_y is the book value of equity in fiscal year y and $FROE_{y+i}$ is the forecast return on equity in year $y + i$. The main inputs to the calculation of ICC are the current book value of equity and analyst forecasts of earnings and growth. In years $y + 1$ and $y + 2$, $FROE$ is calculated from explicit analyst forecasts. $FROE$ for year $y + 3$ and beyond are found using analysts' forecast growth rate and the assumption that the firm's return on equity reverts linearly to the long-term industry median return on equity by year $y + 12$, with constant return on equity occurring thereafter. Since our implementation is the same as that of Gebhardt et al. (2001), we relegate the details to Appendix A. As with the price target-based measure, to ensure data quality, we discard values of ICC that are less than -50% or greater than 100%.

There are several assumptions used in calculating the implied cost of capital (ICC) that limit its applicability in the context of the present research. First, ICC gives the single rate of return that equates the price of the stock to the present value of forecast future cash flows.

The objective of this paper is to analyze cross-sectional relations between short-horizon risk and expected returns. Thus, insofar as the term-structure of expected stock returns is not flat, ICC may differ from the short-horizon expected return. Second, as discussed in Easton and Monahan (2005), inaccurate estimation of the terminal value (the value derived from earnings in years $t + 3$ and beyond) used in the calculation of ICC results in a grossly inaccurate ICC value. The price target-based expected return, on the other hand, uses an explicit forecast of the terminal value, namely the price target, thereby alleviating the necessity to deduce the terminal value from forecast cash flows.

While the above discussion is favorable to the use of ER over ICC for our purposes, an empirical analysis comparing these measures is warranted. The remainder of this section empirically compares ER and ICC.

1.3 Empirical Analysis of ER and ICC

We take two approaches to empirically evaluating the effectiveness of ER and ICC. First, we compare the ex-ante expected return measures to a benchmark generated from regressions of historical realized returns. Second, we examine the ability of ER and ICC to predict the cross section of future realized stock returns.

1.3.1 Regression-Based Expected Returns

Our benchmark measure of expected returns is based on historical relations between stock returns and market beta (β), log of market capitalization ($Size$), and book-to-market ratio (BM). While the empirical asset pricing literature has identified hundreds of variables that are potentially related to the cross section of expected stock returns, recent work has questioned the strength and uniqueness of many of these relations (Hou, Xue, and Zhang (2015), McLean and Pontiff (2016), and Harvey, Liu, and Zhu (2016)). We choose these three variables for inclusion in our model because of their well-established theoretical or empirical relations with expected stock returns. To estimate the relation between expected returns and these variables, we employ the Fama and MacBeth (1973, FM hereafter) regression technique. Each month t from June 1963 through December 2011, we run a cross-sectional regression of one-year-ahead future stock returns on β, $Size$, and BM. The regression specification is:

$$R_{i,t+1:t+12} = \delta_{0,t} + \delta_{1,t}\beta_{i,t} + \delta_{2,t}Size_{i,t} + \delta_{3,t}BM_{i,t} + \epsilon_{i,t}, \tag{4}$$

where $R_{i,t+1:t+12}$ is the return of stock i in the 12-month period covering months $t+1$ through $t+12$, inclusive. $\beta_{i,t}$ is the stock's market beta, calculated as the slope coefficient from a regression of the stock's excess return on the market portfolio's excess return using one year's worth of daily data. Daily market excess returns are gathered from the Fama-French database on Wharton Research Data Systems (WRDS). We require a minimum of 225 daily return observations to calculate β. $Size_{i,t}$ is log of the stock's market capitalization ($MktCap$), defined as the number of shares outstanding times the month-end stock price, recorded in \$millions. BM for June of year y through May of year $y+1$ is calculated following Fama and French (1992, 1993) as the book value of equity at the end of the fiscal year ending in calendar year $y-1$ divided by the market capitalization at the end of that same calendar year.[4]

The time-series averages of the monthly cross-sectional regression coefficients are $\delta_0 = 23.2392$, $\delta_1 = -0.1899$, $\delta_2 = -2.1789$, and $\delta_3 = 3.1318$. We then use these coefficients to calculate our regression-based measure of expected returns ($RegER$), giving:

$$RegER_{i,t} = 23.2392 - 0.1899\beta_{i,t} - 2.1789Size_{i,t} + 3.1318BM_{i,t}. \tag{5}$$

1.3.2 $RegER$ Portfolios

We begin our comparison of ER and ICC with a portfolio analysis examining the relations between $RegER$ and each of the ex-ante measures. Each month t from March 1999 through June 2012, we sort all stocks for which valid values of $RegER$, ER, and ICC

[4]More details on the calculation of these variables are provided in Section II of the Internet Appendix.

are available into quintile portfolios based on an ascending ordering of $RegER$ and calculate the equal-weighted average $RegER$, ER, and ICC for each portfolio. The time series average of the monthly equal-weighted portfolio-level expected returns are presented in Panel A of Table 1. By construction, average values of portfolio-level $RegER$ increase from 2.74% for quintile portfolio one to 14.17% for quintile portfolio five, giving an expected return difference of 11.43% between the quintile five and quintile one portfolios. The results for ER are remarkably similar, with portfolio-level average ER increasing monotonically from 17.15% for quintile portfolio one to 27.56% for quintile portfolio five. The difference in average ER between the fifth and first quintile portfolio of 10.41% is not only highly statistically significant, with a t-statistic of 17.34, but is close to the corresponding value obtained from the regression-based expected returns.[5] Furthermore, the differences between the average $RegER$ and ER of 14.41% (17.15%-2.74%), 11.77% (18.41%-6.64%), 11.34% (20.05%-8.71%), 11.85% (22.46%-10.61%), and 13.39% (27.56%-14.17%) for quintile portfolios 1, 2, 3, 4, and 5, respectively, are quite similar. This indicates that, up to a constant, ER is highly similar in the cross section to the benchmark regression-based measure and suggests that any potential bias inherent in ER is largely unrelated to the variables used to calculate $RegER$.

Average values of ICC also exhibit an increasing pattern across the $RegER$ quintile portfolios from 7.63% for the quintile one portfolio to 9.87% for quintile five, giving a $5-1$ difference of 2.24% (t-statistic = 7.83). While this difference is highly significant, it is substantially less significant, both economically and statistically, than the corresponding value for ER.

1.3.3 Future Returns

We next examine the ability of ER and ICC to predict the cross section of future realized stock returns. Panel B of Table 1 shows the average one-month-ahead realized return for

[5] The high average value of ER is consistent with results from previous studies that use similar measures, and will be discussed in more detail in Section 2.2.

equal-weighted quintile portfolios formed by sorting on each of ER and ICC. Consistent with the hypothesis that both ER and ICC are proxies for ex-ante expected returns, the average future returns of both sets of portfolios tend to increase across the quintile portfolios. When sorting on ER, the difference in future return between the quintile five and quintile one portfolios of 0.82% per month is statistically insignificant at conventional levels, with a t-statistic of 1.93. When sorting on ICC, this difference is 0.72% per month with a corresponding t-statistic of 1.73, both of which are slightly smaller than the corresponding values for the ER-sorted portfolios. Thus, while both ER and ICC produce economically large but statistically weak ability to predict the cross section of future stock returns, the results tend to favor ER over ICC. The low statistical significance of these tests is not surprising in light of the short sample period and the fact that realized returns are a noisy measure of ex-ante expected returns (Elton (1999)). Indeed, this illustrates the potential benefit of using an ex-ante measure of expected return in asset pricing tests, especially tests for which the sample period is short.

In summary, our empirical comparison of ER and ICC suggests that ER performs slightly better than ICC at capturing cross-sectional variation in expected stock returns. This, combined with the conceptual arguments and evidence from previous research suggesting that price targets are the more informative about expected future returns than forecasts of earnings and growth, leads us to use ER as our measure of ex-ante expected return in our focal analyses.

Before proceeding, a few words of caution are warranted. First, our tests relating ER to $RegER$ rely on the assumption that true expected stock returns are indeed related to beta, book-to-market ratio, and market capitalization. While the true set of determinants of expected return is not known – if it were, there would be no need for ER – if beta, book-to-market ratio, and market capitalization do not capture a substantial portion of the cross-sectional variation in expected returns, then the power of our tests using $RegER$ may be weak. Second, ER relies on the assumption that the average price target is a good measure of the expected future price of the stock. This assumption is questionable in light of the large literature on cross-sectional bias in analyst forecasts discussed above. However, for a bias in ER to pose a problem for investigations of the determinants of the cross section of expected stock returns, the bias in ER would need to be cross-sectionally correlated with bias or measurement error in the variable under investigation. For the purposes of this study, which examines the relation between ER and risk-neutral moments inferred from option prices, this seems unlikely to be the case. Nonetheless, to alleviate concern that analyst bias impacts our inference, we are careful to control for variables known to be cross-sectionally related to analyst bias. Third, since ER is calculated by scaling the average price target by an observed market price, insofar as the observed market price is not reflective of true market value, then ER may not accurately reflect equilibrium expected return and any documented relations between ER and variables, such as market capitalization and book-to-market ratio, whose calculation uses the stock price, may be spurious. However, since our risk measures are purely a function of option prices, this concern is unlikely to substantially impact our results. To further mollify this concern, by adding such variables as controls in regression analyses, the coefficients on the variables of interest capture relations that are unrelated to correlations, spurious or otherwise, between ER and other price-based variables. With these caveats in mind, we proceed to our main objective, which is to examine the cross-sectional relations between ex-ante risk and ex-ante expected returns.

2 Ex-Ante Risk and Sample

This section describes our measures of ex-ante risk and the construction the sample we use to examine relations between risk and expected return.

2.1 Ex-Ante Risk

We calculate risk-neutral volatility, skewness, and kurtosis using the methodology of Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003, BKM hereafter). BKM demonstrate that the annualized variance (Var^{BKM}), skewness ($Skew^{BKM}$), and excess kurtosis ($Kurt^{BKM}$) of the risk-neutral distribution of a stock's log return from present (t) until a time τ years in the future are given by:

$$Var^{BKM} = \frac{e^{r\tau}V_{i,t} - \mu^2}{\tau} \tag{6}$$

$$Skew^{BKM} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{3/2}} \tag{7}$$

$$Kurt^{BKM} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2 V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3 \tag{8}$$

where

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V - \frac{e^{r\tau}}{6}W - \frac{e^{r\tau}}{24}X, \tag{9}$$

r is the continuously compounded risk-free rate for the period from time t to time $t+\tau$, and V, W, and X are the risk-neutral expectation of the squared, cubed, and fourth power, respectively, of the log of the stock return during the same period. V, W, and X can theoretically be calculated by weighted integrals (equations (22)-(24) of Appendix B) of time t prices of out-of-the-money (OTM) call and put options with continuous strikes expiring at time $t+\tau$. We follow Dennis and Mayhew (2002), Duan and Wei (2009), Conrad et al. (2013), and Bali and Murray (2013) and use a trapezoidal method to estimate V, W, and X from observed option prices, which have discrete strikes. The details of our implementation are described in Appendix B. Finally, we define the risk-neutral volatility (Vol^{BKM}) to be the annualized standard deviation of the distribution of the log return:

$$Vol^{BKM} = \sqrt{Var^{BKM}}. \tag{10}$$

The month t risk-neutral moments for each stock i are calculated using data from the last trading day during the month t for options that expire in month $t + 2$ (the options have approximately 1.5 months until expiration). Ideally, the time to expiration of the options used to calculate the risk-neutral moments would match the one-year time-horizon of ER. However, stock options with one year to expiration are illiquid and in many cases unavailable, making the measurement of the risk-neutral moments using one-year options inaccurate or unfeasible. Using options with 1.5 months until expiration enables us to calculate the risk-neutral moments for the broadest cross section of stocks of any available expiration. In Section III and Tables A3 and A4 of the Internet Appendix, we show that our results are qualitatively unchanged when we use options with approximately 2.5 months to expiration, suggesting that the maturity of the options used in our tests does not have a substantial impact on our results.

2.2 Sample

Our sample contains stock-month observations for which we are able to calculate values of our focal variables. Specifically, the sample covers months t from March 1999 through December 2012, the period for which price targets are available. Each month t, the sample contains all U.S.-based common stocks in CRSP for which ER, Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are available.

