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Analyst Price Target Expected Returns and Option Implied Risk *

Turan G. Bali† Jianfeng Hu‡ Scott Murray§

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Abstract

Motivated by the nature of asset pricing models, we investigate the cross-sectional relation between the market's *ex-ante* view of a stock's risk and the stock's *ex-ante* expected return. We demonstrate that an ex-ante measure of expected returns based on analyst price targets is highly related to the market's required rate of return. Using this measure, we show that ex-ante measures of volatility, skewness, and kurtosis derived from option prices are positively related to ex-ante expected returns. We then decompose the risk measures into systematic and unsystematic components and find that while expected returns are related to both systematic and unsystematic variance risk, only the unsystematic components of skewness and kurtosis are important for explaining the cross-section of expected stock returns. The results are consistent using two different approaches to measuring ex-ante risk and robust to controls for other variables related to stock returns and analyst bias.

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

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1 Introduction

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

We begin by creating a simple measure of ex-ante expected return derived from analyst price targets. While there is a large literature that uses analyst earnings and growth forecasts to generate measures of the cost of equity capital (Gebhardt, Lee, and Swaminathan (2001) and Hughes, Liu, and Liu (2009), for example), research using price targets for this purpose is scarce. This is surprising given that price targets have been shown to reflect analyst valuations (Bradshaw (2002)) and to subsume the information in earnings and growth forecasts (Asquith, Mikhail, and Au (2005)), while measures based on earnings and growth forecasts fail to reflect analysts' valuations (Bradshaw (2004)) or the market's required rate of return (Hughes et al. (2009)). Despite these findings, only Brav, Lehavy, and Michaely (2005) have previously used price targets to examine relations between risk and the required rate of return on equity.[1,2] Our measure represents an improvement over previously used measures in that, by using the market price taken after the analyst reports are released, we capture the required rate of return as determined by the *market*, not by the analysts. Additionally, the price target measure is flexible enough to account for term structure variation in the risk and expected return profile of the stock, and free from the assumptions inherent in measures that use earnings and growth forecasts. Our analyses demonstrate that our price target-based

[1]Brav et al. (2005) find a positive relation between the cost of equity capital and beta and a negative relation between the cost of equity capital and market capitalization.

[2]Bradshaw, Brown, and Huang (2013), Brav and Lehavy (2003), and Bradshaw (2002) use similar measures in different contexts.

expected return is strongly cross-sectionally related to the rates of return required by the market calculated from historical data. Furthermore, we show that our measure is superior to the implied cost of capital for detecting relations between risk and expected stock returns.

We proceed to examine the relations between ex-ante expected returns, calculated using our price target measure, and ex-ante measures of risk calculated from option prices. Specifically, we examine the relations between expected returns and the volatility, skewness, and kurtosis of the distribution of future returns. Our results indicate that all three measures of risk are strongly positively related to price target-based expected returns. We then decompose the measures into systematic and unsystematic components and examine which components drive these relations. The results indicate that systematic volatility is the most important driver of the cost of equity capital, followed by unsystematic volatility, unsystematic skewness, and unsystematic kurtosis. Neither systematic skewness nor systematic kurtosis is related to expected returns. All of our results are robust when controlling for several other variables that have been shown to be determinants of the cross-section of expected stock returns as well as controls for bias in analyst forecasts.[3]

The positive relation between systematic volatility and cost of capital supports the main prediction of the Capital Asset Pricing Model (CAPM, Sharpe (1964), Lintner (1965), and Mossin (1966)). While the CAPM is one of the foundational asset pricing theories, previous empirical studies show that measures of systematic volatility (beta) based on historical data have little ability to predict future stock returns.[4] Furthermore, theoretical models in which unsystematic risk is priced indicate a positive relation between expected returns and unsystematic volatility (Levy (1978) and Merton (1987)), yet previous empirical work

[3]See Bradshaw et al. (2013), Bonini, Zanetti, Bianchini, and Salvi (2010), Asquith et al. (2005), Brav et al. (2005), Abarbanell and Lehavy (2003), Brav and Lehavy (2003), Bradshaw (2002), Michaely and Womack (1999), Rajan and Servaes (1997), and Womack (1996) for discussions of the biases in analyst forecasts.

[4]See Blume and Friend (1973) and Fama and French (1992, 1993). Fama and French (2004) give a summary of CAPM research. Tinic and West (1986) document difficulties in empirical tests of the CAPM. Kothari, Shanken, and Sloan (1995) provide evidence supporting the CAPM by calculating portfolio level market betas.

(Ang, Hodrick, Xing, and Zhang (2006)) has found a negative relation. Unlike these previous works, our results demonstrate that both systematic and unsystematic volatility risk are important determinants of a security's expected rate of return, with the direction of the relations consistent with theoretical predictions.

Our results for skewness are consistent with the demand-based option pricing models of Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2009). Demand-based option pricing predicts that, when investors anticipate positive returns for a stock, they act on this anticipation by buying calls and/or selling puts. This order flow exerts inventory demand on option market makers causing increases in call prices and decreases in put prices. As a result, when measuring the distribution implied from option prices, implied right-tail probabilities are high (high call prices) and left-tail probabilities are low (low put prices), resulting in high values of implied skewness for stocks with high expected returns. While several previous papers provide empirical evidence consistent with demand-based option pricing (An, Ang, Bali, and Cakici (2014), Rehman and Vilkov (2012), Xing, Zhang, and Zhao (2010), Bali and Hovakimian (2009), and DeMiguel, Plyakha, Uppal, and Vilkov (2013)), our results augment this line of research by demonstrating that this option demand is driven by firm-specific information, since only the unsystematic component of skewness is robustly related to expected stock returns.[5]

Finally, our results for kurtosis support predictions that investors are kurtosis-averse (Dittmar (2002), Kimball (1993)) and prefer stocks with lower probability mass in the tails of the return distribution, causing investors to require higher expected returns from assets with leptokurtic return distributions. As with skewness, our results indicate that this result is driven by firm-specific kurtosis, not systematic kurtosis.

Our work provides several novel contributions. Our first contribution is to demonstrate

[5]In a perfect market equilibrium, theory predicts a negative relation between systematic skewness and the cost of capital (Kraus and Litzenberger (1976), Harvey and Siddique (2000)), with some empirical evidence supporting this prediction (Conrad, Dittmar, and Ghysels (2013) and Bali and Murray (2013)).

that a simple price target-based measure does a good job at capturing cross-sectional variation in the market's required rate of return. This measure is valuable for many reasons. First, the ex-ante nature of our measure is consistent with the true nature of asset pricing models, since such models are designed to describe the relation between ex-ante required rates of return and the market's ex-ante assessment of the security's risk. Second, our measure provides an alternative to the use of ex-post realized returns as a proxy for ex-ante expected returns, which have been shown to be noisy (Elton (1999)) and therefore may require long sample periods to detect relations between risk and rates of return. As our results demonstrate, our measure is capable of discerning such relations using relatively short sample period (1999-2012, the period for which price target data are available).

Second, we contribute the first study to examine relations between ex-ante required rates of return and ex-ante measures of risk. While several previous studies have used ex-ante measures of risk and a few studies have used ex-ante measures of expected returns, no previous study has used ex-ante measures of both. Similar to the use of ex-post realized returns, previous research has demonstrated that measures of risk based on historical data are noisy and inaccurate (Boyer, Mitton, and Vorkink (2010)). Thus, accurate assessment of the determinants of the cost of equity capital requires ex-ante measures of both risk and required rate of return.

Third, we find strong evidence consistent with several theoretically predicted relations between risk and required rate of return that have been evasive or undocumented in previous empirical studies. Specifically, our results demonstate that both systematic volatility and unsystematic volatility are positively related to expected returns. Our finding that unsystematic skewness, but not systematic skewness, drives the relation between skewness and required rate of return indicates that the demand underlying demand-based option pricing is driven by firm-specific information. Finally, we find that while systematic kurtosis is not important in determining required rates of return, unsystematic kurtosis (i.e. fat tails driven by firm-specific information) carries a positive risk premium.

The remainder of this paper proceeds as follows. Section 2 compares the price target-based measure of expected returns to the implied cost of capital measure. Section 3 describes the calculation of the risk variables used in our empirical examinations. Section 4 discusses the construction of our samples and presents summary statistics. Section 5 investigates the relations between total risk-neutral moments and expected returns. Section 6 analyzes the relations between expected returns and the systematic and unsystematic components of risk-neutral moments. Section 7 concludes the paper.

2 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.

2.1 Price Target Expected Returns

The price target-based measure of expected returns 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.[6] 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 analyst price target, we calculate the return implied by the price target ($PrcTgtER$)

[6]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.

to be the price target ($PrcTgt$) divided by the market price at the end of the month during which the price target was announced ($MonthEndPrc$), minus 1.[7] To ensure data quality, we remove observations where either the announcement date or month-end stock price is missing or non-positive.[8] 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 the given month. Therefore, the expected future return for stock i in month t is calculated as:

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

where $n_{i,t}$ is the number of analyst price targets for stock i announced during month t and

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

There are several benefits of the price target-based expected return measure. First, it has the intuitive appeal of being consistent with the definition of the expected return as the expected future security value divided by the current price. While the current market price of a stock is easily observable, the expectation of the future value is not. An analyst price target represents an explicit assessment of the expected future value generated by an informed market observer.

Second, the price target-based expected return has a time horizon of one year. As such,

[7] The end-of-month stock price is taken from CRSP. The CRSP data are matched to I/B/E/S using CUSIPs. Specifically, we merge the CRSP data to the I/B/E/S data by matching the NCUSIP field in the CRSP daily stock names file to the CUSIP field in I/B/E/S.

[8] 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. To ensure that the price target is appropriately compared to the month-end market price, we remove observations where there is a distribution between the announcement date and the last day of the announcement month. A stock is considered to have a distribution between the announcement and month-end dates if there are any distributions listed in CRSP with ex-dividend dates between the announcement date (exclusive) and the month-end date (inclusive). As additional checks, for an observation to be retained, the cumulative factor to adjust price (CFACPR) field in the CRSP database must be the same on the announcement date and the last trading day of the month.

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 requires that the expected rate of return on a stock be constant for all future periods.

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, while several previous papers have used the ratio of the price target to the market price in analyses of price targets (Bradshaw et al. (2013), Brav et al. (2005), Asquith et al. (2005), Brav and Lehavy (2003), Bradshaw (2002)), our measure differs from these works in one important way. Our calculation of price target-based expected return (ER) uses the month-end price of the stock, which comes after the announcement of the price target, whereas previous research has used the market price on or prior to the date of the announcement. This difference is important because our measure can be interpreted as indicative of a rate set by the *market*, as all information presented in the analyst report is publicly available prior to the determination of the month-end market price, which forms the basis of our calculation. Thus, the sequence of events in our setting is: 1) the price target is announced, 2) the market digests the information in the analyst report (including the price target), 3) based on the information in the report and all other available information, the market determines the required rate of return on the stock, and 4) based on the required rate of return and the price the stock is expected to obtain one year from now (the price target), the market prices the stock. Given this chronology, our results cannot be interpreted as evidence that analysts use information related to risk-neutral moments to determine the target price of the stock. If in fact the analyst does use such information in determining the price target, then our results indicate that the market agrees with the use of this information in valuing a stock. Either way, our price target-based expected return (ER) captures the expected rate of return on the stock demanded by the market, not determined by the analyst. Furthermore, as our ex-ante measures of risk are calculated at the end of the month, the analyst will not have access to this information at the time of the price target announcement.

In addition to the conceptual appeal of our measure, 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 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, meaning 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.

2.2 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. Formulaically, the implied cost of capital is the value r that solves:

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

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 last term in equation (3) is the infinite summation of forecast earnings for years $y+12$ and after. The assumption in this term is that return on equity is constant for years $y+12$ and after. For each stock/month observation, ICC is calculated by finding the value of r that equates the stock price (P) 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). As the calculation is fairly complicated, we summarize the important conceptual aspects here, and provide details in Appendix A.

The main inputs to the calculation of ICC are analyst forecasts of earnings and growth. In years $y+1$ and $y+2$, earnings are taken from explicit analyst forecasts. Forecast earnings 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.

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. As the objective of this paper is to analyze relations between relatively short horizon ex-ante risk and ex-ante expected returns, use of ICC would explicitly assume that the required rate of return on a given firm is constant, an assumption that is likely to be incorrect.

Second, as expressed by Botosan and Plumlee (2005), "Since the majority of the expected cash flows reside in the terminal value, successful deduction of cost of equity capital depends largely on the ability to discern the market's terminal value forecast."[9] Easton and Monahan (2005) concur, stating in their abstract that "for the entire cross-section of stocks, [accounting-based measures of expected returns] are unreliable."[10] The price target-based

[9]The terminal value refers to the value of the stock derived from earnings in years $t+3$ and beyond.

[10]The actual quote is "for the entire cross-section of stocks, these proxies are unreliable" where "these proxies" refers to accounting-based measures of expected returns.

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 generally favorable to the price target-based measure of ex-ante expected returns, an empirical analysis comparing these measures is certainly warranted.

2.3 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 relations between historical risk and firm characteristics and each of ER and ICC.

2.3.1 Regression-Based Expected Returns

Our benchmark measure of expected returns is based on historical relations between stock returns and market beta, log of market capitalization, and book-to-market ratio. To estimate this relation, we employ the Fama and MacBeth (1973) regression technique. Each month, we run a cross-sectional regression of one-month ahead future stock returns on these variables. The regression specification is:

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

where $R_{i,t+1}$ is the month $t+1$ return of stock i. $\beta_{i,t}$ is the stock's market beta, calculated as the slope coefficient from a regression of the stock's excess return on the market's excess return using one year's worth of daily data.[11] $SIZE_{i,t}$ is log of the stock's market capitaliza-

[11]The market's excess return is taken to be the value-weighted average excess return of all stocks that trade on the New York Stock Exchange, the American Stock Exchange, and the Nasdaq. 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.

tion ($MktCap$), defined as the number of shares outstanding times the end of month 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 year $y-1$ divided by the market capitalization at the end of that same year.[12]

We run this regression each month from July 1963 through December of 2012. The time-series averages of the monthly cross-sectional regression coefficients are $\delta_0 = 1.807583$, $\delta_1 = 0.037838$, $\delta_2 = -0.177901$, and $\delta_3 = 0.253790$. We then use these coefficients to calculate our regression-based measure of expected returns ($RegER$), giving:[13]

$$RegER_{i,t} = 12\left(1.807583 + 0.037838\beta_{i,t} - 0.177901SIZE_{i,t} + 0.253790BM_{i,t}\right). \quad (5)$$

2.3.2 Portfolio Analysis

We begin our comparison of the price target expected return (ER) and the implied cost of capital (ICC) with a portfolio analysis examining the relations between the regression-based expected return ($RegER$) and each of the ex-ante measures. Each month from March of 1999 through June of 2012, we sort all stocks for which valid values of $RegER$, ER, and ICC are available into quintile portfolios based on an ascending ordering of $RegER$.

The time series averages of the monthly equal-weighted portfolio expected returns, using each of the expected return measures, are presented in Panel A of Table 1. By design, the average regression-based expected return ($RegER$) for the quintile portfolios increases from an average of 2.26% for quintile portfolio one to 13.47% for quintile portfolio five, giving an expected return difference of 11.20% between the quintile five and quintile one portfolios. The results for the price target-based expected returns (ER) are remarkably similar,

[12]Stock return, shares outstanding, and price data are gathered from the CRSP. The book value of equity is calculated using balance sheet data from Compustat. More details on the calculation of these variables are presented in Appendix B.

[13]The multiplication by 12 in equation (5) annualizes $RegER$, facilitating comparison with the price target-based measure (ER) and the implied cost of capital (ICC).

as the average ER increases monotonically from 16.76% in quintile portfolio one to 27.86% in quintile portfolio five. The difference in average ER between the fifth and first quintile portfolio of 11.10% is not only highly statistically significant, with a Newey and West (1987) t-statistic of 18.32, but is also nearly identical to the corresponding value obtained from the regression-based expected returns. This result indicates that, up to a constant, the price target-based expected return is highly similar in the cross-section to the regression-based measure.[14] Furthermore, it is worth noting that the differences between the average $RegER$ and ER of 14.50% (16.76%-2.26%), 12.01% (18.11%-6.10%), 11.83% (20.01%-8.18%), 12.82% (22.89%-10.07%), and 14.39% (27.86%-13.47%) for quintile portfolios 1, 2, 3, 4, and 5, respectively, are quite similar, indicating that any potential bias inherent in our price target-based measure (ER) is largely unrelated to the variables used to calculate $RegER$, namely beta, market capitalization, and book-to-market ratio.

Using the implied cost of capital (ICC) as the measure of expected returns, once again we observe a monotonically increasing pattern across the quintile portfolio, from 7.65% for the quintile one portfolio to 9.84% for quintile five, giving a 5-1 difference of 2.19% (t-statistic = 6.78). While this result is still highly significant, it is substantially less significant, both economically and statistically, than the results for the price target measure.

To assess the relations between each of the ex-ante expected return measures (ER and ICC) and measures of risk and firm characteristics, we repeat the portfolio analyses, sorting on each of market beta (β), log of market capitalization ($Size$), book-to-market ratio (BM), idiosyncratic volatility ($IdioVol$), and co-skewness ($CoSkew$). $IdioVol$ 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).[15] $CoSkew$ is calculated following Harvey and Siddique (2000) as the slope coefficient

[14] The level effect observed in the price target-based expected return measure is consistent with previous studies that have used similar measures, and will be discussed in more detail in Section 3.3.

[15] Daily SMB and HML factor returns are taken from the Fama-French database on WRDS.

on the squared excess market return term from a regression of the stock's excess return on the excess return of the market and the market excess return squared. Both $IdioVol$ and $CoSkew$ are calculated using one year's worth of daily return data.[16]

Panel B of Table 1 shows that the price target-based expected return (ER) has strong relations with each of market beta (β, positive relation), log of market capitalization ($Size$, negative relation), and idiosyncratic volatility ($IdioVol$, positive relation), as the average difference in ER between the quintile five and quintile one portfolio (column 5-1) is economically large (8.36% for β, -12.55% for $Size$, and 14.85% for $IdioVol$) and highly statistically significant, with Newey and West (1987) t-statistics all in excess of 5.82. In each of these cases, the portfolio expected returns exhibit a monotonic pattern across the quintile portfolios. The analysis also detects a negative cross-sectional relation between co-skewness and price target expected returns, as the average difference between the quintile five and quintile one expected return of -2.02% is statistically significant. Finally, the results for portfolios sorted on book-to-market ratio indicate an economically small but marginally statistically significant negative difference in average price target expected return between the quintile five and quintile one portfolios.

We repeat the portfolio analyses using implied cost of capital (ICC) as the measure of ex-ante expected return. The results, shown in Panel C of Table 1, detect no relations between any of the risk variables (β, $IdioVol$, and $CoSkew$) and average ICC. On the other hand, consistent with previous empirical work on realized returns, the results indicate a negative relation between $Size$ and ICC, and a positive relation between BM and ICC.

2.4 Regression Analysis

We continue our comparison of the ex-ante measures of expected returns with Fama and MacBeth (1973) regression analyses. Panel A of Table 2 presents the results for regressions

[16]We require a minimum of 225 daily return observations when calculating both $IdioVol$ and $CoSkew$.

using the price target-based measure of ex-ante expected returns (ER) as the dependent variable. The results are highly consistent with the portfolio analyses. Specifications (1) through (4) detect positive relations between ER and each of β and $IdioVol$, and negative relations between ER and $Size$, BM, and $CoSkew$. When ICC is added to the specification (models (5) through (8)), the results demonstrate that while ICC is highly related to ER, the common component between ER and ICC is not driven by risk or firm characteristics, as the coefficients on these variables are similar to those from specifications without ICC.

The results of regressions using implied cost of capital (ICC) as the dependent variable are presented in Panel B of Table 2. Consistent with the portfolio results, the regressions fail to detect relations between implied cost of capital and any of the risk variables (β, $IdioVol$, $CoSkew$).[17] Also consistent with the portfolio analyses, the regressions detect a negative relation between $Size$ and ICC, and a positive relation between BM and ICC, although in some specifications the former is only marginally statistically significant.

In addition to the results presented in Table 2, we run a univariate Fama and MacBeth (1973) regression analysis of price target expected return (ER) on the regression-based expected return ($RegER$). Consistent with the portfolio analysis, the average slope coefficient from this regression is 1.11 (t-statistic = 24.00), indicating that up to a constant, ER and $RegER$ are highly cross-sectionally similar. The fact that the average coefficient is close to 1.00 shows that the price target-based measure is highly cross-sectionally similar to long-term realized returns measured from a large panel of stocks covering an extended period. This is quite useful because it indicates that the price target-based expected return can be effectively used to estimate the economic magnitude of the impact of risk on ex-ante expected returns. Repeating the analysis using implied cost of capital (ICC) as the dependent variable generates an average slope coefficient of 0.22 (t-statistic = 4.69), once again consistent with the

[17]The one exception is that regression model (8) detects a statistically significant relation between $IdioVol$ and ICC. The economic significance of the coefficient, -0.01, however, is economically negligible.

portfolio analysis. While the relation between ICC and $RegER$ is statistically significant, the results demonstrate that price target-based expected returns (ER) are cross-sectionally much more similar to long-term realized returns than ICC.

In unreported analyses, we examine the ability of our ex-ante expected return measures to predict future stock returns and find no evidence of such predictability. This is not surprising because the sample period for which the price target-based expected returns are available (1999-2012) is quite short and even the most robust asset pricing phenomena such as the size and value effects of Fama and French (1992) and the momentum effect of Jegadeesh and Titman (1993) do not generate statistically significant results over this period. In fact, even the average excess return on the market portfolio is not statistically distinguishable from zero during this period.[18] Furthermore, if we did find a relation between price target-based expected returns and ex-post realized returns, this would obviate the need for an ex-ante measure as it would indicate that ex-post realized returns are not too noisy to detect asset pricing relations over a short period of time. The noise in ex-post realized returns and associated lack of statistical power are the reasons that an ex-ante measure is needed.