Table 2 presents the time-series averages of monthly cross-sectional summary statistics for ER, Vol^{BKM}, $Skew^{BKM}$, $Kurt^{BKM}$, and $MktCap$ for the stocks in our sample. In the average month, ER has a mean and median value of 20.75% and 18.28%, respectively. While these numbers are quite high, they are consistent with previous research (Asquith et al. (2005), Brav and Lehavy (2003), Bradshaw (2002)) that finds an upward bias in expected returns calculated using price targets. Vol^{BKM} is on average (in median) 47.71% (43.40%). The risk-neutral distributions of stock returns tend to be negatively skewed, with a mean (median) value of $Skew^{BKM}$ equal to -0.67 (-0.60). These distributions also tend to be leptukurtic, with a mean (median) value of $Kurt^{BKM}$ of 1.82 (0.73). Stocks in the sample have a mean (median) market capitalization of $9.9 billion ($2.8 billion), but some small capitalization stocks do enter the sample, since the minimum and fifth percentile market capitalizations in the average month are $139 million and $354 million, respectively. In the average month there are 279 stocks in the sample. The small average number of stocks per month is largely a manifestation of the data requirements for calculating the BKM risk-neutral moments. To ensure that our results hold in a broader cross section of stocks, we repeat our main tests using alternative measures of risk-neutral moments that require less data to calculate. Using the alternative measures of the risk-neutral moments allows us to increase the number of stocks in the average month to 988. The results of our tests using this broader sample, presented in Section IV and Tables A5-A8 of the Internet Appendix, are highly similar to those using the BKM risk-neutral moments. We focus on the BKM moments because decomposition of the alternative measures into systematic and unsystematic components is not feasible.

3 Ex-Ante Risk and Expected Returns

We now turn our attention to our main objective of investigating the relations between the ex-ante risk and expected returns.

3.1 Portfolio Analysis

We begin with tri-variate dependent-sort portfolio analyses. Each month t, all stocks in the sample are grouped into portfolios based on ascending sorts of the risk-neutral moments. To test the relation between volatility and expected returns, we first sort all stocks into three groups based on an ascending ordering of $Skew^{BKM}$. Next, within each $Skew^{BKM}$ group we then sort stocks into three groups based on an ascending ordering of $Kurt^{BKM}$. Finally, within each of the nine $Skew^{BKM}$ and $Kurt^{BKM}$ groups, we form three portfolios based on an ascending ordering of Vol^{BKM}, resulting in 27 total portfolios. For each sort, the breakpoints dividing the groups are determined by the 30th and 70th percentile of the sort variable. We then calculate the equal-weighted average ER for each of the 27 portfolios, as well as the difference in average ER between the high and low Vol^{BKM} portfolio (Vol^{BKM} 3−1) within each $Skew^{BKM}$ and $Kurt^{BKM}$ group. To examine the relation between $Skew^{BKM}$ ($Kurt^{BKM}$) and ER, we repeat the analysis, sorting first on $Kurt^{BKM}$ ($Skew^{BKM}$), then on Vol^{BKM}, and then on $Skew^{BKM}$ ($Kurt^{BKM}$). The sorting procedure is designed to enable us to examine the relation between the last sort variable and expected returns after controlling for the effects of each of the first two sort variables. Table 3 presents the time-series means of the average ER for each portfolio. Since the order of the first two sort variables is arbitrary, in Section V and Table A9 of the Internet Appendix, we show that the results are qualitatively the same with the order of the first two sort variables reversed.

The results in Table 3 Panel A indicate a strong positive cross-sectional relation between Vol^{BKM} and ER. The average ER for the Vol^{BKM} 3−1 portfolios range from 9.16% per annum to 15.5% per annum and are all highly statistically significant, with t-statistics of 8.20 and higher. Furthermore, the portfolios exhibit monotonically increasing average ER across the three Vol^{BKM} portfolios in each of the nine $Skew^{BKM}$ and $Kurt^{BKM}$ groups. The results indicate that, consistent with theoretical predictions, investors command a higher expected return for stocks with higher volatility. The results also suggest that previous empirical studies showing that future realized returns are unrelated to historically estimated systematic volatility risk (Black et al. (1972), Fama and French (1992), Frazzini and Pedersen (2014), Bali et al. (2017)) and negatively related to idiosyncratic volatility (Ang et al. (2006)) may not accurately characterize the way investors price securities.

Panel B of Table 3 demonstrates that $Skew^{BKM}$ exhibits a strong positive cross-sectional relation with ER. The nine $Skew^{BKM}$ 3−1 portfolios generate average ER ranging from 3.11% to 11.00% per annum with t-statistics of 2.06 and higher. Within eight of the nine $Kurt^{BKM}$ and Vol^{BKM} groups, the $Skew^{BKM}$ portfolios exhibit monotonically increasing average ER. The positive relation between skewness and expected returns contradicts the negative relation predicted by asset pricing theories (Kraus and Litzenberger (1976), Harvey and Siddique (2000), Mitton and Vorkink (2007)), but supports the predictions of demand-based option pricing (Bollen and Whaley (2004), Garleanu et al. (2009)). The relation we document is also consistent with previous studies that find evidence of positive relation between future realized returns and risk-neutral skewness (Bali and Hovakimian (2009), Xing et al. (2010), Rehman and Vilkov (2012), DeMiguel et al. (2013), and An et al. (2014)). The general consensus of these papers is that this result reflects a combination of informed trading in the option markets and mispricing. Specifically, as shown by Pan and Poteshman (2006), informed investors buy (sell) calls (puts) on stocks that are underpriced. This trading activity pushes the prices of calls (puts) up (down) on stocks with high expected returns, resulting in high values of option-implied skewness. Our finding of a positive relation between $Skew^{BKM}$ and ER, therefore, appears to be more a manifestation of the price impact of this demand for options (i.e. demand-based option pricing) than of a relation between risk and expected return. Thus, the economic conclusions drawn from our results using the price target-based expected return are the same as those reached by similar work.

Finally, Panel C shows that there is a positive cross-sectional relation between $Kurt^{BKM}$ and ER. Eight of the nine $Kurt^{BKM}$ $3-1$ portfolios exhibit positive average ER, six of which have t-statistics greater than 2.00. Equilibrium asset pricing theories (Kimball (1993), Dittmar (2002)) predict a positive relation between systematic kurtosis and expected stock returns. However, we are unaware of any theoretical prediction on the relation between idiosyncratic kurtosis and expected stock return. Therefore, while the results indicate a positive cross-sectional relation between kurtosis and expected returns, without decomposing kurtosis into its systematic and idiosyncratic components, a task we take up in Section 4, it is difficult to evaluate these results in the context of existing theories.

The objective of using an ex-ante measure of expected return is to enable us to detect asset pricing relations that may be difficult to detect using realized returns due to noise (Elton

(1999)). To test whether the use of ER enables us to detect relations between risk and expected return not evident in realized returns, we repeat the tri-variate portfolio analyses, this time using one-month-ahead realized returns instead of ER to measure expected returns. We use one-month-ahead realized returns here, instead of one-year-ahead realized returns used in Section 1 to calibrate $RegER$, to more closely match the time horizon of the returns with the expiration of the options used to measure ex-ante risk. The results of these analyses, presented in Table 4, detect no relation between one-month-ahead realized returns and either Vol^{BKM} or $Kurt^{BKM}$, since all Vol^{BKM} and $Kurt^{BKM}$ $3-1$ portfolios generate insignificant average returns. For $Skew^{BKM}$, however, consistent with previous work, five of the nine $3-1$ portfolios generate a positive and statistically significant average return. Thus, when the realized return analysis does detect a relation, as is the case for $Skew^{BKM}$, this relation is in the same direction as the relation detected by the analysis using price target expected returns. As discussed above, however, the evidence suggests that this relation is more indicative of option demand affecting option prices, and not of an equilibrium relation between risk and expected return. Our ability to detect relations between expected and each of Vol^{BKM} and $Kurt^{BKM}$ using ER that are not detected using ex-post realized returns illustrates the benefits of using an ex-ante measure of expected return.

3.2 Regression Analysis

Having demonstrated strong cross-sectional relations between ER and each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$, we proceed to examine whether these relations can be explained by other measures previously shown to be related to either expected stock returns or bias in analyst forecasts. If the relations between the risk measures and expected stock returns are explained by other previously identified determinants of expected stock returns, it would suggest that the relations we document may be inferred from studies of realized returns that use longer sample periods. If these relations are not explained by other known determinants of expected stock returns, it suggests that the relations we document are distinct from those identified by previous research. If variables known to be related to analyst forecast bias explain the relations between risk and expected return, it would suggest that the bias evident in analyst forecasts extends to the options market as well.

To test whether variables identified by previous research as related to either expected stock returns or analyst bias explain the relations we document, we use FM regression analysis. Specifically, each month t, we run a cross-sectional regression of ER on Vol^{BKM}, $Skew^{BKM}$, $Kurt^{BKM}$, and a set of controls, and test whether the time-series average of the monthly cross-sectional regression coefficients for each independent variable is equal to zero. While the portfolio analyses in Section 3.1 have the benefit of not assuming any functional form of the relation between expected stock returns and the risk-neutral moments, the drawback of portfolio analysis is that it is difficult to simultaneously control for a large number of other potential determinants of expected stock returns without substantially deteriorating the test power. FM regression analysis enables us to simultaneously control for many other effects, but assumes a linear relation between expected returns and the variables on the right hand side of the regression specification.

We first examine whether the FM regression analysis produces results similar to those of the portfolio analyses by running the analysis with Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ as the only independent variables. Specification (1) in Table 5 shows that, consistent with the portfolio analysis, the average coefficients on Vol^{BKM} of 0.31 (t-statistic = 17.52), $Skew^{BKM}$ of 6.98 (t-statistic = 10.13), and $Kurt^{BKM}$ of 0.86 (t-statistic = 7.71), are all positive and highly statistically significant.

We next add several variables associated by previous work with either expected returns or analyst forecast bias as controls and repeat the FM regression analysis. The control variables known to be related to expected stock returns are as follows. β, $Size$, and BM are defined in Section 1.3.1. Since the calculation of $Size$ and BM both rely heavily on the price of the stock, these variables also absorb spurious price-related variation in ER driven by using the stock price in the calculation of ER. Idiosyncratic volatility ($IdioVol$)

is the annualized residual standard error from a regression of the stock's excess return on the market excess return, and the size (SMB) and book-to-market (HML) factors of Fama and French (1993). Coskewness ($CoSkew$) is calculated following Harvey and Siddique (2000) as the slope coefficient on the squared excess market return term in a regression of the stock's excess return on the excess return of the market and the market excess return squared. Cokurtosis ($CoKurt$) is the slope coefficient on the cubed excess market return term in a regression of the stock's excess return on the market excess return, the market excess return squared, and the market excess return cubed. Illiquidity ($Illiq$) is defined following Amihud (2002) as the average of the absolute value of the stock's return divided by the total dollar volume of stock traded (in $thousands). $IdioVol$, $CoSkew$, $CoKurt$, and $Illiq$ are calculated using daily data from the 12-month period covering months $t-11$ through t, inclusive.[6] The short-term reversal effect (Jegadeesh (1990), Lehmann (1990)) and medium-term momentum effect (Jegadeesh and Titman (1993)) are controlled for using the one month return during month t (Rev) and the 11-month return covering months $t-11$ through $t-1$ (Mom), respectively. We control for the effect of lottery demand on expected returns, documented by Bali et al. (2011) and Bali et al. (2017), with Max, defined as the largest one-day return of the given stock in month t. We also control for several variables known to be related to analyst bias (Bonini et al. (2010)). Since past stock returns (Rev, Mom), mispricing ($IdioVol$), valuation ratios (BM), and liquidity ($Illiq$) are all known to be related to analyst bias, several of our controls for known determinants of expected stock returns also serve as controls for analyst bias. As additional controls for analyst bias, we include forecast earnings ($Earn$), defined as the median analyst forecast earnings for the next fiscal year end divided by the month-end price of the stock, analyst coverage ($AnlystCov$), defined as the natural log of one plus the number of analysts who have issued fiscal year earnings forecasts, and long-term growth (LTG), defined as the median long-term growth forecast.

[6] We require a minimum of 225 valid daily observations during the estimation period to calculate these variables. Observations not satisfying this requirement are discarded.

Specification (2) in Table 5 presents the results of the FM regression analysis that includes the control variables in the cross-sectional regression specification. The average coefficients on each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ in specification (2) are all positive and highly statistically significant, indicating that the positive relations between the risk-neutral moments and ER are not explained by any linear combination of the control variables. The inability of the controls to explain the relation between expected returns and risk-neutral moments suggests that these relations are not simply a recreation of previously documented pricing effects or analyst bias.