In summary, our comparison of the price target (ER) and implied cost of capital (ICC) measures of ex-ante expected returns lead to two conclusions. First, the price target-based measure is highly similar in the cross-section to the benchmark regression-based measure based on historical data. Second, the price target measure is strongly related to risk, whereas implied cost of capital appears related to firm characteristics, but fails to exhibit any relations with risk. In addition to the empirical evidence, conceptual arguments based on the definition of expected return and the assumptions used in calculating the implied cost of capital also favor the use of the price target-based measure. Finally, the results of previous research

[18] The average returns of the market (MKTRF, 0.21% per month), size (SMB, 0.46% per month), value (HML, 0.32% per month), and momentum (UMD, 0.30% per month) factor mimicking portfolios for the period from 1999 through 2012 are all statistically insignificant. Monthly factor return data are taken from Kenneth French's data library.

indicate that price targets contain more information relevant to the market and produce more accurate measures of valuation than the earnings and growth forecasts used in the calculation of ICC. For these reasons, we assess that the price target-based expected return measure is the better measure for our purposes. The remainder of the analyses in this paper use the price target expected return (ER) as the measure of ex-ante expected return.

We proceed now to the main focus of this paper, analysis of the relations between ex-ante risk and ex-ante expected return. We begin by describing our measures of ex-ante risk and other variables used in the study.

3 Ex-Ante Risk and Control Variables

We calculate risk-neutral moments (volatility, skewness, kurtosis) using two different methodologies, one based on Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003, BKM hereafter), and the other a nonparametric approach based on taking differences in the implied volatilities of options with different moneynesses.

3.1 BKM Risk-Neutral Moments

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 can be calculated as:

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

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

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

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 represents the continuously compounded risk-free rate for the period from time t to time $t+\tau$, and V, W, and X represent the risk-neutral expectation of the squared, cubed, and fourth power, respectively, of the log of the stock return during the same period.[19] V, W, and X can theoretically be calculated by weighted integrals (equations (25)-(27) of Appendix C) 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 real option prices with discrete strikes. The exact implementation is described in detail in Appendix C. Finally, we define the BKM-based 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 risk-neutral moments for a stock for month m are calculated using data from the last trading day during the month m for options that expire in the month $m+2$ (the options have approximately 1.5 months until expiration).[20] The data are thus contemporaneous to the price used as the denominator in the calculation of the price target-based expected return (ER).

3.2 Nonparametric Risk Neutral Moments

We calculate alternative measures of risk-neutral moments by taking differences in the implied volatility of options at different strikes. We define the at-the-money (ATM) call and

[19] The calculation of the risk-free rate r is described in Section I of the online appendix.

[20] Robustness checks demonstrate that the results are not sensitive to the expiration of the options used to calculate the risk-neutral moments.

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 nonparametric 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.[21]

$$Vol^{NonPar} = \frac{CIV_{50} + PIV_{50}}{2} \tag{11}$$

$$Skew^{NonPar} = CIV_{25} - PIV_{25} \tag{12}$$

$$Kurt^{NonPar} = CIV_{25} + PIV_{25} - CIV_{50} - PIV_{50} \tag{13}$$

3.3 Control Variables

To ensure that the main findings of this paper, namely strong relations between expected returns and risk-neutral moments, are not driven by other confounding factors, we control for several variables that have previously been shown to be related to returns. As several previous papers have found that analyst forecasts are biased (Abarbanell and Lehavy (2003), Michaely and Womack (1999), Rajan and Servaes (1997), Womack (1996)), with bias being

[21] 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.

related to both general overoptimism (Bradshaw et al. (2013), Asquith et al. (2005), Brav et al. (2005), Brav and Lehavy (2003), Bradshaw (2002), Bonini et al. (2010)) as well as other firm level variables such as the market capitalization, amount of analyst coverage, ratio of book-value of equity to market-value of equity, predicted growth, and forecast earnings (Brav and Lehavy (2003), Bradshaw (2002), Bonini et al. (2010)), we employ controls for these effects as well.

In addition to the variables discussed here, our measures of beta (β), idiosyncratic volatility ($IdioVol$), co-skewness ($CoSkew$), market capitalization ($MktCap$), size ($Size$), and book-to-market ratio (BM) were described in Section 2. A more detailed discussion of the calculation of all control variables is presented in Appendix B.

We define co-kurtosis ($CoKurt$) as 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 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). Both $CoKurt$ and $Illiq$ are calculated using one year's worth of daily data.[22] 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. To control for potential bias in price targets, we include a few additional variables that have been shown to be related to this bias (Bonini et al. (2010)). We define the forecast earnings ($Earn$) to be the median analyst forecast earnings for the next fiscal year end divided by the month-end price of the stock. Analyst coverage ($AnlystCov$) is defined as the natural log of one plus the number of analysts who have issued fiscal year earnings forecasts, and long-term growth (LTG) is

[22] We require a minimum of 225 valid daily observations to calculate $CoKurt$ and $Illiq$. Observations not satisfying this requirement are discarded.

taken to be the median long-term growth forecast.

A few words about how we handle analyst forecast bias are warranted. The constant (general analyst optimism) portion of the bias, evidenced by unrealistically large price target-based expected returns (our sample has an average expected return of more than 20% per annum, in line with previous research) is captured by the intercept term in our regression analyses. As the focus of our study is the cross-sectional relations between risk and expected return, this has no impact on our conclusions. As for cross-sectional variation in analyst bias, including variables related to bias in the regression model is econometrically identical to adjusting the the expected returns for bias prior to executing the regressions. Regression coefficients on risk-neutral moments therefore measure the cross-sectional relation between expected returns and risk-neutral moments after controlling for variation in price target-based expected returns driven by bias in analyst price targets.

4 Samples

We use two main samples for the analyses in this paper. The BKM sample contains observations for which valid values for the BKM-based risk-neutral moments (Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$) are available. The $NonPar$ sample contains observations for which valid values of the nonparametric risk variables (Vol^{NonPar}, $Skew^{NonPar}$ and $Kurt^{NonPar}$) are available. To create each sample, we begin with all stock-month observations for stocks denoted by CRSP as U.S.-based common stocks and months from March 1999 through December 2012 (the period for which price targets are available).[23] We then remove all entries for which a valid price target-based expected return (ER) is not available. The BKM ($NonPar$) sample is then created by further removing data points for which valid values of the BKM-based (nonparametric) risk-neutral moments are not available.

[23]U.S.-based common stocks are those with share code (SHRCD) 10 or 11 in the CRSP database.

Table 3 presents summary statistics for the BKM (Panel A) and $NonPar$ (Panel B) samples. For the BKM sample, price target-based expected returns (ER) have a mean and median of 20.75% and 18.28%, respectively. While these numbers are quite high, they are consistent with previous research (Bradshaw et al. (2013), Asquith et al. (2005), Brav and Lehavy (2003), Bradshaw (2002)).

BKM-based risk-neutral volatility (Vol^{BKM}) is on average (in median) 47.71% (43.40%). The risk-neutral distributions of stock returns tend to be negatively skewed, with mean (median) value of $Skew^{BKM}$ equal to -0.67 (-0.60), and exhibit higher kurtosis than a normal distribution, as the mean (median) value of $Kurt^{BKM}$, which measures excess kurtosis, is 1.82 (0.73). Stocks in the BKM sample have a mean (median) market capitalization ($MktCap$) of \$9.9 billion (\$2.8 billion), but some small stocks do enter the sample. Finally, there are on average 279 stocks in the BKM sample each month.

Summary statistics for the $NonPar$ sample are presented in Table 3, Panel B. The distribution of expected returns (ER) for the $NonPar$ sample is similar to that of the BKM sample, as is that of volatility (Vol^{NonPar}). Also similar to the BKM measure, values of nonparametric risk-neutral skewness ($Skew^{NonPar}$) are predominantly negative. Risk-neutral kurtosis ($Kurt^{NonPar}$) is positive on average, indicating that out-of-the-money implied volatilities tend to be higher than at-the-money implied volatilities, consistent with a positive excess kurtosis of the risk-neutral distribution. Finally, the mean and median market capitalization of stocks in the $NonPar$ sample are smaller than those of the BKM sample. This is due to the fact that the $NonPar$ sample has substantially more stocks (988 compared to 279 in the average month) than the BKM sample. This result is because the volatility surface data, upon which the nonparametric measures of risk-neutral moments are based, provides interpolated option data for options not actually traded, whereas the BKM based measures require actual option prices.

5 Risk-Neutral Moments and Expected Returns

Having summarized the data, we now turn our attention to analyses of the relations between the risk-neutral moments and expected returns.

5.1 Tri-Variate Dependent Sort Portfolio Analysis

We begin our investigation with tri-variate dependent sort portfolio analyses. Each month, all stocks in the sample (BKM or $NonPar$) are grouped into portfolios based on ascending sorts of the risk-neutral moments. To test the relation between risk-neutral volatility and expected returns, we group all stocks into 27 portfolios using a tri-variate dependent sort on skewness, kurtosis, and then volatility, with the breakpoints for each sort determined by the 30th and 70th percentile of the sort variable. We then calculate the equal-weighted average price target-based expected return (ER) for each of the 27 portfolios, as well as the difference in expected return between the high and low (3-1) volatility portfolio, for each skewness and kurtosis group. To examine the relation between skewness (kurtosis) and expected returns, we repeat the analysis, sorting first on kurtosis (skewness), then volatility (volatility), and then skewness (kurtosis).[24]

Table 4 presents the time-series averages of the portfolios' price target-based expected returns (ER). The results in Panels A1 and B1 indicate a strong positive relation between risk-neutral volatility (Vol^{BKM} and Vol^{NonPar}) and price target-based expected returns (ER). For the BKM ($NonPar$) sample, the 3-1 differences in expected returns across the nine skewness and kurtosis sorted portfolios range from 9.29% per annum to 15.80% per annum (11.20% to 18.55%), and the average 3-1 portfolio expected returns range from 11.33% to 13.26% (13.08% to 16.98%). All of these differences are highly statistically significant, with

[24] In all analyses, the sorts are designed 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. Results of the portfolio analyses with the order of the first two sort variables reversed are presented in Section III and Table A1 of the online appendix. The results are qualitatively the same.

the smallest t-statistic in any of these analyses being 7.68. Furthermore, for both the BKM and $NonPar$ samples, the results indicate a monotonically positive relation between risk-neutral volatility and price target-based expected returns for each of the nine skewness and kurtosis portfolios.

Panel A2 of Table 4 demonstrates that BKM-based risk-neutral skewness ($Skew^{BKM}$) exhibits a strong positive relation with price target-based expected returns (ER). The nine 3-1 expected return differences range from 3.16% to 11.00% per annum with a minimum Newey and West (1987) t-statistic of 2.15. Furthermore, the skewness-based sorts within each of the nine kurtosis and volatility-based portfolios all show a monotonically increasing relation with expected returns. The average 3-1 differences range from 4.56% to 7.75% per annum, with t-statistics ranging from 4.32 to 9.23. The results for nonparametric risk-neutral skewness, presented in Panel B2, are highly similar, albeit not quite as strong. These results provide empirical support for the predictions of the demand-based option pricing models of Bollen and Whaley (2004) and Garleanu et al. (2009).

Finally, the results of the analysis of the relation between risk-neutral kurtosis ($Kurt^{BKM}$ and $Kurt^{NonPar}$) and price target-based expected returns (ER) are presented in Panel A3 (BKM sample) and B3 ($NonPar$ sample) of Table 4. As predicted by preference for assets with lower kurtosis (Dittmar (2002), Kimball (1993)), the results in both panels indicate generally positive relations between risk-neutral kurtosis and expected returns, with some small deviations from the general pattern for stocks with low levels of volatility and skewness. In the BKM ($NonPar$) sample, eight (seven) of the nine 3-1 portfolios exhibit positive expected return differences with six of the 3-1 portfolios producing t-statistics greater than 2.00. In both samples, the average 3-1 difference is positive and highly statistically significant for all three skewness portfolios.

5.2 Regression Analysis

To control for additional factors that have been shown to be related to either returns or forecast bias, we employ the Fama and MacBeth (1973) (FM) regression methodology. Table 5 presents the results of the FM regressions of firm-level price target expected returns (ER) on the risk variables with and without controls. Specifications $BKM1$ and $NonPar1$ indicate that each of risk-neutral volatility, skewness, and kurtosis is positively related to expected returns, as the average coefficient on each of the risk-neutral moments is positive and highly significant, with Newey and West (1987) t-statistics ranging from 3.56 to 20.32. The models labeled $BKM2$ and $NonPar2$ demonstrate that these positive relations are not driven by other factors known to be related to returns or analyst bias. Most importantly, risk-neutral moments contain information relevant to expected returns that cannot be ascertained from historical measures of systematic risk (co-variance (β), co-skewness ($CoSkew$), co-kurtosis ($CoKurt$)) or idiosyncratic volatility ($IdioVol$). Controlling for these risks and other firm characteristics, the slope coefficients on all risk-neutral moments remain positive and highly statistically significant, with t-statistics ranging from 2.18 to 13.33.

To assess the economic significance of the results from Table 5, we calculate the effect of a one standard deviation change in a given risk-neutral moment on expected returns, holding all other risk-neutral moments constant by multiplying the average regression coefficient by the average cross-sectional standard deviation of the risk-neutral moment from Table 3. Focussing on regression model $BKM1$, the results indicate that a one standard deviation difference in BKM-based risk-neutral volatility (Vol^{BKM}) corresponds to a difference of 6.27% (0.31×20.22) per annum in expected returns. The effect of a one standard deviation difference in BKM-based risk-neutral skewness ($Skew^{BKM}$) is 5.72% (6.98×0.82) per annum, and that of kurtosis is 4.80% (0.86×5.58) per annum.

As for the control variables, the average coefficients on beta (β), idiosyncratic volatility ($IdioVol$), co-skewness ($CoSkew$), co-kurtosis ($CoKurt$), illiquidity ($Illiq$), and reversal

(Rev) all have the predicted signs, and all (with the exception of co-kurtosis) are statistically significant at the 5% level. The coefficient on log of market capitalization ($Size$) 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 log of market capitalization, consistent with most empirical studies. The regression analysis finds that price target-based expected returns (ER) have a positive and statistically insignificant relation with book-to-market ratio (BM) and a negative and highly statistically significant relation with momentum (Mom), both of which are consistent with previous research on price target-based expected returns (Brav et al. (2005)). Finally, the regressions detect statistically significant relations between price target-based expected returns and the controls for price target bias (forecast earnings - $Earn$, analyst coverage - $AnlystCov$, and forecast long term growth - LTG).

As a robustness check, we examine whether the results persist using a different option maturity by repeating the portfolio and regression analyses using BKM-based measures calculated from options with approximately 2.5 months until expiration, and nonparametric measures using implied volatilities for 60 day options. The results of the portfolio and regression analyses, presented in Section IV and Tables A2 and A3 of the online appendix, are highly consistent with the results in Tables 4 and 5.

In summary, the portfolio and regression analyses demonstrate strong, positive relations between expected returns and each of risk-neutral volatility, skewness, and kurtosis. The relations are found using both the BKM-based and nonparametric measures of risk-neutral moments, are highly economically and statistically significant, and are robust to the inclusion of controls for variables related to returns and analyst bias.

6 Systematic and Unsystematic Moments

In this section, we decompose the BKM-based total risk-neutral moments into systematic and unsystematic components and examine the relations between each component of the risk-neutral moments and price target-based expected returns.[25]

6.1 Calculation of Systematic and Unsystematic Moments

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

$$r_{i,t} = a_i + \beta_{RN,i} r_{m,t} + \epsilon_{i,t} \tag{14}$$

where $r_{i,t}$ and $r_{m,t}$ are the 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 portion of the return, assumed to be independent of $r_{m,t}$. The risk-neutral variance can then be written as:

$$\sigma^2_{RN,i} = \beta^2_{RN,i}\sigma^2_m + \sigma^2_{\epsilon,i} \tag{15}$$

where σ^2_i (σ^2_m) is the risk-neutral variance of stock i's (the market's) return and $\sigma^2_{\epsilon,i}$ is the variance of $\epsilon_{i,t}$. We therefore define the systematic variance of stock i as:[26]

$$Var^{BKM}_S = \beta^2_{RN} Var^{BKM}_m \tag{16}$$

where Var^{BKM}_m is the BKM measure of the market return's risk-neutral variance, found by applying the BKM procedure to S&P 500 index options. The unsystematic stock return

[25] As the nonparametric measures of the risk-neutral distribution do not represent values of the moments, decomposition of the nonparametric moments is not possible.

[26] The stock subscripts i in equations (16), (17), (19), (20), (22), and (23) have been removed for ease of reading. The subscript S is used to indicate that this is the systematic portion of the variance.

variance is defined as the difference between the total variance and the systematic variance:

$$Var_U^{BKM} = Var^{BKM} - Var_S^{BKM} \tag{17}$$

BKM demonstrate that risk-neutral skewness can be decomposed into systematic and unsystematic components as follows:[27]

$$Skew_i = \frac{\beta_{RN,i}^3 \sigma_m^3}{\sigma_i^3} Skew_m + \frac{\sigma_{\epsilon,i}^3}{\sigma_i^3} Skew_{\epsilon,i} \tag{18}$$

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:

$$Skew_S^{BKM} = \frac{\beta_{RN}^3 \left(Var_m^{BKM}\right)^{3/2}}{\left(Var^{BKM}\right)^{3/2}} Skew_m^{BKM}, \tag{19}$$

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

$$Skew_U^{BKM} = Skew^{BKM} - Skew_S^{BKM}. \tag{20}$$

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

$$Kurt_i = \frac{\beta_{RN,i}^4 \sigma_m^4}{\sigma_i^4} Kurt_m + \frac{\sigma_{\epsilon,i}^4}{\sigma_i^4} Kurt_{\epsilon,i} \tag{21}$$

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 ($Kurt_S^{BKM}$) and

[27] The skewness decomposition is identical to that presented in equations (21)-(23) of BKM. Our presentation of decomposed skewness, however, is slightly different, and designed to be intuitive for our application.

unsystematic ($Kurt_U^{BKM}$) risk-neutral excess kurtosis to be:

$$Kurt_S^{BKM} = \frac{\beta_{RN}^4 \left(Var_m^{BKM}\right)^2}{\left(Var^{BKM}\right)^2} Kurt_m^{BKM} \tag{22}$$

and

$$Kurt_U^{BKM} = Kurt^{BKM} - Kurt_S^{BKM}. \tag{23}$$

The equations that describe the decomposition of the total risk-neutral moments into systematic and unsystematic components (equations (16), (17), (19), (20), (22), (23)) require an estimate of the risk-neutral beta of the stock (β_{RN}). 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.[28] We therefore use our measure of physical beta (β) as a proxy for the risk-neutral beta when decomposing the risk-neutral moments.[29]

6.2 Summary Statistics for Decomposed Moments

Table 6 presents summary statistics for the systematic and unsystematic risk-neutral moments. The table shows that unsystematic variance (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 systematic variance (Var_S^{BKM}, mean is 0.09 and median is 0.07), indicating that unsystem-

[28]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.

[29]In Section V of the online appendix we develop an alternative measure of risk-neutral beta. Using this measure to decompose the risk-neutral moments and repeating our analyses using this decomposition generates similar results. The results, presented in Table A4 of the online appendix, are actually somewhat stronger when the risk-neutral beta-based decomposition is used. We therefore view the results in the main paper as conservative assessments of the roles of the systematic and unsystematic components of risk in determining the cross-section of expected stock returns.

atic variance is the dominant component of total variance. Systematic skewness ($Skew_S^{BKM}$) is almost always negative, with an average monthly mean (median) of -0.47 (-0.38). The negativity of systematic skewness is driven by the fact that risk-neutral market skewness is always negative and beta is almost always positive (see equation (19)). Unsystematic skewness ($Skew_U^{BKM}$) is also negative in mean and median (mean is -0.21 and median is -0.15), but takes on a positive value for a substantial number of stocks, since the 75th percentile of unsystematic skewness is 0.32. Finally, while systematic excess kurtosis ($Kurt_S^{BKM}$) is always positive, a result driven by the positivity of risk-neutral market excess kurtosis, unsystematic excess kurtosis ($Kurt_U^{BKM}$) is negative for more than half of the stocks in the sample, as the median value is -0.30. On average, however, unsystematic kurtosis is positive, with a mean of 0.57.

6.3 Regressions with Systematic and Unsystematic Components

To analyze the relations between the systematic and unsystematic portions of the risk-neutral moments, we perform Fama and MacBeth (1973) regressions of price target-based expected returns (ER) on combinations of the systematic and unsystematic moments. The regression results are presented in Table 7. Regression specification (1) indicates positive and statistically significant relations between expected returns and each of systematic variance (Var_S^{BKM}) and skewness ($Skew_S^{BKM}$), while no relation between systematic kurtosis ($Kurt_S^{BKM}$) and expected returns is detected. When controls are added to the regression specification (specification (2)), only the relation between systematic variance and expected returns remains statistically significant, indicating that the positive relation between systematic skewness and expected returns detected in specification (1) is explained by the control variables.[30,] Regression models (3) and (4) show that the unsystematic portions of

[30]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.

each of the risk-neutral moments exhibit positive and statistically significant relations with expected returns regardless of whether controls are excluded (specification (3)) or included (specification (4)). When both the systematic and unsystematic portions of the risk-neutral moments are 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 statistically significant (with the exception of systematic kurtosis) relations with expected returns. The results generated by augmenting this specification with the control variables (specification (6)) demonstrate that the unsystematic components of the risk-neutral moments are all positively related to expected returns. As for the systematic components, only systematic variance exhibits a positive and statistically significant relation with expected returns. No relations between systematic skewness and kurtosis found.[31]

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 systematic variance (Var_S^{BKM}) corresponds to a 3.84% per annum (54.90×0.07) difference in price target-based expected return (ER), while a one standard deviation difference in unsystematic variance (Var_U^{BKM}) is associated with a 2.84% (10.15×0.28) expected return difference. A one standard deviation difference in unsystematic skewness ($Skew_U^{BKM}$) generates a 2.68% difference in expected return (2.76×0.97), and the corresponding value for unsystematic kurtosis is 1.71% (6.13×0.28). 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.

[31] We test an alternative specification in which idiosyncratic volatility ($IdioVol$), co-skewness ($CoSkew$), and co-kurtosis ($CoKurt$) are not included as control variables. The results are qualitatively the same.

7 Conclusion

In this paper, we examine the relations between measures of risk and expected stock returns using ex-ante measures of each. We begin by comparing the ability of two different measures of ex-ante expected returns, one based on analyst price targets and the other the implied cost of capital based on analyst earnings and growth forecasts, to serve as proxies for the required rate of return demanded by the market on individual stocks. We find that both measures have a strong cross-sectional relation with the market's required rate of return, but the relation is stronger for the price target-based measure. Furthermore, we demonstrate that the ability of the price target-based measure to capture the market's expected return is driven by relations between the price target expected return and risk, while the implied cost of capital captures the effect of other firm characteristics such as size and book-to-market ratio on expected returns. We therefore take the price target-based measure to be our primary measure of ex-ante expected stock returns.