As for the control variables, the average coefficients on β, $IdioVol$, $CoSkew$, $CoKurt$, $Illiq$, and Rev all have the predicted signs, and all, with the exception of $CoKurt$, are statistically significant at the 5% level. The coefficient on $Size$ is positive. This result is due to the inclusion of the controls for bias in price targets ($Earn$, $AnlystCov$, LTG) in the model. In unreported results, when these controls are removed, we find a negative sign on $Size$, consistent with most empirical studies. The average coefficient on BM is positive and insignificant, and the average coefficient on Mom is negative and highly significant. Both of these results contradict the prevalent findings in the empirical asset pricing research that uses future realized returns to proxy for expected returns, but are consistent with previous work on price target-based expected returns (Brav et al. (2005)). The results indicate a positive and statistically significant relation between lottery demand, measured by Max, and expected returns. This finding is consistent with the positive relation between risk-neutral skewness and expected returns, since the salient characteristic of lottery investments is positive skewness, but inconsistent with previous studies that find a negative relation between Max and future realized returns (Bali et al. (2011), Bali et al. (2017)). Finally, the regressions detect statistically significant relations between ER and each of $Earn$, $AnlystCov$, LTG, suggesting that while ER may be subject to analyst bias, the relations between risk and expected return we document are not a manifestation of analyst bias.

4 Systematic and Unsystematic Risk

Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ measure the total volatility, skewness, and kurtosis, respectively, of the stock return's risk-neutral distribution. In frictionless markets, asset pricing theory predicts that only the systematic component of total risk is related to expected return (e.g. Ross (1976)). In markets with frictions, however, unsystematic risk may also be an important determinant of a stock's expected return (Levy (1978), Merton (1987), and Mitton and Vorkink (2007)). In this section, we decompose the risk-neutral moments into systematic and unsystematic components and examine the relations between ER and each of the components of risk.

4.1 Calculation of Systematic and Unsystematic Moments

To calculate the systematic and unsystematic components of the risk-neutral moments, we follow BKM in assuming that the risk-neutral stock return process follows a one-factor market model:

$$r_{i,t} = a_i + \beta_{RN,i} r_{m,t} + \epsilon_{i,t} \tag{11}$$

where $r_{i,t}$ and $r_{m,t}$ are the excess returns of the stock and the market portfolio, respectively, $\beta_{RN,i}$ is the risk-neutral beta of stock i, and $\epsilon_{i,t}$ is the unsystematic component of the return, assumed to be independent of $r_{m,t}$. The risk-neutral variance can then be written as:

$$\sigma^2_{RN,i} = \beta^2_{RN,i}\sigma^2_m + \sigma^2_{\epsilon,i} \tag{12}$$

where σ^2_i (σ^2_m) is the risk-neutral variance of stock i's (the market portfolio's) return and $\sigma^2_{\epsilon,i}$ is the variance of $\epsilon_{i,t}$. We therefore define the systematic component of stock i's variance as

$$Var^{BKM}_{S,i} = \beta^2_{RN,i} Var^{BKM}_m \tag{13}$$

where Var_m^{BKM} is the BKM measure of the market portfolio return's risk-neutral variance, estimated by applying the BKM procedure to S&P 500 index options. The unsystematic component of the stock return variance is defined as the difference between the total variance and the systematic variance:

$$Var_{U,i}^{BKM} = Var_i^{BKM} - Var_{S,i}^{BKM}. \tag{14}$$

BKM demonstrate that risk-neutral skewness can be decomposed into systematic and unsystematic components as follows:

$$Skew_i = \frac{\beta_{RN,i}^3 \sigma_m^3}{\sigma_i^3} Skew_m + \frac{\sigma_{\epsilon,i}^3}{\sigma_i^3} Skew_{\epsilon,i} \tag{15}$$

where $Skew_i$ ($Skew_m$) is the total risk-neutral skewness of stock i's (the market's) return and $Skew_{\epsilon,i}$ is the risk-neutral skewness of $\epsilon_{i,t}$. Based on this decomposition, we define the systematic skewness of stock i to be:

$$Skew_{S,i}^{BKM} = \frac{\beta_{RN,i}^3 \left(Var_m^{BKM}\right)^{3/2}}{\left(Var_i^{BKM}\right)^{3/2}} Skew_m^{BKM}, \tag{16}$$

and define unsystematic risk-neutral skewness as the difference between the total and systematic skewness:

$$Skew_{U,i}^{BKM} = Skew_i^{BKM} - Skew_{S,i}^{BKM}. \tag{17}$$

Using the same approach as BKM, a similar decomposition of total risk-neutral excess kurtosis into systematic and unsystematic components yields:

$$Kurt_i = \frac{\beta_{RN,i}^4 \sigma_m^4}{\sigma_i^4} Kurt_m + \frac{\sigma_{\epsilon,i}^4}{\sigma_i^4} Kurt_{\epsilon,i} \tag{18}$$

where $Kurt_i$ ($Kurt_m$) is the risk-neutral excess kurtosis of stock i's (the market's) return and $Kurt_{\epsilon,i}$ is the risk-neutral excess kurtosis of $\epsilon_{i,t}$. We define systematic ($Kurt_{S,i}^{BKM}$) and unsystematic ($Kurt_{U,i}^{BKM}$) risk-neutral excess kurtosis to be:

$$Kurt_{S,i}^{BKM} = \frac{\beta_{RN,i}^4 \left(Var_m^{BKM}\right)^2}{\left(Var_i^{BKM}\right)^2} Kurt_m^{BKM} \tag{19}$$

and

$$Kurt_{U,i}^{BKM} = Kurt_i^{BKM} - Kurt_{S,i}^{BKM}. \tag{20}$$

Calculation of the systematic and unsystematic components of the risk-neutral moments requires an estimate of the risk-neutral beta of the stock ($\beta_{RN,i}$). While several approaches to solving for risk-neutral stock beta have been proposed (French, Groth, and Kolari (1983), Duan and Wei (2009), Chang, Christoffersen, Jacobs, and Vainberg (2012), Buss and Vilkov (2012)), for different reasons, none of these approaches are applicable in the present context. Duan and Wei (2009) and Chang et al. (2012) make the assumption that the unsystematic component of the stock's return is normally distributed. Under this assumption, unsystematic skewness and excess kurtosis are equal to zero by definition. The measures developed by French et al. (1983) and Buss and Vilkov (2012) are not ex-ante measures because they calculate correlations from historical data. We therefore use our measure of physical beta (β) as a proxy for the risk-neutral beta when decomposing the risk-neutral moments.

Table 6 presents summary statistics for the systematic and unsystematic components of the risk-neutral moments. The table shows that Var_U^{BKM} has a mean and median of 0.19 and 0.12, respectively. These values are much larger than the corresponding values for Var_S^{BKM}, which has a mean (median) of 0.09 (0.07), indicating that unsystematic variance is the dominant component of total variance. $Skew_S^{BKM}$ is almost always negative, with an average monthly mean (median) of -0.47 (-0.38). The negativity of $Skew_S^{BKM}$ is a manifestation of the fact that, in our sample, $Skew_m^{BKM}$ is always negative and β_{RN} is almost always positive (see equation (16)). $Skew_U^{BKM}$ is also negative in both mean (-0.21) and median (-0.15), but has a positive 75th percentile, indicating that a non-trivial number of stocks have positive unsystematic skewness. Finally, $Kurt_S^{BKM}$ is always positive, a manifestation of the fact that $Kurt_m^{BKM}$ is always positive in our sample, and $Kurt_U^{BKM}$ has a positive (negative) mean (median) value of 0.57 (-0.30).

4.2 Systematic and Unsystematic Risk Regressions

To analyze the relations between ER and the systematic and unsystematic components of risk, we perform FM regressions of ER on combinations of Var_S^{BKM}, Var_U^{BKM}, $Skew_S^{BKM}$, $Skew_U^{BKM}$, $Kurt_S^{BKM}$, $Kurt_U^{BKM}$, and controls. The regression results are presented in Table 7. Regression specification (1) indicates positive and statistically significant relations between ER and each of Var_S^{BKM} and $Skew_S^{BKM}$, while no relation between ER and $Kurt_S^{BKM}$ is detected. When controls are added to the regression specification (specification (2)), the average coefficient on Var_S^{BKM} remains positive and statistically significant, but the average coefficient on $Skew_S^{BKM}$ becomes insignificant, indicating that the positive relation between systematic skewness and expected returns detected in specification (1) is explained by the control variables.[7] Regression models (3) and (4) show that Var_U^{BKM}, $Skew_U^{BKM}$, and $Kurt_U^{BKM}$ each exhibits a positive and statistically significant relation with ER, regardless of whether controls are included in the regression model. When the systematic and unsystematic portions of the risk-neutral moments are simultaneously included in the regression specification (specification (5)), the results indicate that both the systematic and unsystematic components of each of the risk-neutral moments have positive and, with the exception of $Kurt_S^{BKM}$, statistically significant relations with ER. When the control variables are added to this regression (specification (6)), the results demonstrate that the unsystematic components of the risk-neutral moments all have positive and highly statistically significant relations with ER, but of the systematic moments, only Var_S^{BKM} exhibits a positive and statistically significant relation with ER. No relation between $Skew_S^{BKM}$ or $Kurt_S^{BKM}$ is found. In an unreported test, we examine a specification in which $IdioVol$, $CoSkew$, and

[7]We do not include beta (β) as a control variable because cross-sectional variation in systematic variance is driven entirely by beta. Thus, including beta as a control would introduce a high level of collinearity between beta and systematic variance.

$CoKurt$ are not included as control variables, and find qualitatively similar results.

The positive relation between systematic variance and expected stock returns supports the main prediction of the CAPM, that market risk is priced. However, contrary to what the CAPM predicts, we find that unsystematic risk is also an important determinant of the cross section of expected stock returns. Specifically, our results indicate that investors demand higher rates of return on stocks with higher unsystematic variance and kurtosis. The positive relation between unsystematic variance and expected returns is consistent with asset pricing models that account for market frictions (Levy (1978), Merton (1987)). While we are unaware of any theoretical work examining the relation between unsystematic kurtosis and expected stock returns, it seems plausible that a theory combining kurtosis aversion and market frictions would predict this relation. Finally, as discussed previously, we attribute the positive relation between total skewness and expected stock returns to the pricing of options, not to an equilibrium relation between risk and expected return. Our results indicate that both the systematic and unsystematic components of skewness are positively related to expected stock returns. The fact that the relation between systemic skewness and expected returns disappears when the control variables are added indicates that this relation is either captured by some combination of other known stock return predictors, or a manifestation of analyst bias. The positive relation between unsystematic skewness and expected stock returns contradicts the theoretical prediction of Mitton and Vorkink (2007) of a negative relation. At first glance, the results also seem to contradict the empirical findings of Boyer et al. (2010), who detect a negative relation between idiosyncratic skewness and expected stock returns. However, there are several differences between our paper and that of Boyer et al. (2010) that may drive these differences. First, we measure skewness from option prices, whereas Boyer et al. (2010) measure skewness using daily stock returns. As discussed earlier, the positive relation between option-implied skewness and expected return is likely more indicative of an option pricing phenomenon than of an equilibrium relation between risk and expected return. Second, unlike variance, which scales with time, skewness does not. The central limit theorem tells us that if daily log stock returns are identically and independently distributed (i.i.d.), then as the number of days increases, the holding period log return becomes normally distributed. If daily log returns are not i.i.d., then the skewness of daily log returns may not be indicative of the skewness of holding period log returns, which is captured by option-implied skewness.

We assess the economic significance of the coefficients by multiplying the average coefficient from regression model (6) in Table 7 by the standard deviation of the corresponding variable from Table 6. The results indicate that a one standard deviation difference in Var_S^{BKM} corresponds to a 3.94% per annum (56.35×0.07) difference in ER, while a one standard deviation difference in Var_U^{BKM} is associated with a 2.58% (9.07×0.28) ER difference. A one standard deviation difference in $Skew_U^{BKM}$ is associated with a 2.61% difference in ER (2.69×0.97), and the corresponding value for $Kurt_U^{BKM}$ is 1.84% (0.30×6.13). These results indicate that systematic variance plays the largest role in determining the cross section of expected returns, followed by unsystematic variance. The premia associated with unsystematic skewness and kurtosis, while smaller, are also economically important.

5 Conclusion

In this paper, we examine cross-sectional relations between measures of risk and expected stock returns using ex-ante measures of each. We develop a measure of ex-ante expected return based on analyst price targets and compare its ability to capture cross-sectional variation in ex-ante expected stock returns to that of the implied cost of capital used in previous work. We find that both measures have a positive relation with a benchmark regression-based expected return measure, but the relation is stronger for the price target-based measure. We also find that in the short sample for which the price target-based measure and implied cost of capital can be calculated, while both have a positive but insignificant relation with future realized returns, the relation is stronger, both economically and statistically, for the price target-based measure. Combining these empirical results with conceptual arguments and evidence from previous work, we proceed using the price target-based measure of expected return as our measure of ex-ante expected stock return.