Using two different measures of risk-neutral volatility, skewness, and kurtosis to measure ex-ante risk, one based on Bakshi et al. (2003) and the other a nonparametric approach based on taking differences in implied volatilities of options with different strike prices, we find highly robust evidence that each of the risk-neutral moments is positively related to price target-based expected stock returns. Regression analyses demonstrate that these relations remain robust after controlling for measures of risk based on historical data and other variables known to be related to expected stock returns, indicating that risk-neutral moments carry information relevant to expected returns that is not contained in measures of historical risk. The results for risk-neutral volatility and kurtosis are consistent with equilibrium asset pricing models, while the result for skewness is predicted by the demand-based option pricing models of Bollen and Whaley (2004) and Garleanu et al. (2009).

We then decompose risk-neutral variance, skewness, and kurtosis into systematic and unsystematic components. We demonstrate that both the systematic and unsystematic components of risk-neutral variance are positively related to ex-ante expected returns. The positive relation between expected returns and systematic variance supports the main prediction of the Capital Asset Pricing Model (Sharpe (1964), Lintner (1965), Mossin (1966)). The positive effect of unsystematic variance on expected returns is consistent with the predictions of models in which unsystematic risk is priced (Levy (1978), Merton (1987)).

Our analyses also demonstrate a positive relation between systematic skewness and ex-ante expected returns, but inclusion of controls in the regression specification explains this relation. Unsystematic skewness, however, remains positively related to expected returns even after controlling for other variables related to expected returns. This result indicates that the positive relation between expected returns and risk-neutral skewness, detected both in our study and in previous empirical work using ex-post realized returns (Xing et al. (2010) and Rehman and Vilkov (2012)), is driven by firm-specific information that investors use to place bets in the option markets. As predicted by demand-based option pricing models (Bollen and Whaley (2004) and Garleanu et al. (2009)), the pressure exerted on option prices by investors looking to capitalize on this firm-specific information results in a high (low) levels of unsystematic skewness for stocks for with high (low) levels of expected returns. Finally, we find that the positive relation between risk-neutral kurtosis and expected returns is completely driven by firm-specific kurtosis, as systematic kurtosis exhibits no discernable relation with expected returns while unsystematic kurtosis remains positively related to expected returns in all specifications.

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:

$$P_t = B_t + \sum_{i=1}^{11} \frac{FROE_{t+i} - r}{(1+r)^i} B_{t+i-1} + \frac{FROE_{t+12} - r}{r(1+r)^{11}} B_{t+11} \tag{24}$$

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.[32] $FROE_{t+2}$ 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}, it is estimated as $B_t + FEPS_{t+1}(1-k)$, where k is the proportion of earnings paid out

[32] 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.

as dividends, calculated as the ratio of dividends to earnings during the last fiscal year for which earnings have been announced.[33] 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.[34]

Appendix B 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

[33] 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.

[34] 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.

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.

Appendix C Estimation of BKM Risk-Neutral Moments

This appendix describes in detail 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 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 I of the online appendix.

C.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 II of the online appendix.

C.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.

C.3 Calculation of Risk-Neutral Moments

BKM demonstrate that the values V, W, and X, necessary for calculating the risk-neutral variance, skewness, and excess kurtosis, given by equations (6), (7), (8) respectively, can be calculated as:

$$\begin{aligned} V = & \int_{K=S}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S}\right]\right)}{K^2} C(K)dK \\ & + \int_{K=0}^{S} \frac{2\left(1 + ln\left[\frac{S}{K}\right]\right)}{K^2} P(K)dK \end{aligned} \tag{25}$$

$$\begin{aligned} W = & \int_{K=S}^{\infty} \frac{6ln\left[\frac{K}{S}\right] - 3\left(ln\left[\frac{K}{S}\right]\right)^2}{K^2} C(K)dK \\ & - \int_{K=0}^{S} \frac{6ln\left[\frac{S}{K}\right] + 3\left(ln\left[\frac{S}{K}\right]\right)^2}{K^2} P(K)dK, \end{aligned} \tag{26}$$

and

$$X = \int_{K=S}^{\infty} \frac{12\left(ln\left[\frac{K}{S}\right]\right)^2 + 4\left(ln\left[\frac{K}{S}\right]\right)^3}{K^2} C(K)dK + \int_{K=0}^{S} \frac{12\left(ln\left[\frac{S}{K}\right]\right)^2 + 4\left(ln\left[\frac{S}{K}\right]\right)^3}{K^2} P(K)dK \tag{27}$$

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 (25), (26), and (27) 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:

$$\begin{aligned} V =& v_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[v_C(K_i^C)C_i + v_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &+ v_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[v_P(K_i^P)P_i + v_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P, \end{aligned} \tag{28}$$

$$\begin{aligned} W =& w_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[w_C(K_i^C)C_i + w_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &- w_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[w_P(K_i^P)P_i + w_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P, \end{aligned} \tag{29}$$

and

$$\begin{aligned} X =& x_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[x_C(K_i^C)C_i + x_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C \\ &+ x_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[x_P(K_i^P)P_i + x_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P \end{aligned} \tag{30}$$

where:

$$v_C(K) = \frac{2\left(1 - ln\left[\frac{K}{S^*}\right]\right)}{K^2}, \tag{31}$$

$$v_P(K) = \frac{2\left(1 + ln\left[\frac{S^*}{K}\right]\right)}{K^2}, \tag{32}$$

$$w_C(K) = \frac{6ln\left[\frac{K}{S^*}\right] - 3\left(ln\left[\frac{K}{S^*}\right]\right)^2}{K^2}, \tag{33}$$

$$w_P(K) = \frac{6ln\left[\frac{S^*}{K}\right] + 3\left(ln\left[\frac{S^*}{K}\right]\right)^2}{K^2}, \tag{34}$$

$$x_C(K) = \frac{12\left(ln\left[\frac{K}{S^*}\right]\right)^2 + 4\left(ln\left[\frac{K}{S^*}\right]\right)^3}{K^2}, \tag{35}$$

and

$$x_P(K) = \frac{12\left(ln\left[\frac{S^*}{K}\right]\right)^2 + 4\left(ln\left[\frac{S^*}{K}\right]\right)^3}{K^2}. \tag{36}$$

Plugging the values from equations (28), (29), and (30) 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 $t + \tau$.

References

Abarbanell, J. and Lehavy, R. 2003. Biased forecasts or biased earnings? the role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. Journal of Accounting and Economics, 36(1-3), 105–146.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56.

An, B.-J., Ang, A., Bali, T. G., and Cakici, N. 2014. The joint cross section of stocks and options. Journal of Finance, 69(5), 2279–2337.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. 2006. The cross-section of volatility and expected returns. Journal of Finance, 61(1), 259–299.

Asquith, P., Mikhail, M. B., and Au, A. S. 2005. Information content of equity analyst reports. Journal of Financial Economics, 75(2), 245–282.

Bakshi, G., Kapadia, N., and Madan, D. 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies, 16(1), 101–143.

Bakshi, G. and Madan, D. 2000. Spanning and derivative-security valuation. Journal of Financial Economics, 55(2), 205–238.

Bali, T. G. and Hovakimian, A. 2009. Volatility spreads and expected stock returns. Management Science, 55(11), 1797–1812.

Bali, T. G. and Murray, S. 2013. Does risk-neutral skewness predict the cross-section of equity option portfolio returns? Journal of Financial and Quantitative Analysis, 48(4), 1145–1171.

Blume, M. E. and Friend, I. 1973. A new look at the capital asset pricing model. Journal of Finance, 28(1), 19–33.

Bollen, N. P. B. and Whaley, R. E. 2004. Does net buying pressure affect the shape of implied volatility functions. Journal of Finance, 59(2), 711–753.

Bonini, S., Zanetti, L., Bianchini, R., and Salvi, A. 2010. Target price accuracy in equity research. Journal of Business, Finance and Accounting, 37(9-10), 1177–1217.

Botosan, C. A. and Plumlee, M. A. 2005. Assessing alternative proxies for the expected risk premium. The Accounting Review, 80(1), 21–53.

Boyer, B., Mitton, T., and Vorkink, K. 2010. Expected idiosyncratic skewness. Review of Financial Studies, 23(1), 169–202.

Bradshaw, M. T. 2002. The use of target prices to justify sell-side analysts' stock recommendations. Accounting Horizons, 16(1), 27–41.

Bradshaw, M. T. 2004. How do analysts use their earnings forecasts in generating stock recommendations. The Accounting Review, 79(1), 25–50.

Bradshaw, M. T., Brown, L. D., and Huang, K. 2013. Do sell-side analysts exhibit differential target price forecasting ability? Review of Accounting Studies.

Brav, A. and Lehavy, R. 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. Journal of Finance, 58(5), 1933–1968.

Brav, A., Lehavy, R., and Michaely, R. 2005. Using expectations to test asset pricing models. Financial Management, 34(3), 5–37.

Buss, A. and Vilkov, G. 2012. Measuring equity risk with option-implied correlations. Review of Financial Studies, 25(10), 3113–3140.

Chang, B.-Y., Christoffersen, P., Jacobs, K., and Vainberg, G. 2012. Option-implied measures of equity risk. Review of Finance, 16(2), 385–428.

Conrad, J. S., Dittmar, R. F., and Ghysels, E. 2013. Ex ante skewness and expected stock returns. Journal of Finance, 68(1), 85–124.

Cremers, M. and Weinbaum, D. 2010. Deviations from put-call parity and stock return predictability. Journal of Financial Quantitative Analysis, 45(2), 335–367.

DeMiguel, V., Plyakha, Y., Uppal, R., and Vilkov, G. 2013. Improving portfolio selection using option-implied volatility and skewness. Journal of Financial and Quantitative Analysis, forthcoming.

Dennis, P. and Mayhew, S. 2002. Risk-neutral skewness: Evidence from stock options. Journal of Financial Quantitative Analysis, 37(3), 471–493.

Dittmar, R. F. 2002. Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. Journal of Finance, 57(1), 369–403.

Duan, J.-C. and Wei, J. 2009. Systematic risk and the price structure of individual equity options. Review of Financial Studies, 22(5), 1981–2006.

Easton, P. D. and Monahan, S. J. 2005. An evaluation of accounting-based measures of expected returns. The Accounting Review, 80(2), 501–538.

Elton, E. J. 1999. Expected return, realized return, and asset pricing tests. Journal of Finance, 54, 1199–1220.

Fama, E. F. and French, K. R. 1992. The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465.

Fama, E. F. and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

Fama, E. F. and French, K. R. 1997. Industry costs of equity. Journal of Financial Economics, 43, 153–193.

Fama, E. F. and French, K. R. 2004. The capital asset pricing model: Theory and evidence. Journal of Economic Perspectives, 18(3), 25–46.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607.

French, D. W., Groth, J. C., and Kolari, J. W. 1983. Current investor expectations and better betas. Journal of Portfolio Management, 10(1), 12–17.

Garleanu, N., Pedersen, L. H., and Poteshman, A. M. 2009. Demand-based option pricing. Review of Financial Studies, 22(10), 4259–4299.

Gebhardt, W. R., Lee, C. M., and Swaminathan, B. 2001. Toward an implied cost of capital. Journal of Accounting Research, 39(1), 135–176.

Harvey, C. R. and Siddique, A. 2000. Conditional skewness in asset pricing tests. Journal of Finance, 55(3), 1263–1295.

Hughes, J., Liu, J., and Liu, J. 2009. On the relation between expected returns and implied cost of capital. Review of Accounting Studies, 14(2-3), 246–259.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. Journal of Finance, 45(3), 881–898.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91.

Kimball, M. S. 1993. Standard risk aversion. Econometrica, 61(3), 589–611.

Kothari, S. P., Shanken, J., and Sloan, R. G. 1995. Another look at the cross-section of expected stock returns. Journal of Finance, 50(1), 185–224.

Kraus, A. and Litzenberger, R. H. 1976. Skewness preference and the valuation of risk assets. Journal of Finance, 31(4), 1085–1100.

Lehmann, B. N. 1990. Fads, martingales, and market efficiency. Quarterly Journal of Economics, 105(1), 1–28.

Levy, H. 1978. Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio. American Economic Review, 68, 643–658.

Lintner, J. 1965. Security prices, risk, and maximal gains from diversification. Journal of Finance, 20(4), 687–615.

Merton, R. C. 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance, 42, 483–510.

Michaely, R. and Womack, K. L. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. Review of Financial Studies, 12(4), 653–686.

Mossin, J. 1966. Equilibrium in a capital asset market. Econometrica, 34(4), 768–783.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Rajan, R. and Servaes, H. 1997. Analyst following of initial public offerings. Journal of Finance, 52(2), 507–529.

Rehman, Z. and Vilkov, G. 2012. Risk-neutral skewness: Return predictability and its sources. SSRN eLibrary.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19(3), 425–442.

Tinic, S. M. and West, R. R. 1986. Risk, return, and equilibrium: A revisit. Journal of Political Economy, 94(1), 126–147.

Womack, L. K. 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance, 51(1), 137–167.

Xing, Y., Zhang, X., and Zhao, R. 2010. What does the individual option volatility smirk tell us about future equity returns? Journal of Financial Quantitative Analysis, 45(3), 641–662.

Table 1: Portfolio Analysis of Ex-Ante Expected Returns

The table below presents the results of univariate portfolio analyses of the relations between the measures of expected returns as well as the relations between expected returns and measures of risk and firm characteristics. Each month, all stocks with valid values of all three expected return measures ($RegER$, ER, and ICC) are sorted into quintile portfolios based on the sort variable. The average expected return for each of the quintile portfolios, as well as the difference between the fifth and first quintile portfolios, is then calculated. The table presents the time-series averages of the monthly average portfolio expected returns. The column labeled 5-1 t-stat presents the Newey and West (1987) t-statistic, adjusted using six lags, testing the null hypothesis that the average expected return difference between the fifth and first quintile portfolios is equal to zero. Panel A presents the results for portfolios formed by sorting on regression-based expected return ($RegER$). Average expected returns are calculated using each of the measures of expected return, as indicated in the column labeled Dependent Variable. Panels B and C present the results for portfolios formed by sorting on measures of risk and firm characteristics (β, $Size$, BM, $IdioVol$, and $CoSkew$, as indicated in the Sort Variable column) with price target-based expected return (ER, Panel B) and implied cost of capital (ICC, Panel C) as the measure of expected return.

Panel A: Portfolios Sorted on Regression-Based Expected Return ($RegER$)

Dependent Variable	1	2	3	4	5	5-1	5-1 t-stat
$RegER$	2.26	6.10	8.18	10.07	13.47	11.20	44.77
ER	16.76	18.11	20.01	22.89	27.86	11.10	18.32
ICC	7.65	8.16	8.54	8.86	9.84	2.19	6.78

Panel B: Average Price Target Expected Return (ER)

Sort Variable	1	2	3	4	5	5-1	5-1 t-stat
β	18.03	18.89	20.25	22.07	26.39	8.36	5.82
$Size$	29.22	22.34	19.47	17.93	16.67	-12.55	-18.69
BM	21.85	21.57	21.26	20.84	20.13	-1.73	-1.89
$IdioVol$	13.79	17.81	21.01	24.39	28.64	14.85	13.39
$CoSkew$	24.21	20.22	19.13	19.88	22.19	-2.02	-2.40

Panel C: Average Implied Cost of Capital (ICC)

Sort Variable	1	2	3	4	5	5-1	5-1 t-stat
β	8.60	8.60	8.69	8.69	8.46	-0.14	-0.21
$Size$	9.45	8.69	8.60	8.36	7.94	-1.51	-4.63
BM	6.91	7.97	8.63	9.33	10.21	3.30	14.80
$IdioVol$	8.21	8.70	8.86	8.75	8.53	0.32	1.34
$CoSkew$	8.76	8.60	8.55	8.64	8.50	-0.26	-1.74

Table 2: Fama and MacBeth (1973) Regressions of Ex-Ante Expected Returns The table below presents the results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER, Panel A) and implied cost of capital (ICC, Panel B) on combinations of market beta (β), log of market capitalization ($Size$), book-to-market ratio (BM), idiosyncratic volatility ($IdioVol$), co-skewness ($CoSkew$), implied cost of capital (ICC), and price target-based expected return (ER). Each month, a cross-sectional regression is performed on all data points for which values of the variables used in the given specification are available. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series average of the cross-sectional regression coefficients. Newey and West (1987) t-statistics, adjusted for six lags, testing the null hypothesis that the average coefficient is equal to zero are in parentheses. The last two rows present the average adjusted R-squared values and the average number of cross-sectional observations.

Panel A: Dependent Variable is ER

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	4.80		4.49	2.65	5.78		5.00	2.82
	(4.69)		(5.19)	(3.17)	(6.03)		(5.90)	(3.55)
$Size$		-3.35	-3.23	-2.03		-2.51	-2.30	-1.21
		(-32.18)	(-29.31)	(-11.45)		(-21.98)	(-20.61)	(-8.91)
BM		-4.34	-3.34	-2.74		-6.03	-4.86	-4.32
		(-7.03)	(-6.45)	(-7.44)		(-8.18)	(-7.88)	(-8.88)
$IdioVol$				0.19				0.19
				(10.51)				(11.25)
$CoSkew$				-0.09				-0.07
				(-1.91)				(-1.84)
ICC					0.86	1.01	1.08	1.13
					(9.41)	(8.68)	(11.42)	(13.35)
Intercept	16.48	48.74	42.52	27.97	6.79	33.77	25.81	11.98
	(9.58)	(25.54)	(24.36)	(10.25)	(5.59)	(14.99)	(14.87)	(5.87)
Adj. R^2	0.03	0.08	0.10	0.13	0.06	0.08	0.11	0.13
n	1409	1210	1205	1205	1139	996	992	992

Panel B: Dependent Variable is ICC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	-0.31		0.06	0.05	-0.18		0.08	0.23
	(-0.31)		(0.12)	(0.18)	(-0.34)		(0.23)	(1.02)
$Size$		-0.29	-0.27	-0.25		-0.15	-0.13	-0.19
		(-2.93)	(-2.83)	(-1.80)		(-2.31)	(-2.04)	(-1.76)
BM		2.13	2.08	2.07		2.41	2.33	2.29
		(7.43)	(6.55)	(6.52)		(11.05)	(9.87)	(9.78)
$IdioVol$				0.00				-0.01
				(0.72)				(-2.02)
$CoSkew$				-0.00				-0.00
				(-0.01)				(-0.05)
ER					0.02	0.02	0.02	0.02
					(9.16)	(6.99)	(9.51)	(10.87)
Intercept	9.21	9.60	9.34	9.14	8.37	8.08	7.74	8.47
	(8.34)	(11.19)	(7.73)	(4.64)	(24.04)	(15.33)	(9.13)	(6.02)
Adj. R^2	0.02	0.12	0.14	0.14	0.04	0.15	0.16	0.17
n	2274	1980	1972	1972	1139	996	992	992

Table 3: Summary Statistics

The table below presents summary statistics for the BKM and $NonPar$ samples. Both samples contain stock/month observations covering U.S. based common stocks from March 1999 through December 2012 for which price target-based expected returns are available. The BKM ($NonPar$) sample consists of only those observations for which BKM-based (nonparametric) measures of risk-neutral moments are available. ER is the price target-based expected return. Vol^{BKM}, $Skew^{BKM}$, and $Kurt^{BKM}$ are BKM-based measures of risk-neutral volatility, skewness, and kurtosis. Vol^{NonPar}, $Skew^{NonPar}$, and $Kurt^{NonPar}$ are nonparametric measures of the risk-neutral moments. $MktCap$ is the market capitalization of the firm, measured in $millions. All statistics presented in the table are the time-series averages of monthly cross-sectional values, and thus represent the average month.

Panel A: BKM Sample

	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

Panel B: $NonPar$ Sample

	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 4: Tri-Variate Dependent Sort Portfolios

Each month, all stocks in the sample (BKM sample in Panel A, $NonPar$ sample in Panel B) are grouped into 27 portfolios based on tri-variate dependent sorts of the risk-neutral moments. All stocks in the sample are first sorted into three portfolios based on the first sort variable. Each of the three portfolios is then sorted into three portfolios based on the second variable. Finally, each of the nine resulting portfolios is sorted into three portfolios based on the third sort variable. For each sort, the 30% of stocks with the lowest values of the sort variable are put in portfolio one, the next 40% are put in portfolio two, and the stocks with the highest values are put in portfolio three. The table below presents the time-series average of the monthly equal-weighted average expected returns (ER) for each of the 27 portfolios. The first sort variable, along with the corresponding portfolio number, is presented in the upper left of each table. Portfolios of the second sort variable are represented by columns. Portfolios of the third sort variable are represented by rows. The portfolio row labeled "3-1" presents the time series average of monthly differences between portfolio three and portfolio one of the third sort variable, for the given sort variable one and sort variable two portfolios. The t-statistic testing the null hypothesis that the average difference between portfolio three and portfolio one of the third sort variable is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses. The columns labeled "Avg." present the average expected return of the three sort variable two portfolios for the given sort variable one and sort variable three portfolio. Panels A1 and B1 present results of portfolio analyses designed to examine the relation between volatility and expected returns after controlling for skewness and kurtosis, by sorting first on skewness, then on kurtosis, and finally on volatility. Panels A2 and B2 sort on kurtosis, volatility, then skewness, and therefore examine the relation between skewness and expected returns. Panels A3 and B3 examine the relation between kurtosis and expected returns by sorting first on skewness, then on volatility, and finally on kurtosis.