We then examine the cross-sectional relation between expected stock returns and ex-ante measures of stock return volatility, skewness, and kurtosis calculated from option prices. Portfolio and regression analyses demonstrate that ex-ante expected returns have a significantly positive relation to all three moments and that these relations remain robust after controlling for variables previously shown to be related to expected stock returns or analyst forecast bias. The positive relations between expected stock returns and each of volatility and kurtosis provide empirical evidence supporting risk-based theories that have received little empirical support in the literature. The positive relation between expected stock returns and option-implied skewness, which has been documented by previous work as well, contradicts the theoretical prediction of a negative relation but is consistent with demand-based option pricing, and thus seems to be more of a reflection of option pricing rather than stock pricing.

We then decompose the risk measures into systematic and unsystematic components. We find that both the systematic and unsystematic components of variance are positively related to ex-ante expected returns, while only the unsystematic components of skewness and kurtosis have relations with ex-ante expected returns that are not explained by other known determinants of expected stock returns or analyst bias. The results suggest that the main prediction of the CAPM, that systematic variance is positively related to the cross-section of expected returns, is true. However, contrary to the predictions of the CAPM, the results indicate that unsystematic risk is also priced. The positive relation between expected returns and unsystematic variance and kurtosis are consistent with theories based on market frictions. The positive relation between unsystematic skewness and expected stock returns suggests that demand-based option pricing is a manifestation of investors buying (selling) calls (puts) on stocks for which the high expected return is a manifestation of unsystematic risk.

Appendix A Implied Cost of Capital

We calculate the implied cost of capital following Gebhardt et al. (2001). Conceptually, the implied cost of capital (ICC) is found by solving for the discount rate (r) that equates the current book value of equity plus the present value of expected future earnings to the current stock price. Explicitly, the implied cost of capital is the value r that solves:

$$P_t = B_t + \sum_{i=1}^{11} \frac{FROE_{t+i} - r}{(1+r)^i} B_{t+i-1} + \frac{FROE_{t+12} - r}{r(1+r)^{11}} B_{t+11} \tag{21}$$

where B_t is the book value of equity in fiscal year t and $FROE_{t+i}$ is the forecast return on equity in year $t+i$. Equation 3 presents forecast earnings as the product of forecast return on equity and book value. The last term in equation 3 is the infinite summation of forecast earnings for years $t+12$ and after. The assumption in this term is that return on equity is constant for years $t+12$ and after.

For each stock/month observation, ICC is calculated by finding the value of r that equates the stock price (P_t) on the date that I/B/E/S releases their earnings forecast summary data (the third Thursday of each month) to the right side of equation 3. $FROE_{t+1}$ is the median analyst earnings forecast for the next fiscal year for which earnings have not been announced ($FEPS_{t+1}$), divided by B_t. B_t is the book value of equity for the last fiscal year for which earnings have been announced, taken from CompuStat.[8] $FROE_{t+2}$ is the median analyst earnings forecast for the second fiscal year for which earnings have not been announced ($FEPS_{t+2}$), divided by B_{t+1}. As it is not possible to know the value of B_{t+1},

[8]As earnings are usually announced prior to the release of the annual report, it is possible that the value B_t is not known. Following Gebhardt et al. (2001), to account for this potential look-ahead bias, we assume that annual report data is available in the fourth month following the end of the fiscal year. In the months where earnings for the previous fiscal year have been announced, but the book value for that same year is not yet available, we estimate the book value to be the book value at the end of the previous fiscal year plus the announced earnings per share minus the dividends paid to common shareholders.

it is estimated as $B_t + FEPS_{t+1}(1-k)$, where k is the proportion of earnings paid out as dividends, calculated as the ratio of dividends to earnings during the last fiscal year for which earnings have been announced.[9] B_{t+i} is calculated similarly for years $t+2$ through $t+11$ ($B_{t+i} = B_{t+i-1}(1 + FROE_{t+i}(1-k))$). The payout ratio k is held constant. Forecast earnings for year $t+3$ ($FEPS_{t+3}$) are taken to be the forecast earnings for year $t+2$ times the long term earnings growth forecast provided by I/B/E/S. Forecast return on equity for year $t+3$ ($FROE_{t+3}$) is then calculated as the forecast earnings ($FEPS_{t+3}$) divided by the previous book value (B_{t+2}). For years $t+4$ through $t+12$, forecast return on equity is assumed to linearly approach the long term industry median return on equity. Thus, $FROE_{t+i} = FROE_{t+3} + \frac{i-3}{9}(ROE_{Median} - FROE_{t+3})$ for $i \in \{4, ..., 12\}$. Industry median return on equity (ROE_{Median}) is taken to be the median return on equity for all firms in the same industry.[10]

Appendix B Estimation of BKM Risk-Neutral Moments

This appendix describes our implementation of the Bakshi et al. (2003) approach to calculating moments of the risk neutral distribution of a stock's future return from the prices of out-of-the-money (OTM) call and put options. The procedure is applied to a given stock i on a given date t using OTM options with a fixed expiration date $t+\tau$. The data required for performing the calculations are the price of stock i on date t, the date t prices of options on stock i with expiration date $t+\tau$, and the continuously compounded rate of return on a risk-free investment purchased on date t to be withdrawn on date $t+\tau$. We denote the stock price as S, the risk-free rate as r, and the time until option expiration as τ. All of the

[9]Following Gebhardt et al. (2001), for firms with negative earnings, the payout ratio k is taken to be the dividends paid divided by 6% of total assets. Calculated values of k less than zero are assigned the value zero. Calculated values of k greater than one are assigned the value one. If dividend information is missing from Compustat, k is taken to be zero.

[10]Industry classifications follow Fama and French (1997). We begin by calculating, for each firm, the average return on equity, defined as fiscal year earnings divided by book value of equity at the end of the previous fiscal year, over the ten most recent fiscal years. The industry median return on equity is taken to be the median of these ten year return on equity averages across all firms in the chosen industry.

necessary data come from the OptionMetrics database provided through Wharton Research Data Services. We take the price of all options to be the average of the bid price and the offer price. The calculation of the risk-free rate is discussed in Section VI of the Internet Appendix.

B.1 Adjusting the Spot Price

We adjust the spot price of the stock to account for dividends with ex-dates between dates t (exclusive) and $t + \tau$ (inclusive). Doing so ensures that our risk-neutral moments represent moments of distribution of the total return, not the price return, of the stock. To account for the effect of dividends, we take the adjusted spot price of the stock, denoted S^*, to be the current spot price (S) minus the present value of all dividends paid on the stock with ex-dates between date t and $t + \tau$ ($S^* = S - PVDivs$). The calculation of the present value of dividends ($PVDivs$) is discussed in Section VII of the Internet Appendix.

B.2 Screening the Data

We implement several screens on the option data to ensure that the option price data used in the estimation of the Bakshi et al. (2003) integrals are both valid and do not violate any arbitrage conditions. We begin by removing all entries for which the bid or offer price is missing, the bid is equal to zero, the offer is less than or equal to the bid, as well as duplicate entries. As the BKM formulae require only OTM option prices, we retain only calls (puts) with strikes that are greater (less) than or equal to the adjusted spot price (S^*).

Next, we sort the calls (puts) in ascending (descending) order by strike prices. Letting n_C (n_P) denote the number of call (put) options that pass the data screens, we denote the prices of the call (put) options as C_i (P_i) and the strike prices of the call (put) options as K_i^C, $i \in \{1, ..., n_C\}$ (K_i^P, $i \in \{1, ..., n_P\}$), where $K_{i+1}^C > K_i^C$ for $i \in \{1, ..., n_C - 1\}$ ($K_{i+1}^P < K_i^P$ for $i \in \{1, ..., n_P - 1\}$).

No-arbitrage conditions require that option prices strictly decrease as the option strike goes further out-of-the-money. Thus, if $C_i \leq C_{i+1}$ for any $i \in \{1, ..., n_C - 1\}$ or $P_i \leq P_{i+1}$ for any $i \in \{1, ..., n_P - 1\}$, we deem the values of the risk-neutral moments for the given date/stock/expiration combination to be incalculable.

B.3 Calculation of Risk-Neutral Moments

BKM show that the values V, W, and X, used to calculate the risk-neutral variance, skewness, and excess kurtosis, given by equations (6), (7), (8) respectively, are given by:

$$\begin{aligned} V = & \int_{K=S}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S}\right]\right)}{K^2} C(K) dK \\ & + \int_{K=0}^{S} \frac{2\left(1 + ln\left[\frac{S}{K}\right]\right)}{K^2} P(K) dK \end{aligned} \tag{22}$$

$$\begin{aligned} W = & \int_{K=S}^{\infty} \frac{6ln\left[\frac{K}{S}\right] - 3\left(ln\left[\frac{K}{S}\right]\right)^2}{K^2} C(K) dK \\ & - \int_{K=0}^{S} \frac{6ln\left[\frac{S}{K}\right] + 3\left(ln\left[\frac{S}{K}\right]\right)^2}{K^2} P(K) dK, \end{aligned} \tag{23}$$

and

$$\begin{aligned} X = & \int_{K=S}^{\infty} \frac{12\left(ln\left[\frac{K}{S}\right]\right)^2 + 4\left(ln\left[\frac{K}{S}\right]\right)^3}{K^2} C(K) dK \\ & + \int_{K=0}^{S} \frac{12\left(ln\left[\frac{S}{K}\right]\right)^2 + 4\left(ln\left[\frac{S}{K}\right]\right)^3}{K^2} P(K) dK \end{aligned} \tag{24}$$

where $C(K)$ $(P(K))$ is the price of a call (put) option with strike K.

We implement a trapezoidal approach to estimating the integrals in equations (22), (23), and (24) from prices of options with discrete strikes. To do so, we define the strike differences for calls (puts) as $\Delta K_i^C = K_i^C - K_{i-1}^C$ for $i \in \{2, ..., n_C\}$ and $\Delta K_1^C = K_1^C - S^*$ ($\Delta K_i^P = K_{i-1}^P - K_i^P$ for $i \in \{2, ..., n_P\}$ and $\Delta K_1^P = S^* - K_1^P$). We then approximate the BKM integrals for V, X, and W as:

$$\begin{aligned} V =& v_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[v_C(K_i^C)C_i + v_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &+ v_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[v_P(K_i^P)P_i + v_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P, \end{aligned} \tag{25}$$

$$\begin{aligned} W =& w_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[w_C(K_i^C)C_i + w_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &- w_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[w_P(K_i^P)P_i + w_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P, \end{aligned} \tag{26}$$

and

$$\begin{aligned} X =& x_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[x_C(K_i^C)C_i + x_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &+ x_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[x_P(K_i^P)P_i + x_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P \end{aligned} \tag{27}$$

where:

$$v_C(K) = \frac{2\left(1 - ln\left[\frac{K}{S^*}\right]\right)}{K^2}, \tag{28}$$

$$v_P(K) = \frac{2\left(1 + ln\left[\frac{S^*}{K}\right]\right)}{K^2}, \tag{29}$$

$$w_C(K) = \frac{6ln\left[\frac{K}{S^*}\right] - 3\left(ln\left[\frac{K}{S^*}\right]\right)^2}{K^2}, \tag{30}$$

$$w_P(K) = \frac{6ln\left[\frac{S^*}{K}\right] + 3\left(ln\left[\frac{S^*}{K}\right]\right)^2}{K^2}, \tag{31}$$

$$x_C(K) = \frac{12\left(ln\left[\frac{K}{S^*}\right]\right)^2 + 4\left(ln\left[\frac{K}{S^*}\right]\right)^3}{K^2}, \tag{32}$$

and

$$x_P(K) = \frac{12\left(ln\left[\frac{S^*}{K}\right]\right)^2 + 4\left(ln\left[\frac{S^*}{K}\right]\right)^3}{K^2}. \tag{33}$$

Plugging the values from equations (25), (26), and (27) into equations (6), (7), and (8) yields discrete strike price-based estimates of the variance, skewness, and kurtosis of the risk-neutral distribution of the stock's return for the period from t to $t + \tau$.

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Table 1: Portfolio Analysis of Ex-Ante Expected Returns

The table below presents the results of portfolio analyses examining the cross-sectional relations between expected stock returns and each of ER and ICC. Each month t, all stocks are sorted into quintile portfolios based on a sort variable. The sort variable is one of $RegER$ (Panel A), ER, and ICC (Panel B, as indicated in the column labeled "Sort Variable"). We then calculate the equal-weighted average month t value of $RegER$, ER, ICC (Panel A, as indicated in the column labeled "Dependent Variable"), or month $t+1$ realized return across all stocks in each portfolio, as well as for a portfolio that is long stocks in the quintile 5 portfolio and short stocks in the quintile 1 portfolio (5−1 portfolio). The columns labeld 1, 2, 3, 4, 5, and 5−1 present the time-series averages of these monthly values for the quintile portfolio indicated in the column header. The column labeled 5−1 t-stat presents the t-statistic, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the average expected return of the 5−1 portfolio is equal to zero. The tests cover months t from March 1999 through June 2012, inclusive. $RegER$ is the regression-based benchmark measure of expected return. ER is the price target-based expected return. ICC is the implied cost of capital.

Panel A: Portfolios Sorted on $RegER$

Dependent Variable	1	2	3	4	5	$5-1$	$5-1$ t-stat
$RegER$	2.74	6.64	8.71	10.61	14.17	11.43	(58.14)
ER	17.15	18.41	20.05	22.46	27.56	10.41	(17.34)
ICC	7.63	8.16	8.52	8.87	9.87	2.24	(7.83)

Panel B: One-Month-Ahead Realized Returns

Sort Variable	1	2	3	4	5	$5-1$	$5-1$ t-stat
ER	0.40	0.81	1.11	1.40	1.22	0.82	(1.93)
ICC	0.60	0.85	0.95	1.13	1.32	0.72	(1.73)

Table 2: Summary Statistics

The table below presents summary statistics for our sample. The sample contains stock, month observations for months t from March 1999 through December 2012 for which values of ER, Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ can be calculated. Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are BKM-based measures of risk-neutral volatility, skewness, and kurtosis, respectively. $MktCap$ is market capitalization, measured in $millions. The table shows the time-series averages of monthly cross-sectional values.

Variable	Mean	SD	Min	5%	25%	Median	75%	95%	Max	n
ER	20.75	18.44	−31.19	−4.34	9.17	18.28	29.99	54.73	88.79	279
Vol^{BKM}	47.71	20.22	17.78	24.91	34.30	43.40	55.83	84.83	156.83	279
$Skew^{BKM}$	−0.67	0.82	−4.11	−1.94	−1.00	−0.60	−0.24	0.32	2.69	279
$Kurt^{BKM}$	1.82	5.58	−1.96	−1.23	−0.32	0.73	2.41	7.72	56.92	279
$MktCap$	9891	22441	139	354	1020	2829	8804	39745	220628	279

Table 3: Portfolio ER

The table presents the results of portfolio analyses examining the relations between ER and each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$. Each month t, all stocks in the sample are grouped into 27 portfolios based on a tri-variate sort. In Panel A (Panel B) [Panel C], stocks are first sorted into three groups by $Skew^{BKM}$ ($Kurt^{BKM}$) [$Skew^{BKM}$]. Stocks in each group are then sorted into three groups based on $Kurt^{BKM}$ (Vol^{BKM}) [Vol^{BKM}], forming nine groups of stocks. Stocks in each of these nine groups are then sorted into three groups based on Vol^{BKM} ($Skew^{BKM}$) [$Kurt^{BKM}$]. For each sort, the breakpoints used to form the portfolios are the 30th and 70th percentile values of the sort variable. We then calculate the equal-weighted average ER for each portfolio, as well as for the portfolio that is long (short) stocks with high (low) values of the third sort variable within each of the nine groups, the 3−1 portfolio. The table below presents the time-series average of these average ER values for each portfolio. The first sort variable, along with the corresponding portfolio number, is presented in the upper left of portion of the table. Portfolios of the second sort variable are shown in columns. Portfolios of the third sort variable are shown in rows. The t-statistic testing the null hypothesis that the average value for the 3−1 portfolio is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses.

Panel A: Vol^{BKM}

$Skew^{BKM}$ 1	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 2	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 3	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3
Vol^{BKM} 1	12.40	12.91	12.39		14.33	14.26	13.96		17.80	18.27	17.57
Vol^{BKM} 2	15.94	17.47	19.60		19.65	19.52	19.15		24.44	26.12	24.20
Vol^{BKM} 3	21.55	24.19	27.97		24.82	25.52	26.38		31.09	31.30	30.67
Vol^{BKM} $3-1$	9.16	11.28	15.58		10.49	11.26	12.43		13.29	13.02	13.10
	(8.56)	(12.10)	(13.46)		(8.20)	(10.35)	(10.14)		(10.36)	(11.05)	(12.61)

Panel B: $Skew^{BKM}$

$Kurt^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Skew^{BKM}$ 1	13.65	18.32	22.65		12.14	17.24	21.70		11.31	16.21	26.08
$Skew^{BKM}$ 2	15.76	21.62	28.77		14.50	20.22	25.07		13.65	18.56	25.89
$Skew^{BKM}$ 3	18.61	25.41	33.66		17.00	24.97	32.10		15.64	22.31	29.19
$Skew^{BKM}$ $3-1$	4.96	7.09	11.00		4.86	7.73	10.40		4.33	6.10	3.11
	(5.21)	(8.93)	(8.72)		(5.72)	(7.96)	(9.21)		(4.85)	(4.66)	(2.06)

Panel C: $Kurt^{BKM}$

$Skew^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Kurt^{BKM}$ 1	12.23	15.66	23.26		13.68	18.89	24.66		17.24	22.61	31.29
$Kurt^{BKM}$ 2	12.89	16.80	25.96		13.98	19.30	24.56		18.03	24.92	30.90
$Kurt^{BKM}$ 3	12.20	18.54	27.18		14.84	20.21	27.57		18.14	26.39	33.21
$Kurt^{BKM}$ $3-1$	−0.02	2.88	3.92		1.16	1.32	2.91		0.91	3.78	1.92
	(−0.05)	(4.46)	(3.30)		(2.44)	(1.91)	(4.17)		(1.12)	(3.61)	(2.10)

Table 4: Portfolio Realized Returns

The table presents the results of portfolio analyses examining the relations between future realized returns and each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$. The procedure is identical to that used to generate Table 3, except that here we calculate the equal-weighted average one-month-ahead return for each portfolio. The table below presents the time-series average one-month-ahead return for each portfolio. The first sort variable, along with the corresponding portfolio number, is presented in the upper left of portion of the table. Portfolios of the second sort variable are shown in columns. Portfolios of the third sort variable are shown in rows. The t-statistic testing the null hypothesis that the average value for the 3−1 portfolio is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses. Panel A (B) [C] presents results examining the relation between Vol^{BKM} ($Skew^{BKM}$) [$Kurt^{BKM}$] and one-month-ahead realized stock returns.

Panel A: Vol^{BKM}

$Skew^{BKM}$ 1	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 2	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 3	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3
Vol^{BKM} 1	0.26	0.16	0.74		0.44	0.81	1.06		1.43	1.23	1.03
Vol^{BKM} 2	0.69	1.08	0.85		0.67	0.72	0.89		1.18	1.17	1.44
Vol^{BKM} 3	−0.13	0.47	0.82		0.10	0.22	1.31		−0.17	1.04	0.28
Vol^{BKM} 3 − 1	−0.39	0.32	0.08		−0.34	−0.59	0.25		−1.60	−0.19	−0.74
	(−0.46)	(0.33)	(0.11)		(−0.39)	(−0.84)	(0.44)		(−1.97)	(−0.24)	(−1.04)

Panel B: $Skew^{BKM}$

$Kurt^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Skew^{BKM}$ 1	0.54	0.15	0.17		0.48	0.76	−0.42		0.65	0.84	1.23
$Skew^{BKM}$ 2	1.27	0.85	0.25		0.82	0.73	0.68		0.45	0.58	0.40
$Skew^{BKM}$ 3	1.71	1.41	−0.08		1.05	1.35	1.26		1.22	1.08	0.15
$Skew^{BKM}$ 3 − 1	1.18	1.27	−0.25		0.56	0.59	1.68		0.56	0.24	−1.08
	(2.89)	(2.04)	(−0.30)		(2.12)	(1.12)	(2.18)		(2.04)	(0.72)	(−1.17)

Panel C: $Kurt^{BKM}$

$Skew^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Kurt^{BKM}$ 1	0.07	1.06	−0.13		0.66	0.77	0.36		1.45	1.25	−0.20
$Kurt^{BKM}$ 2	0.36	0.82	0.65		0.90	0.69	−0.17		1.14	1.49	0.35
$Kurt^{BKM}$ 3	0.52	0.72	0.85		1.05	0.96	0.94		1.28	1.20	0.71
$Kurt^{BKM}$ 3 − 1	0.45	−0.34	0.99		0.38	0.18	0.58		−0.17	−0.05	0.91
	(1.21)	(−0.81)	(1.66)		(1.22)	(0.38)	(1.16)		(−0.57)	(−0.07)	(1.19)

Table 5: Fama-MacBeth Cross-Sectional Regressions

The table below presents the results of FM regressions examining the relation between ER and Vol^{BKM}, $Skew^{BKM}$, $Kurt^{BKM}$, and controls. Each month t, we run a cross-sectional regression of ER on Vol^{BKM}, $Skew^{BKM}$, $Kurt^{BKM}$, and in specification (2), controls. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series averages of the cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the average coefficient is equal to zero, are in parentheses. The column labeled "Adj. R^2" presents the time-series average adjusted R^2 from the cross-sectional regressions. The column labeled "n" presents the average number of observations for the cross-sectional regressions.

Specification	Vol^{BKM}	$Skew^{BKM}$	$Kurt^{BKM}$	β	$IdioVol$	$CoSkew$	$CoKurt$	$Size$	BM	$Illiq$	Rev	Mom	Max	$Earn$	$AnlystCov$	LTG	Intercept	Adj. R^2	n
(1)	0.31	6.98	0.86														8.97	0.13	279
	(17.52)	(10.13)	(7.71)														(12.79)		
(2)	0.18	3.05	0.36	2.59	4.09	−0.14	0.01	0.27	0.15	171.10	−47.13	−4.02	11.92	25.33	−1.72	0.21	5.56	0.27	226
	(9.22)	(6.84)	(4.80)	(3.82)	(2.20)	(−2.01)	(1.54)	(1.30)	(0.32)	(3.08)	(−27.71)	(−8.84)	(2.67)	(5.78)	(−6.57)	(11.25)	(2.05)		

Table 6: Summary Statistics - Systematic and Unsystematic Components

The table below presents summary statistics for ER, $MktCap$, β, and the systematic and unsystematic components of the risk-neutral moments. The systematic components (unsystematic) of the moments are denoted with a subscript S (U). The table shows the time-series averages of monthly cross-sectional values.

Variable	Mean	SD	Min	5%	25%	Median	75%	95%	Max	n
ER	20.68	18.42	−30.21	−4.36	9.16	18.17	29.88	54.53	88.26	255
$MktCap$	9853	22286	140	348	1005	2800	8707	39901	209658	255
β	1.19	0.50	0.09	0.51	0.83	1.12	1.49	2.12	2.81	255
Vol_S^{BKM}	25.95	10.97	1.73	10.96	18.02	24.42	32.53	46.23	62.04	255
Var_S^{BKM}	0.09	0.07	0.00	0.02	0.04	0.07	0.12	0.24	0.44	255
$Skew_S^{BKM}$	−0.47	0.37	−1.62	−1.19	−0.69	−0.38	−0.18	−0.05	0.01	255
$Kurt_S^{BKM}$	1.33	1.29	0.00	0.06	0.35	0.92	1.94	4.00	5.91	255
Vol_U^{BKM}	37.78	20.60	6.37	15.04	24.60	33.38	45.31	75.52	151.02	255
Var_U^{BKM}	0.19	0.28	0.01	0.03	0.06	0.12	0.22	0.60	2.57	255
$Skew_U^{BKM}$	−0.21	0.97	−3.92	−1.74	−0.65	−0.15	0.32	1.03	3.52	255
$Kurt_U^{BKM}$	0.57	6.13	−6.50	−4.03	−1.74	−0.30	1.52	7.31	55.52	255

Table 7: Regressions - Systematic and Unsystematic Components

The table below presents the results of FM regressions examining the relation between ER and the systematic and unsystematic components of risk, and controls. Each month t, we run a cross-sectional regression of ER on combinations of Vol_S^{BKM}, Vol_U^{BKM}, $Skew_S^{BKM}$, $Skew_U^{BKM}$, $Kurt_S^{BKM}$, $Kurt_U^{BKM}$, and controls. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series averages of the cross-sectional regression coefficients. t-statistics, adjusted following Newey and West (1987) using six lags, testing the null hypothesis that the average coefficient is equal to zero, are in parentheses. The column labeled "Adj. R^2" presents the time-series average adjusted R^2 from the cross-sectional regressions. The column labeled "n" presents the average number of observations for the cross-sectional regressions.