Table 4: Tri-Variate Dependent Sort Portfolios - continued

Panel A: BKM Sample

A1: Vol^{BKM}

	$Skew^{BKM}$ 1				$Skew^{BKM}$ 2				$Skew^{BKM}$ 3			
	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$
Vol^{BKM} 1	12.39	12.92	12.32	12.54	14.33	14.37	13.88	14.19	17.78	18.25	17.54	17.86
Vol^{BKM} 2	15.91	17.37	19.49	17.59	19.73	19.45	19.12	19.43	24.55	26.09	24.18	24.94
Vol^{BKM} 3	21.68	24.31	28.12	24.70	24.68	25.47	26.42	25.53	31.20	31.44	30.70	31.11
Vol^{BKM} 3-1	9.29	11.39	15.80	12.16	10.36	11.11	12.54	11.33	13.42	13.19	13.16	13.26
	(9.20)	(12.45)	(13.69)	(14.63)	(7.68)	(11.12)	(10.38)	(10.33)	(10.20)	(11.24)	(12.91)	(12.79)

A2: $Skew^{BKM}$

	$Kurt^{BKM}$ 1				$Kurt^{BKM}$ 2				$Kurt^{BKM}$ 3			
	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}
$Skew^{BKM}$ 1	13.63	18.28	22.73	18.21	12.13	17.31	21.58	17.01	11.29	16.22	25.97	17.82
$Skew^{BKM}$ 2	15.76	21.60	28.83	22.06	14.55	20.14	24.94	19.87	13.69	18.54	26.19	19.47
$Skew^{BKM}$ 3	18.69	25.47	33.73	25.96	17.00	24.98	32.28	24.75	15.64	22.38	29.13	22.38
$Skew^{BKM}$ 3-1	5.06	7.18	11.00	7.75	4.87	7.67	10.69	7.74	4.35	6.17	3.16	4.56
	(5.19)	(9.48)	(8.64)	(9.23)	(5.76)	(7.56)	(9.54)	(8.75)	(4.87)	(4.97)	(2.15)	(4.32)

A3: $Kurt^{BKM}$

	$Skew^{BKM}$ 1				$Skew^{BKM}$ 2				$Skew^{BKM}$ 3			
	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}	Vol^{BKM} 1	Vol^{BKM} 2	Vol^{BKM} 3	Avg. Vol^{BKM}
$Kurt^{BKM}$ 1	12.32	15.56	23.31	17.07	13.67	18.87	24.60	19.05	17.20	22.44	31.22	23.62
$Kurt^{BKM}$ 2	12.83	16.81	25.91	18.51	13.95	19.27	24.55	19.26	18.02	24.90	31.14	24.69
$Kurt^{BKM}$ 3	12.19	18.58	27.25	19.34	14.85	20.25	27.69	20.93	18.20	26.15	33.19	25.84
$Kurt^{BKM}$ 3-1	-0.13	3.02	3.94	2.28	1.18	1.38	3.09	1.88	1.00	3.70	1.97	2.22
	(-0.25)	(4.47)	(3.31)	(4.41)	(2.38)	(1.91)	(4.51)	(4.43)	(1.28)	(3.52)	(2.13)	(3.44)

Table 4: Tri-Variate Dependent Sort Portfolios - continued

Panel B: $NonPar$ Sample

B1: Vol^{NonPar}

$Skew^{NonPar}$ 1	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
Vol^{NonPar} 1	14.82	14.51	12.75	14.03
Vol^{NonPar} 2	21.61	19.96	21.92	21.16
Vol^{NonPar} 3	29.05	27.74	31.13	29.31
Vol^{NonPar} 3-1	14.23	13.23	18.38	15.28
	(12.32)	(9.53)	(12.51)	(11.84)

$Skew^{NonPar}$ 2	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
Vol^{NonPar} 1	13.21	13.15	13.48	13.28
Vol^{NonPar} 2	18.61	17.36	19.50	18.49
Vol^{NonPar} 3	26.85	24.35	27.88	26.36
Vol^{NonPar} 3-1	13.63	11.20	14.40	13.08
	(9.37)	(8.86)	(13.05)	(10.31)

$Skew^{NonPar}$ 3	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
Vol^{NonPar} 1	14.22	13.81	13.60	13.88
Vol^{NonPar} 2	21.39	20.46	22.56	21.47
Vol^{NonPar} 3	30.61	29.80	32.15	30.85
Vol^{NonPar} 3-1	16.39	16.00	18.55	16.98
	(14.65)	(14.84)	(19.95)	(17.51)

B2: $Skew^{NonPar}$

$Kurt^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Skew^{NonPar}$ 1	13.28	18.88	27.77	19.98
$Skew^{NonPar}$ 2	13.76	19.86	28.39	20.67
$Skew^{NonPar}$ 3	14.08	21.64	30.82	22.18
$Skew^{NonPar}$ 3-1	0.80	2.76	3.05	2.20
	(1.40)	(5.71)	(4.52)	(4.97)

$Kurt^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Skew^{NonPar}$ 1	13.36	17.67	25.16	18.73
$Skew^{NonPar}$ 2	13.79	18.53	26.01	19.44
$Skew^{NonPar}$ 3	13.81	20.02	29.32	21.05
$Skew^{NonPar}$ 3-1	0.44	2.35	4.16	2.32
	(0.79)	(4.33)	(8.14)	(5.43)

$Kurt^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Skew^{NonPar}$ 1	12.06	20.36	29.78	20.73
$Skew^{NonPar}$ 2	14.02	21.50	29.96	21.83
$Skew^{NonPar}$ 3	13.83	23.09	33.06	23.33
$Skew^{NonPar}$ 3-1	1.78	2.73	3.28	2.59
	(2.75)	(4.84)	(3.42)	(4.87)

B3: $Kurt^{NonPar}$

$Skew^{NonPar}$ 1	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Kurt^{NonPar}$ 1	13.86	20.24	28.83	20.97
$Kurt^{NonPar}$ 2	14.68	20.25	28.56	21.16
$Kurt^{NonPar}$ 3	13.38	22.54	30.89	22.27
$Kurt^{NonPar}$ 3-1	-0.48	2.30	2.06	1.29
	(-1.03)	(4.51)	(3.82)	(3.97)

$Skew^{NonPar}$ 2	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Kurt^{NonPar}$ 1	12.77	17.94	26.43	19.05
$Kurt^{NonPar}$ 2	13.52	17.91	25.24	18.89
$Kurt^{NonPar}$ 3	13.21	19.19	27.67	20.02
$Kurt^{NonPar}$ 3-1	0.44	1.25	1.24	0.98
	(1.42)	(2.87)	(2.77)	(3.82)

$Skew^{NonPar}$ 3	Vol^{NonPar} 1	Vol^{NonPar} 2	Vol^{NonPar} 3	Avg. Vol^{NonPar}
$Kurt^{NonPar}$ 1	13.82	20.59	30.64	21.68
$Kurt^{NonPar}$ 2	14.05	20.96	30.32	21.78
$Kurt^{NonPar}$ 3	13.52	22.43	31.96	22.64
$Kurt^{NonPar}$ 3-1	-0.30	1.84	1.32	0.95
	(-0.69)	(5.37)	(2.18)	(3.12)

Table 5: Fama-MacBeth Cross-Sectional Regressions

The table below presents the results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER) on combinations of the risk-neutral moments and controls. The columns whose names begin with BKM ($NonPar$) contain results for the BKM ($NonPar$) sample. Each month, a cross-sectional regression of expected returns is performed on all data points in the sample. 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. Newey and West (1987) t-statistics, adjusted for six lags, testing the null hypothesis that the average coefficient is equal to zero are in parentheses. The last two rows present the average adjusted R-squared values and the average number of cross-sectional observations. Beta (β) is the slope coefficient from a regression of excess stock returns on the market excess return. Idiosyncratic volatility is the annualized residual standard error from the Fama and French (1993) three factor model. Co-skewness ($CoSkew$) is the slope coefficient on the squared market excess return from a regression of excess stock returns on the market excess return and the squared market excess return. Co-kurtosis ($CoKurt$) is the slope coefficient on the cubed market excess return from a regression of excess stock returns on the market excess return, the market excess return squared, and the cubed market excess return. β, $IdioVol$, $CoSkew$ and $CoKurt$ are calculated using one year of daily return data. Log of market capitalization ($Size$) is the natural log of month-end market capitalization. Book-to-market ratio (BM) is calculated following Fama and French (1992). Illiquidity ($Illiq$) is calculated following Amihud (2002). Short-term reversal (Rev) is taken to be the one-month return during month t. Momentum (Mom) is taken to be the 11-month return covering months $t-11$ through $t-1$. $Earn$ is the median analyst forecast earnings, divided by the stock price. $AnlystCov$ is the natural log of one plus the number of analysts covering the stock. LTG is the median analyst forecast of long-term earnings growth.

Table 5: Fama-MacBeth Cross-Sectional Regressions - continued

	$BKM1$	$NonPar1$	$BKM2$	$NonPar2$
Vol^{BKM}	0.31		0.18	
	(16.43)		(10.13)	
$Skew^{BKM}$	6.98		3.11	
	(10.09)		(7.57)	
$Kurt^{BKM}$	0.86		0.34	
	(7.70)		(4.38)	
Vol^{NonPar}		0.38		0.23
		(20.32)		(13.33)
$Skew^{NonPar}$		0.18		0.07
		(7.56)		(5.03)
$Kurt^{NonPar}$		0.08		0.03
		(3.56)		(2.18)
β			2.62	2.48
			(3.62)	(3.67)
$IdioVol$			0.05	0.04
			(2.82)	(2.97)
$CoSkew$			-0.14	-0.11
			(-1.87)	(-2.23)
$CoKurt$			0.01	0.01
			(1.09)	(0.67)
$Size$			0.34	0.61
			(1.61)	(3.54)
BM			0.67	0.24
			(1.33)	(0.75)
$Illiq$			195.19	209.32
			(3.09)	(5.28)
Rev			-0.46	-0.49
			(-28.17)	(-36.35)
Mom			-0.04	-0.04
			(-8.48)	(-9.63)
$Earn$			29.79	27.39
			(6.34)	(6.84)
$AnlystCov$			-1.74	-1.35
			(-6.49)	(-9.25)
LTG			0.23	0.26
			(11.62)	(11.72)
Intercept	8.97	3.94	4.32	-1.33
	(12.32)	(4.79)	(1.66)	(-0.61)
Adj. R^2	0.13	0.13	0.26	0.26
n	279	988	222	778

Table 6: Summary Statistics - Systematic and Unsystematic Components
The table below presents summary statistics for the decomposed BKM-based risk-neutral moments. Each of the risk-neutral moments (variance, skewness, and kurtosis) is decomposed into systematic and unsystematic components. The systematic portions of volatility (Vol^{BKM}), variance (Var^{BKM}), skewness ($Skew^{BKM}$), and excess kurtosis ($Kurt^{BKM}$) are denoted with a subscript S. The unsystematic components of the risk-neutral moments are denoted with a subscript U. All statistics presented in the table are the time-series averages of monthly cross-sectional values, and thus represent the average month.

	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
β	1.19	0.50	0.09	0.51	0.83	1.12	1.49	2.12	2.81	255
$Vol_{S,P}^{BKM}$	25.95	10.97	1.73	10.96	18.02	24.42	32.53	46.23	62.04	255
$Var_{S,P}^{BKM}$	0.09	0.07	0.00	0.02	0.04	0.07	0.12	0.24	0.44	255
$Skew_{S,P}^{BKM}$	-0.47	0.37	-1.62	-1.19	-0.69	-0.38	-0.18	-0.05	0.01	255
$Kurt_{S,P}^{BKM}$	1.33	1.29	0.00	0.06	0.35	0.92	1.94	4.00	5.91	255
$Vol_{U,P}^{BKM}$	37.78	20.60	6.37	15.04	24.60	33.38	45.31	75.52	151.02	255
$Var_{U,P}^{BKM}$	0.19	0.28	0.01	0.03	0.06	0.12	0.22	0.60	2.57	255
$Skew_{U,P}^{BKM}$	-0.21	0.97	-3.92	-1.74	-0.65	-0.15	0.32	1.03	3.52	255
$Kurt_{U,P}^{BKM}$	0.57	6.13	-6.50	-4.03	-1.74	-0.30	1.52	7.31	55.52	255
$MktCap$	9853	22286	140	348	1005	2800	8707	39901	209658	255

Table 7: Regressions - Systematic and Unsystematic Components

The table below presents the results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER) on combinations of the decomposed components of BKM-based risk-neutral moments and controls. Each month, a cross-sectional regression of expected returns is performed on all data points in the sample. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series average of the cross-sectional regression coefficients. Newey and West (1987) t-statistics, adjusted for six lags, testing the null hypothesis that the average coefficient is equal to zero are in parentheses. The last two rows present the average adjusted R-squared values and the average number of cross-sectional observations.