Specification	Var_S^{BKM}	Var_U^{BKM}	$Skew_S^{BKM}$	$Skew_U^{BKM}$	$Kurt_S^{BKM}$	$Kurt_U^{BKM}$	$IdioVol$	$CoSkew$	$CoKurt$	$Size$	BM	$Illiq$	Rev	Mom	Max	$Earn$	$AnlystCov$	LTG	Intercept	Adj. R^2	n
(1)	94.17		36.47		5.87														20.93	0.08	255
	(8.43)		(7.58)		(1.55)														(17.75)		
(2)	58.32		3.48		−7.93		10.91	−0.13	0.01	0.13	0.34	212.38	−52.20	−4.16	19.78	23.42	−1.60	0.22	11.29	0.25	211
	(6.69)		(0.56)		(−1.15)		(5.53)	(−1.94)	(1.55)	(0.60)	(0.71)	(3.49)	(−29.13)	(−9.60)	(4.32)	(5.34)	(−5.78)	(12.74)	(4.41)		
(3)		28.45		6.09		0.68													16.64	0.10	255
		(11.39)		(8.72)		(5.82)													(20.17)		
(4)		11.27		2.49		0.25	13.10	−0.11	0.01	0.06	0.46	137.68	−49.70	−3.86	22.22	25.45	−1.67	0.23	11.14	0.25	211
		(6.37)		(6.00)		(3.78)	(7.93)	(−1.57)	(1.43)	(0.30)	(1.00)	(2.57)	(−26.37)	(−7.51)	(4.45)	(5.69)	(−5.89)	(12.99)	(4.55)		
(5)	61.54	18.99	16.08	6.67	0.52	0.74													18.96	0.14	255
	(6.39)	(7.79)	(2.76)	(10.20)	(0.15)	(7.53)													(15.64)		
(6)	56.35	9.20	−0.42	2.69	−9.00	0.30	6.39	−0.13	0.01	0.23	0.32	183.81	−48.14	−4.04	15.46	26.22	−1.69	0.22	11.59	0.26	211
	(6.54)	(4.68)	(−0.06)	(6.44)	(−1.40)	(4.33)	(3.52)	(−2.01)	(1.60)	(1.12)	(0.64)	(3.22)	(−28.07)	(−8.99)	(3.66)	(6.18)	(−6.01)	(12.23)	(4.58)		

Option Implied Volatility, Skewness, and Kurtosis and the Cross-Section of Expected Stock Returns

Internet Appendix

Section I shows that our results are robust when using an alternative measure of price target-based expected return that adds dividends to the price target when calculating a stock's expected return. Section II defines the control variables used in our study. Section III demonstrates that the main results of the paper persist when risk-neutral moments are calculated using two-month options. Section IV shows that our main results hold when using a much broader cross section of stocks and alternative measures of the risk-neutral moments. Section V shows that the results of portfolio analyses of the relations between expected returns and risk-neutral moments are robust to alternative orderings of the sort variables. Section VI describes the calculation of risk-free rates. Section VII describes the calculation of the present value of dividends.

I Dividend-Adjusted Price Target Expected Returns

In this section, we examine the relations between price target-based expected returns and risk-neutral moments using an alternative measure of price target-based expected returns that includes dividends in the numerator of the expected return calculation. Specifically, we modify the definition of price target-based expected return, given in equation (1) of the main paper by adding the dividend yield of the stock to the value of ER. This measure, denoted ER^{Div}, is defined as:

$$ER_{i,t}^{Div} = ER_{i,t} + DY_{i,t} \tag{1}$$

where DY is the annual dividend yield of the stock. The dividend yield for stock i at the end of month t ($DY_{i,t}$) is calculated using forward prices provided in OptionMetrics' standardized option table. To calculate the dividend yield, we must first determine the risk-free rate for an investment maturing on the delivery date of the forward contract. We do so using forward prices, spot prices, and dividend yields on the S&P 500 index provides by OptionMetrics. We define the risk-free rate at the end of month t for an investment with maturity in d days to be:

$$rf_t^d = \frac{\ln F_{SP500,t}^d - \ln S_{SP500,t}}{d/365} + dy_{SP500,t} \tag{2}$$

where $F_{SP500,t}^d$ is the d-day forward price on the S&P 500 index, $S_{SP500,t}$ is the level of the S&P 500 index, and $dy_{SP500,t}$ is the continuously compounded dividend yield on the S&P 500 index, taken from OptionMetrics' index dividend yield table. All inputs to the calculate of rf_t^d are taken as of the end of the last trading day of the given month t. The continuously compounded dividend yield for stock i as of the end of month t is then calculated as:

$$dy_{i,t}^d = \frac{\ln S_{i,t} - \ln F_{i,t}^d}{d/365} + rf_t^d \tag{3}$$

where $F_{i,t}^d$ is the d-day forward price for stock i and $S_{i,t}$ is the spot price of stock i. Finally, because ER is expressed as a periodic return, not a continuously compounded return, we define:

$$DY_{i,t}^d = e^{dy_{i,t}^d} - 1. \tag{4}$$

DY is calculated using 365-day ($d = 365$) forward prices, when available. If a 365-day forward price for the stock is not available, then DY is calculated using 182-day ($d = 182$) forward prices. Finally, if neither a 365-day nor a 182-day forward price is available for the stock, DY is calculated using 91-day ($d = 91$) forward prices. In the small number of cases where 365-day, 182-day, and 91-day forward prices are all unavailable, DY is not calculated and these observations are dropped from the analyses using ER^{Div} as the measure of expected return.

I.A Portfolio Analysis

We begin our analysis of the relation between the dividend-adjusted price target-based expected return (ER^{Div}) and moments of the risk-neutral distribution using portfolio analysis. Table A1 presents the results of tri-variate dependent sort portfolio analyses of these relations. The details of the portfolio analyses are identical to those of the analyses presented in Section 3.1 and Table 3 of the main paper, with the exception that we use ER^{Div} instead of ER. The results of the analyses using ER^{Div} are extremely similar to those presented in the main paper. The analyses demonstrate a strong positive relation between price target-based expected returns and each of risk-neutral volatility, risk-neutral skewness, and risk-neutral kurtosis.

I.B Regression Analysis

We continue our analysis of the relations between the risk-neutral moments and dividend-adjusted price target-based expected returns (ER^{Div}) using Fama and MacBeth (1973) regression analyses. These analyses are identical to those whose results are discussed and presented in Section 3.2 and Table 5 of the main paper. The only difference is that here we use ER^{Div} instead of ER as the dependent variable in the monthly cross-sectional regressions.

The results of the Fama and MacBeth (1973) regression analyses of the relations between the risk-neutral moments and ER^{Div}, shown in Table A2, are once again extremely similar to the results of the analyses presented in the main paper. Regardless of which measures of risk-neutral moments are used, all specifications demonstrate a positive, economically important, and highly statistically significant relation between price target-based expected returns and each of risk-neutral volatility, risk-neutral skewness, and risk-neutral kurtosis.

II Control Variables

Beta: We define beta (β) to be the estimated slope coefficient from a regression of the stock's excess return on the excess return of the market using one year worth of daily return data up to and including month t. The market excess return is taken to be the value-weighted average excess return of all CRSP common stocks taken from the Fama-French database available through Wharton Research Data Services (WRDS).

Idiosyncratic Volatility: Idiosyncratic volatility ($IdioVol$) is defined following Ang et al. (2006) as $\sqrt{252}$ times the standard deviation of the residuals from a Fama and French (1992, 1993) three-factor regression of the stock's excess return on the market, size (SMB), and book-to-market ratio (HML) factors using one year worth of daily data up to and including month t. Daily factor returns are taken from the Fama-French database on WRDS.

Co-Skewness: Following Harvey and Siddique (2000), we define co-skewness ($CoSkew$) to be the estimated slope coefficient on the squared market excess return from a regression of the stock's excess return on market's excess return and the squared market excess return using one year of daily data up to and including month t.

Co-Kurtosis: Following Dittmar (2002), we define co-kurtosis ($CoKurt$) to be the estimated slope coefficient on the cubed market excess return in a regression of the stock's excess return on the market's excess return, the squared market excess return, and the cubed market excess return, using one year of daily data up to and including month t.

Market Capitalization: Market capitalization ($MktCap$) is defined as the month-end stock price times the number of shares outstanding, measured in millions of dollars. As the distribution of $MktCap$ is highly skewed, we will use $Size$, defined as the natural log of $MktCap$, in most statistical analyses.

Book-to-Market Ratio: Following Fama and French (1992, 1993), we define the book-to-market ratio (BM) for the months from June of year y through May of year $y + 1$ to be the book value of equity of the stock, calculated from balance sheet data for the fiscal year ending in calendar year $y - 1$, divided by the market capitalization of the stock at the end of calendar year $y - 1$. The book value of equity is defined as stockholders' equity plus balance sheet deferred taxes plus investment tax credit minus the book value of preferred stock. The book value of preferred stock is taken to be either the redemption value, the liquidating value, or the convertible value, taken as available in that order. For observations where the book value is negative, we deem the book-to-market ratio to be missing

Illiquidity: We define illiquidity ($Illiq$) following Amihud (2002) as the average of the absolute value of the stock's return divided by the dollar volume traded in the stock (in \$thousands), calculated using one year's worth of daily data up to and including month t.

Short Term Reversal: We control for the short-term reversal effect of Jegadeesh (1990) and Lehmann (1990) with our reversal variable (Rev), defined as the stock return in month t.

Momentum: To control for the medium-term momentum effect of Jegadeesh and Titman (1993), we define our momentum variable (Mom) to be the stock return during the 11-month period including months $t - 11$ through $t - 1$ (skipping the short-term reversal month).

Earnings Forecast: Bonini et al. (2010) demonstrate that consensus earnings forecasts are related to price target accuracy. To control for this effect, we define our earnings forecast variable ($Earn$) to be the median earnings forecast for the next unannounced fiscal year, divided by the month end price of the stock. The earnings forecast used in the calculation comes from the I/B/E/S EPS summary file and the month end stock price comes from the CRSP monthly stock file.

Analyst Coverage: Bonini et al. (2010) show that price target bias is related to the amount of analyst coverage. We therefore define analyst coverage ($AnlystCov$) to be the log of one plus the number of analysts that make forecasts of the next unannounced fiscal year earnings, taken from the I/B/E/S EPS summary file.

Growth Forecast: Bradshaw (2004) and Bonini et al. (2010) find evidence that bias in analyst price targets is related to forecasts of long-term growth. We define the forecast long-term growth of a firm (LTG) to be the median analyst long-term growth forecast, taken from the I/B/E/S EPS summary file.

III Two-Month Samples

In this section, we analyze the relations between price target-based expected returns (ER) and moments of the risk-neutral distribution calculated using options with longer times until expiration than our main samples. Specifically, here we calculate the risk-neutral moments using options that expire in month $t+3$ (approximately 2.5 months after the end of month t). We refer to these measures as the two-month measures, and denote them in a similar fashion to the one-month measures used in the main sample, with a $2Month$ subscript.

The results of tri-variate dependent sort portfolio analyses are presented in Table A3 of this Internet Appendix. The results indicate positive relations between price target-based expected returns and the two-month risk-neutral moments, consistent with the main results of the paper.

The results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER) and the two-month risk-neutral moments are presented in Table A4. Regardless of regression specification, the average coefficient on each of the moments is positive and significantly greater than zero.

Consistent with the results for the one-month samples in the main paper, both portfolio and Fama and MacBeth (1973) regression analysis using the two-month risk-neutral moments indicate positive relations between expected returns and each of risk-neutral volatility, skewness, and kurtosis.

IV Alternative Measures of Risk-Neutral Moments

In this section, we examine whether our main results are robust when using alternative measures of the risk-neutral moments, which we refer to as non-parametric measures. The main objective of these analyses is to lessen the requirements on the data used to calculate risk-neutral moments, thereby enable us broaden the sample of stocks used in our analyses. Specifically, we calculate the alternative measures of risk-neutral moments by taking differences in implied volatilities of options at different strikes. We define the at-the-money (ATM) call and put implied volatilities as the implied volatilities of the 0.50 delta call (CIV_{50}) and the -0.50 delta put (PIV_{50}) respectively, taken from OptionMetrics' 30 day fitted implied volatility surface on the last trading day of the month. Out-of-the-money (OTM) call and put implied volatilities are defined as the implied volatility of the 0.25 delta call (CIV_{25}) and the -0.25 delta put (PIV_{25}) respectively. The volatilities used to calculate the non-parametric risk-neutral moments are recorded in percent.

The non-parametric risk-neutral volatility (Vol^{NonPar}) is defined as the average of the ATM call and put implied volatilities. We measure risk-neutral skewness ($Skew^{NonPar}$) as the difference between the OTM call and OTM put implied volatilities. Finally, risk-neutral kurtosis ($Kurt^{NonPar}$) is calculated as the sum of the OTM call and OTM put implied volatilities minus the sum of the ATM call and ATM put implied volatilities.[1]

$$Vol^{NonPar} = \frac{CIV_{50} + PIV_{50}}{2} \tag{5}$$

$$Skew^{NonPar} = CIV_{25} - PIV_{25} \tag{6}$$

$$Kurt^{NonPar} = CIV_{25} + PIV_{25} - CIV_{50} - PIV_{50} \tag{7}$$

We create the sample used in our analyses of the relation between ER and the non-parametric measures of risk in the same manner as the sample used in the main paper, except that we include all stocks for which the non-parametric measures (instead of the BKM moments) can be calculated. Since the non-parametric moments are calculated from OptionMetrics' implied volatility data, this enables us to substantially broaden the sample. Table A5 present summary statistics for the non-parametric sample. The most notable result is that there are 988 (instead of 279) stocks in the sample in the average month.

The results of portfolio analyses examining the relations between ER and the non-parametric moments, shown in Table A6, are qualitatively the same as those in the main paper. Each of the measures of risk exhibits a positive and statistically significant relation with ER. Table A7 shows that, consistent with the finds in the main paper, there is a positive and statistically significant cross-sectional relation between $Skew^{NonPar}$ and future realized returns, but no evidence of a relation between Vol^{NonPar} or $Kurt^{NonPar}$ and future returns. Finally, Table A8 shows the results of Fama and MacBeth (1973) regression analyses of the relation between ER and the non-parametric measures of risk. Consistent with the results in the main paper using the BKM moments, we find positive and statistically significant relations between ER and each of the non-parametric risk-neutral moments.

[1]Our nonparametric measures of skewness and kurtosis are not directly comparable to the skewness and kurtosis of the distribution, but are simple measures very positively related to skewness and kurtosis. Bakshi et al. (2003) show that implied volatility differences are good proxies for implied skewness. Xing et al. (2010) use a skewness measure similar to (the negative of) ours. Cremers and Weinbaum (2010) use a call minus put implied volatility spread based on deviations from put-call parity. Our definitions of skewness and kurtosis also follow a standard quoting convention used in over-the-counter options trading.

The results of the analyses using our non-parametric sample demonstrate that our findings are generalizable to a broad cross section of stocks.

V Alternative Sort Order Portfolios

In this section, we repeat the tri-variate dependent sort portfolio analyses of Section 3.1 and Table 3 of the main paper with the order of the first two sort variables reversed. Thus, when testing the relation between price target-based expected returns (ER) and risk-neutral volatility, we sort first on risk-neutral kurtosis, then on risk-neutral skewness, and then on risk-neutral volatility. To test the relation between expected returns and skewness, we sort first on volatility and then on kurtosis. Finally, to test the relation between expected returns and kurtosis, we sort first on volatility and then on skewness.

The results of the alternative sort order portfolios, presented in Table A9 of this Internet Appendix, are qualitatively the same as those in the main paper (Table 3). The portfolio analyses indicate strong positive relations between each of the risk-neutral moments and expected returns.

VI Calculation of Risk-Free Rates

This section describes the calculation of the risk-free rates used in the Bakshi et al. (2003)-based estimation of the moments of the risk-neutral distribution. For each date t, we estimate the continuously compounded rate of return r earned on a risk-free investment purchased on date t and to be withdrawn on any date $t+\tau$ where $\tau > 0$. The data used to calculate risk-free rates come from the OptionMetrics database. Each trading day t, OptionMetrics provides the continuously compounded risk-free rate for the period starting on date t and ending at several different dates in the future. The future dates are indicated by the difference, in days, between the future date and date t. To determine the risk-free rate for the periods from t to any future date, we apply a cubic spline to the risk-free rate data provided by

OptionMetrics. On days when the U.S. equity and option markets are open but banks are closed, OptionMetrics does not provide risk-free rate data. On these days, we use the risk-free rate data in OptionMetrics from the previous trading day.

VII Calculation of Present Value of Dividends

This section describes the calculation of the present value of future dividends used to adjust the price of a stock before estimating the Bakshi et al. (2003) (BKM) integrals. The calculation is applied to any stock i on any day t and for any future ending date $t + \tau$ where $\tau > 0$. The date t can be thought of as the date on which the BKM-based risk-neutral moments are calculated, and the date $t + \tau$ can be thought of as the expiration date of the options being used to estimate the BKM integrals. The resulting value is the present value of all dividends on the stock i with ex-dividend dates between date t (exclusive) and $t + \tau$ (inclusive). The data for the present value of dividends calculations come from OptionMetrics. OptionMetrics provides distribution data for several different types of distributions. We take only distributions of types 1 (regular dividend) and 5 (special dividend) as indicated by the "Distribution Type" field in the OptionMetrics distribution file.

For any given stock i and dates t and $t+\tau$, we calculate the present value of dividends by taking all dividends on stock i with ex-dividend dates after date t and on or before date $t+\tau$. We denote these dividends d_j, $j \in \{1, 2, ..., n_d\}$, where n_d denotes the number of dividends for the given stock in the given date range. All dividends are appropriately adjusted for splits so that the dividend amount reflects the amount received by an investor who purchased one share of the stock on date t. Furthermore, we let τ_j be the amount of time, in years, between date t and the payment date of the j^{th} dividend. In cases where the payment date is not available, the ex-dividend date is used in its place. It is important to note that while we include all dividends with *ex-dividend* dates between t (exclusive) and $t + \tau$ (inclusive), we discount the dividends from their *payment* date, as this is when the actual cash dividend is received by the investor. The present value of each of the n_d dividends is calculated by discounting the dividend back to date t at the appropriate risk-free rate. The present value of all of the dividends is then found by summing the present values of the individual dividends. The present value of dividends calculation is therefore given by:

$$PVDivs = \sum_{j=1}^{n_d} d_j e^{-r_j \tau_j} \tag{8}$$

where r_j is the risk-free rate for the period from t to $t + \tau_j$. The calculation of the risk-free rates is described in VI of this Internet Appendix.

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Table A1: Portfolio ER^{Div}

The table presents the results of portfolio analyses examining the relations between ER^{Div} and each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$. The methodology is identical to that used to generate Table 3 of the main paper, except that ER is replaced by ER^{Div}.

Panel A: Vol^{BKM}

$Skew^{BKM}$ 1	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 2	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 3	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3
Vol^{BKM} 1	13.58	14.37	14.37		15.42	15.58	15.73		18.56	19.39	19.15
Vol^{BKM} 2	16.43	18.11	20.32		20.07	20.09	19.96		24.80	26.58	24.86
Vol^{BKM} 3	21.97	24.55	28.22		25.14	25.81	26.75		31.33	31.58	31.05
Vol^{BKM} $3-1$	8.38	10.18	13.85		9.73	10.23	11.02		12.77	12.19	11.91
	(7.73)	(11.12)	(11.95)		(7.52)	(9.41)	(9.06)		(9.90)	(10.18)	(11.61)

Panel B: $Skew^{BKM}$

$Kurt^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Kurt^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Skew^{BKM}$ 1	14.68	18.74	22.95		13.46	17.76	22.06		13.22	17.03	26.33
$Skew^{BKM}$ 2	16.78	22.01	29.05		15.91	20.82	25.39		15.39	19.35	26.22
$Skew^{BKM}$ 3	19.50	25.79	33.86		18.39	25.46	32.35		17.49	23.10	29.51
$Skew^{BKM}$ $3-1$	4.82	7.05	10.91		4.92	7.69	10.29		4.27	6.08	3.18
	(4.99)	(8.90)	(8.62)		(5.72)	(7.81)	(9.17)		(4.82)	(4.66)	(2.11)

Panel C: $Kurt^{BKM}$

$Skew^{BKM}$ 1	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 2	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	$Skew^{BKM}$ 3	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3
$Kurt^{BKM}$ 1	13.53	16.20	23.68		14.95	19.38	24.98		18.20	23.01	31.52
$Kurt^{BKM}$ 2	14.39	17.34	26.28		15.43	19.88	24.84		19.22	25.39	31.19
$Kurt^{BKM}$ 3	14.20	19.26	27.46		16.50	20.79	27.89		19.63	26.93	33.48
$Kurt^{BKM}$ $3-1$	0.67	3.05	3.78		1.55	1.41	2.92		1.43	3.91	1.97
	(1.26)	(4.83)	(3.18)		(3.06)	(2.06)	(4.17)		(1.73)	(3.68)	(2.15)

Table A2: Fama-MacBeth Cross-Sectional Regressions Using ER^{Div}

The table below presents the results of FM regressions examining the relation between ER^{Div} and Vol^{BKM}, $Skew^{BKM}$, $Kurt^{BKM}$, and controls. The methodology is identical to that used to generate Table 5 of the main paper, except that ER is replaced by ER^{Div}.

Specification	Vol^{BKM}	$Skew^{BKM}$	$Kurt^{BKM}$	β	$IdioVol$	$CoSkew$	$CoKurt$	$Size$	BM	$Illiq$	Rev	Mom	Max	$Earn$	$AnlystCov$	LTG	Intercept	Adj. R^2	n
(1)	0.29	6.97	0.93														10.62	0.12	279
	(16.62)	(9.99)	(7.91)														(14.88)		
(2)	0.18	3.17	0.42	2.40	2.62	−0.14	0.01	0.50	0.46	188.40	−47.57	−4.27	12.36	27.24	−1.87	0.18	5.79	0.26	226
	(9.25)	(7.06)	(5.50)	(3.64)	(1.45)	(−2.03)	(1.55)	(2.30)	(0.96)	(3.24)	(−27.63)	(−8.92)	(2.76)	(6.22)	(−7.15)	(10.10)	(2.17)		

Table A3: Portfolio ER - 2-Month Risk Measures

The table presents the results of portfolio analyses examining the relations between ER and each of Vol^{BKM}_{2Month}, $Skew^{BKM}_{2Month}$, and $Kurt^{BKM}_{2Month}$. The methodology is identical to that used to generate Table 3 of the main paper, except that Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are replaced by Vol^{BKM}_{2Month}, $Skew^{BKM}_{2Month}$, and $Kurt^{BKM}_{2Month}$, respectively.

Panel A: Vol^{BKM}_{2Month}

$Skew^{BKM}_{2Month}$ 1	$Kurt^{BKM}_{2Month}$ 1	$Kurt^{BKM}_{2Month}$ 2	$Kurt^{BKM}_{2Month}$ 3	$Skew^{BKM}_{2Month}$ 2	$Kurt^{BKM}_{2Month}$ 1	$Kurt^{BKM}_{2Month}$ 2	$Kurt^{BKM}_{2Month}$ 3	$Skew^{BKM}_{2Month}$ 3	$Kurt^{BKM}_{2Month}$ 1	$Kurt^{BKM}_{2Month}$ 2	$Kurt^{BKM}_{2Month}$ 3
Vol^{BKM}_{2Month} 1	13.56	11.70	11.66		16.26	14.98	14.63		20.92	20.18	17.07
Vol^{BKM}_{2Month} 2	16.16	16.28	15.70		20.72	19.28	17.41		26.16	24.56	24.16
Vol^{BKM}_{2Month} 3	19.91	21.56	22.87		24.57	25.35	25.60		31.43	32.62	32.55
Vol^{BKM}_{2Month} $3-1$	6.35	9.86	11.22		8.31	10.37	10.97		10.51	12.43	15.48
	(4.21)	(7.35)	(7.88)		(7.96)	(10.15)	(7.69)		(7.04)	(8.48)	(10.14)

Panel B: $Skew^{BKM}_{2Month}$

$Kurt^{BKM}_{2Month}$ 1	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3	$Kurt^{BKM}_{2Month}$ 2	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3	$Kurt^{BKM}_{2Month}$ 3	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3
$Skew^{BKM}_{2Month}$ 1	15.18	20.19	24.55		12.98	15.50	22.09		11.00	14.09	23.24
$Skew^{BKM}_{2Month}$ 2	17.58	22.94	29.78		15.17	19.23	25.82		12.19	16.13	22.75
$Skew^{BKM}_{2Month}$ 3	20.24	28.47	34.02		17.88	24.63	30.86		14.38	19.43	28.74
$Skew^{BKM}_{2Month}$ $3-1$	5.06	8.28	9.47		4.89	9.13	8.77		3.39	5.35	5.50
	(5.22)	(7.15)	(5.22)		(5.93)	(5.91)	(4.49)		(4.38)	(3.59)	(3.21)

Panel C: $Kurt^{BKM}_{2Month}$

$Skew^{BKM}_{2Month}$ 1	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3	$Skew^{BKM}_{2Month}$ 2	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3	$Skew^{BKM}_{2Month}$ 3	Vol^{BKM}_{2Month} 1	Vol^{BKM}_{2Month} 2	Vol^{BKM}_{2Month} 3
$Kurt^{BKM}_{2Month}$ 1	11.42	16.38	21.63		14.48	19.94	24.44		18.46	25.13	31.03
$Kurt^{BKM}_{2Month}$ 2	11.15	15.62	22.89		15.21	19.22	25.19		19.78	24.48	32.09
$Kurt^{BKM}_{2Month}$ 3	11.22	15.53	23.54		14.82	18.87	27.11		17.65	26.57	34.77
$Kurt^{BKM}_{2Month}$ $3-1$	-0.20	-0.85	1.90		0.35	-1.07	2.67		-0.81	1.44	3.74
	(-0.28)	(-0.84)	(1.14)		(0.49)	(-1.19)	(2.52)		(-1.06)	(1.06)	(2.22)

Table A4: Fama-MacBeth Cross-Sectional Regressions - 2-Month Risk Measures

The table below presents the results of FM regressions examining the relation between ER^{Div} and Vol^{BKM}_{2Month}, $Skew^{BKM}_{2Month}$, $Kurt^{BKM}_{2Month}$, and controls. The methodology is identical to that used to generate Table 5 of the main paper, except that Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are replaced by Vol^{BKM}_{2Month}, $Skew^{BKM}_{2Month}$, and $Kurt^{BKM}_{2Month}$, respectively.

Specification	Vol^{BKM}_{2Month}	$Skew^{BKM}_{2Month}$	$Kurt^{BKM}_{2Month}$	β	$IdioVol$	$CoSkew$	$CoKurt$	$Size$	BM	$Illiq$	Rev	Mom	Max	$Earn$	$AnlystCov$	LTG	Intercept	Adj. R^2	n
(1)	31.16	7.74	0.84														10.28	0.14	109
	(14.43)	(10.12)	(5.37)														(11.19)		
(2)	20.94	4.01	0.47	2.10	6.51	−0.11	0.01	0.72	0.47	347.83	−38.28	−3.61	−1.91	53.11	−2.34	0.30	−0.51	0.29	90
	(7.06)	(6.27)	(3.41)	(2.36)	(2.75)	(−2.40)	(1.35)	(2.42)	(0.54)	(4.09)	(−15.42)	(−4.69)	(−0.19)	(5.14)	(−2.31)	(5.44)	(−0.17)		

Table A5: Summary Statistics - Non-Parametric Sample

The table below presents summary statistics for the non-parametric sample. The sample contains stock, month observations for months t from March 1999 through December 2012 for which values of ER, Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$ can be calculated. The table shows the time-series averages of monthly cross-sectional values.

Variable	Mean	SD	Min	5%	25%	Median	75%	95%	Max	n
ER	20.67	19.21	−41.33	−5.16	8.48	17.87	30.12	56.86	96.67	988
Vol^{NonPar}	46.14	18.40	9.28	23.32	33.14	42.85	55.72	79.07	168.24	988
$Skew^{NonPar}$	−4.59	8.52	−85.22	−14.97	−7.37	−4.57	−1.92	6.15	69.29	988
$Kurt^{NonPar}$	4.23	10.29	−67.50	−4.40	0.22	2.29	5.80	19.55	109.08	988
$MktCap$	9158	27097	70	271	805	2040	6313	36699	392409	988

Table A6: Portfolio ER - Non-Parametric Risk Measures

The table presents the results of portfolio analyses examining the relations between ER and each of Vol^{BKM}_{2Month}, $Skew^{BKM}_{2Month}$, and $Kurt^{BKM}_{2Month}$. The methodology is identical to that used to generate Table 3 of the main paper, except that Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are replaced by Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$, respectively.

Panel A: Vol^{NonPar}

$Skew^{NonPar}$ 1	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	$Skew^{NonPar}$ 2	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	$Skew^{NonPar}$ 3	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3
Vol^{NonPar} 1	14.81	14.53	12.78		13.23	13.15	13.48		14.21	13.80	13.59
Vol^{NonPar} 2	21.60	19.93	21.92		18.60	17.38	19.48		21.40	20.48	22.56
Vol^{NonPar} 3	29.06	27.73	31.12		26.83	24.35	27.86		30.55	29.80	32.09
Vol^{NonPar} $3-1$	14.25	13.21	18.34		13.60	11.21	14.38		16.35	16.00	18.50
	(13.08)	(10.14)	(13.14)		(10.16)	(9.38)	(13.66)		(14.58)	(15.54)	(20.35)

Panel B: $Skew^{NonPar}$

$Kurt^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Kurt^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Kurt^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3
$Skew^{NonPar}$ 1	13.28	18.87	27.73		13.37	17.66	25.15		12.06	20.35	29.78
$Skew^{NonPar}$ 2	13.76	19.85	28.42		13.81	18.53	26.04		14.03	21.47	29.97
$Skew^{NonPar}$ 3	14.11	21.63	30.82		13.80	20.00	29.31		13.84	23.09	33.00
$Skew^{NonPar}$ $3-1$	0.82	2.76	3.09		0.43	2.35	4.16		1.78	2.73	3.22
	(1.47)	(5.67)	(4.60)		(0.82)	(4.42)	(7.97)		(2.87)	(4.74)	(3.42)

Panel C: $Kurt^{NonPar}$

$Skew^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Skew^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Skew^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3
$Kurt^{NonPar}$ 1	13.85	20.24	28.86		12.77	17.96	26.41		13.82	20.52	30.64
$Kurt^{NonPar}$ 2	14.69	20.22	28.53		13.52	17.89	25.23		14.07	20.95	30.32
$Kurt^{NonPar}$ 3	13.39	22.54	30.92		13.22	19.15	27.65		13.52	22.40	31.93
$Kurt^{NonPar}$ $3-1$	-0.46	2.30	2.06		0.45	1.19	1.24		-0.31	1.88	1.29
	(-0.97)	(4.47)	(3.92)		(1.42)	(2.77)	(2.78)		(-0.74)	(5.29)	(1.82)

Table A7: Portfolio Realized Returns - Non-Parametric Risk Measures

The table presents the results of portfolio analyses examining the relations between future realized returns and each of Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$. The methodology is identical to that used to generate Table 4 of the main paper, except that Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are replaced by Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$, respectively.

Panel A: Vol^{NonPar}

$Skew^{NonPar}$ 1	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	$Skew^{NonPar}$ 2	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	$Skew^{NonPar}$ 3	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3
Vol^{NonPar} 1	0.67	0.42	0.94		0.51	0.54	0.82		0.95	0.84	1.16
Vol^{NonPar} 2	0.62	0.54	0.70		1.05	0.91	0.85		1.78	1.16	1.32
Vol^{NonPar} 3	0.94	0.24	0.79		1.50	1.14	0.90		1.52	1.25	1.40
Vol^{NonPar} $3-1$	0.27	-0.17	-0.15		0.99	0.60	0.08		0.57	0.41	0.24
	(0.32)	(-0.23)	(-0.17)		(1.50)	(1.10)	(0.13)		(0.83)	(0.59)	(0.44)

Panel B: $Skew^{NonPar}$

$Kurt^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Kurt^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Kurt^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3
$Skew^{NonPar}$ 1	0.51	0.80	0.69		0.40	0.66	0.63		0.76	0.72	-0.08
$Skew^{NonPar}$ 2	0.70	1.03	1.27		0.77	0.94	1.04		0.94	1.13	1.07
$Skew^{NonPar}$ 3	0.87	1.49	1.71		0.83	1.23	0.89		1.29	1.39	1.36
$Skew^{NonPar}$ $3-1$	0.37	0.69	1.02		0.43	0.58	0.26		0.53	0.67	1.44
	(1.98)	(2.74)	(2.24)		(2.18)	(2.69)	(0.72)		(2.86)	(2.46)	(2.32)

Panel C: $Kurt^{NonPar}$

$Skew^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Skew^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	$Skew^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3
$Kurt^{NonPar}$ 1	0.47	0.75	0.75		0.45	1.04	1.48		0.95	1.63	1.39
$Kurt^{NonPar}$ 2	0.64	0.63	0.38		0.49	0.99	1.13		0.92	1.18	1.32
$Kurt^{NonPar}$ 3	0.81	0.69	0.47		0.85	0.91	0.80		1.13	1.31	1.56
$Kurt^{NonPar}$ $3-1$	0.34	-0.06	-0.28		0.40	-0.13	-0.68		0.18	-0.32	0.17
	(1.59)	(-0.24)	(-0.65)		(3.17)	(-0.73)	(-2.40)		(1.44)	(-1.24)	(0.43)

Table A8: Fama-MacBeth Cross-Sectional Regressions - Non-Parametric Risk Measures

The table below presents the results of FM regressions examining the relation between ER^{Div} and Vol^{NonPar}, $Skew^{NonPar}$, $Kurt^{NonPar}$, and controls. The methodology is identical to that used to generate Table 5 of the main paper, except that Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are replaced by Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$, respectively.

Specification	Vol^{NonPar}	$Skew^{NonPar}$	$Kurt^{NonPar}$	β	$IdioVol$	$CoSkew$	$CoKurt$	$Size$	BM	$Illiq$	Rev	Mom	Max	$Earn$	$AnlystCov$	LTG	Intercept	Adj. R^2	n
(1)	0.38	0.18	0.08														3.94	0.13	988
	(21.58)	(7.71)	(3.74)														(4.97)		
(2)	0.23	0.07	0.03	2.46	2.88	−0.12	0.01	0.53	−0.03	180.89	−50.22	−3.90	11.16	21.42	−1.37	0.24	0.11	0.26	792
	(13.82)	(4.81)	(2.55)	(4.08)	(2.44)	(−2.62)	(1.36)	(3.10)	(−0.11)	(5.49)	(−36.34)	(−10.63)	(4.22)	(6.58)	(−9.45)	(12.37)	(0.05)		

Table A9: Portfolio ER - Alternative Sort Order

The table presents the results of portfolio analyses examining the relations between ER and each of Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$. The methodology is identical to that used to generate Table 3 of the main paper, except that in all sorts, the order of the first two sort variables is reversed.

Panel A: Vol^{BKM}

$Kurt^{BKM}$ 1	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	$Kurt^{BKM}$ 2	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3
Vol^{BKM} 1	13.56	15.90	19.40		12.41	14.61	17.17		13.15	13.29	14.91
Vol^{BKM} 2	17.60	22.18	25.66		16.87	20.43	24.49		20.16	17.04	20.28
Vol^{BKM} 3	22.77	28.28	33.27		21.85	25.24	31.98		27.27	25.69	27.84
Vol^{BKM} $3-1$	9.21	12.38	13.87		9.44	10.63	14.80		14.12	12.40	12.92
	(7.17)	(10.60)	(10.47)		(9.48)	(10.07)	(12.89)		(13.09)	(14.08)	(12.43)

Panel B: $Skew^{BKM}$

Vol^{BKM} 1	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Vol^{BKM} 2	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Vol^{BKM} 3	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3
$Skew^{BKM}$ 1	12.58	12.64	11.56		17.57	17.27	16.45		22.34	22.44	26.46
$Skew^{BKM}$ 2	14.90	14.45	13.82		20.80	20.22	18.76		27.83	25.60	26.92
$Skew^{BKM}$ 3	16.90	16.74	16.45		23.92	25.60	23.53		33.91	32.21	29.80
$Skew^{BKM}$ $3-1$	4.31	4.10	4.88		6.35	8.33	7.08		11.57	9.76	3.34
	(5.27)	(4.85)	(4.92)		(7.19)	(8.25)	(5.20)		(8.76)	(7.15)	(2.29)

Panel C: $Kurt^{BKM}$

Vol^{BKM} 1	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Vol^{BKM} 2	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Vol^{BKM} 3	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3
$Kurt^{BKM}$ 1	12.28	13.47	16.27		16.31	18.86	23.18		23.04	24.29	30.99
$Kurt^{BKM}$ 2	12.90	13.90	17.15		16.74	19.95	24.89		26.05	24.92	31.63
$Kurt^{BKM}$ 3	12.05	14.55	17.70		17.76	20.88	26.54		26.31	27.80	32.74
$Kurt^{BKM}$ $3-1$	−0.23	1.08	1.43		1.44	2.01	3.36		3.26	3.51	1.75
	(−0.45)	(2.15)	(1.74)		(2.31)	(3.12)	(3.43)		(3.55)	(4.35)	(1.73)