	(1)	(2)	(3)	(4)	(5)	(6)
$Var^{BKM}_{S,P}$	94.17	58.22			61.54	54.90
	(7.82)	(6.45)			(6.22)	(5.90)
$Var^{BKM}_{U,P}$			28.45	12.40	18.99	10.15
			(10.75)	(7.11)	(7.62)	(5.04)
$Skew^{BKM}_{S,P}$	36.47	2.58			16.08	-1.57
	(7.49)	(0.41)			(2.73)	(-0.23)
$Skew^{BKM}_{U,P}$			6.09	2.59	6.67	2.76
			(8.57)	(6.51)	(10.23)	(7.12)
$Kurt^{BKM}_{S,P}$	5.87	-8.53			0.52	-9.23
	(1.55)	(-1.16)			(0.15)	(-1.41)
$Kurt^{BKM}_{U,P}$			0.68	0.22	0.74	0.28
			(5.79)	(3.16)	(7.31)	(3.79)
$IdioVol$		0.13		0.15		0.08
		(6.27)		(7.69)		(4.39)
$CoSkew$		-0.13		-0.10		-0.13
		(-1.75)		(-1.35)		(-1.86)
$CoKurt$		0.01		0.01		0.01
		(1.11)		(1.04)		(1.22)
$Size$		0.17		0.11		0.27
		(0.81)		(0.57)		(1.24)
BM		0.85		1.04		0.79
		(1.65)		(2.22)		(1.59)
$Illiq$		239.49		166.29		212.15
		(3.55)		(2.78)		(3.30)
Rev		-0.50		-0.47		-0.46
		(-26.96)		(-25.82)		(-26.39)
Mom		-0.04		-0.04		-0.04
		(-9.31)		(-7.04)		(-8.56)
$Earn$		28.46		30.06		31.01
		(5.79)		(6.09)		(6.65)
$AnlystCov$		-1.63		-1.66		-1.68
		(-5.75)		(-5.82)		(-5.89)
LTG		0.24		0.25		0.24
		(13.28)		(13.02)		(13.06)
Intercept	20.93	10.27	16.64	10.19	18.96	10.67
	(17.49)	(4.27)	(18.58)	(4.38)	(14.81)	(4.50)
$Adj.\ R^2$	0.08	0.25	0.10	0.25	0.14	0.26
n	255	207	255	207	255	207

Analyst Price Target Expected Returns and Option Implied Risk

Online Appendix

Section I describes the calculation of risk-free rates. Section II describes the calculation of the present value of dividends. In Section III we show 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 IV demonstrates that the main results of the paper persist when risk-neutral moments are calculated using two-month options. Section V presents the results of analyses using the systematic and unsystematic components of the risk-neutral moments calculated using risk-neutral beta.

I 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.

II 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:

$$PVDivs = \sum_{j=1}^{n_d} d_j e^{-r_j \tau_j} \tag{A1}$$

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 I of this online appendix.

III Alternative Sort Order Portfolios

In this section, we repeat the tri-variate dependent sort portfolio analyses of Section 5.1 and Table 4 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 are presented in Table A1 of this online appendix. The results for both the BKM sample (Panel A) and the $NonPar$ sample (Panel B) are qualitatively the same as those in the main paper (Table 4). The portfolio analyses indicate strong positive relations between each of the risk-neutral moments and expected returns.

IV 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 measure the Bakshi et al. (2003)-based moments of the risk-neutral distribution using options that expire in month $t + 3$ (approximately 2.5 months after the end of month t), and we calculate the nonparametric moments using the fitted volatility surface for 60 day fitted option values provided by OptionMetrics. 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 $2M$ subscript.

The results of tri-variate dependent sort portfolio analyses are presented in Table A2 of this online appendix. As the two-month BKM sample has a reduced number of data points, for the analysis of the BKM sample, we form only two portfolios based on the third sort variable. The results indicate generally 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 A3. Regardless of regression specification or method of calculating the risk-neutral moments, 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.

V Moment Decomposition Using Risk-Neutral Beta

In this section, we generate a measure of risk-neutral beta based on the relation between the implied volatilities of the given stock and the market portfolio. We then use this measure of risk-neutral beta to decompose risk-neutral variance, skewness, and kurtosis into systematic and unsystematic components. Finally, we examine the relation between ex-ante expected returns and the systematic and unsystematic components of the risk-neutral moments.

V.A Calculating Risk-Neutral Beta

Calculation of the systematic and unsystematic risk-neutral moments requires an estimate of risk-neutral beta ($\beta_{RN,i}$). We calculate risk-neutral beta from regressions of the risk-neutral variance of the stock on the risk-neutral variance of the market. The assumption behind our calculation is that the risk-neutral stock return process follows a one-factor market model given by equation (14) of the main paper. If this assumption holds, the risk-neutral variance of stock i, $\sigma^2_{RN,i}$, can be expressed as in equation (15) of the main paper. To generate an estimate of the value of $\beta^2_{RN,i}$, therefore, we use the regression specification:

$$IV^2_{i,d} = \delta_0 + \delta_1 IV^2_{m,d} + \nu_{i,d} \tag{A2}$$

where $IV_{i,d}$ ($IV_{m,d}$) is the implied volatility of stock i (the market, taken to be the S&P 500 index) on day d. Regressions are performed for each stock at the end of each month using one year's worth of implied volatility data taken from the OptionMetrics implied volatility surface.[1] Specifically, IV is taken to be the average of the 30-day 0.50 delta call and -0.50 delta put implied volatilities. The positive square root of the estimated slope coefficient (δ_1) is taken to be the risk-neutral beta. Thus, we define risk-neutral beta as $\beta_{RN} = \sqrt{\hat{\delta}_1}$ where $\hat{\delta}_1$ is the estimated value of δ_1 generated by the regression.

V.B Relations with Expected Returns

In Table A4, we present the results of Fama and MacBeth (1973) regressions of price target-based expected returns on the systematic and unsystematic components of the risk-neutral moments and controls. The results are qualitatively similar to those that use the decomposed components calculated using physical beta, presented in Table 7 of the main paper. We therefore discuss only the differences. The main difference is that in the present analysis, which uses risk-neutral beta to perform the decomposition of the risk-neutral moments (Table A4 of this online appendix), systematic kurtosis exhibits a positive and statistically significant relation with expected returns. Additionally, the systematic component of risk-neutral skewness retains its positive and statistically significant relation with expected returns even in specifications in which controls are included in the model.[2] A potential explanation for the difference between the results presented here and the results found in the main paper is

[1] We use implied volatilities from the volatility surface instead of using the BKM-based measure because using the volatility surface allows us to hold the maturity and the delta (moneyness) constant.

[2] We rerun specifications (2), (4), and (6) in Table A4 with physical beta (β) included as an additional control variable. The results (unreported) are qualitatively unchanged.

that the estimation of risk-neutral beta is likely to be very noisy, making the decomposition of the risk-neutral moments into systematic and unsystematic components inaccurate. As a result, it is possible that for a substantial fraction of the stocks in the sample, a portion of unsystematic component of the moment is still captured in the variable intended to capture only the systematic component. Given that the total risk-neutral moments are positively related to expected returns, this would result in overestimating the relation between the systematic components and expected returns.

References

Bakshi, G., Kapadia, N., and Madan, D. 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies, 16(1), 101–143.

Fama, E. F. and MacBeth, J. D. 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy, 81(3), 607.

Newey, W. K. and West, K. D. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Table A1: Tri-Variate Dependent Sort Portfolios - Alternative Sort Order
Each month, all stocks in the sample (BKM sample in Panel A, $NonPar$ sample in Panel B) are grouped into 27 portfolios based on tri-variate dependent sorts of the risk-neutral moments. All stocks in the sample are first sorted into three portfolios based on the first sort variable. Each of the three portfolios is then sorted into three portfolios based on the second variable. Finally, each of the nine resulting portfolios is sorted into three portfolios based on the third sort variable. For each sort, the 30% of stocks with the lowest values of the sort variable are put in portfolio one, the next 40% are put in portfolio two, and the stocks with the highest values are put in portfolio three. The table below presents the time-series average of the monthly equal-weighted average expected returns (ER) for each of the 27 portfolios. The first sort variable, along with the corresponding portfolio number, is presented in the upper left of each table. Portfolios of the second sort variable are represented by columns. Portfolios of the third sort variable are represented by rows. The portfolio row labeled "3-1" presents the time series average of monthly differences between portfolio three and portfolio one of the third sort variable, for the given sort variable one and sort variable two portfolios. The t-statistic testing the null hypothesis that the average difference between portfolio three and portfolio one of the third sort variable is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses. The columns labeled "Avg." present the average expected return of the three sort variable two portfolios for the given sort variable one and sort variable three portfolio. Panels A1 and B1 present results of portfolio analyses designed to examine the relation between volatility and expected returns after controlling for skewness and kurtosis, by sorting first on kurtosis, then on skewness, and finally on volatility. Panels A2 and B2 sort on volatility, kurtosis, then skewness, and therefore examine the relation between skewness and expected returns. Panels A3 and B3 examine the relation between kurtosis and expected returns by sorting first on volatility, then on skewness, and finally on kurtosis.

Table A1: Tri-Variate Dependent Sort Portfolios - Alternative Sort Order - continued

Panel A: BKM Sample

A1: Vol^{BKM}

$Kurt^{BKM}$ 1	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$	$Kurt^{BKM}$ 2	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$	$Kurt^{BKM}$ 3	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$
Vol^{BKM} 1	13.58	15.88	19.42	16.29		12.39	14.62	17.15	14.72		13.20	13.28	14.85	13.78
Vol^{BKM} 2	17.62	22.10	25.73	21.82		16.84	20.53	24.57	20.64		20.07	16.94	20.30	19.10
Vol^{BKM} 3	22.78	28.28	33.20	28.09		21.90	25.13	31.98	26.34		27.36	25.85	27.80	27.00
Vol^{BKM} 3-1	9.20	12.41	13.78	11.80		9.51	10.52	14.84	11.62		14.15	12.57	12.96	13.23
	(7.01)	(10.41)	(9.97)	(9.94)		(9.36)	(10.13)	(12.59)	(12.02)		(13.02)	(13.30)	(13.20)	(19.32)

A2: $Skew^{BKM}$

Vol^{BKM} 1	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$	Vol^{BKM} 2	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$	Vol^{BKM} 3	$Kurt^{BKM}$ 1	$Kurt^{BKM}$ 2	$Kurt^{BKM}$ 3	Avg. $Kurt^{BKM}$
$Skew^{BKM}$ 1	12.58	12.62	11.53	12.24		17.56	17.23	16.49	17.09		22.40	22.20	26.39	23.66
$Skew^{BKM}$ 2	14.88	14.41	13.83	14.37		20.79	20.36	18.84	20.00		27.83	25.65	27.12	26.87
$Skew^{BKM}$ 3	16.93	16.73	16.49	16.72		23.92	25.55	23.57	24.35		33.98	32.29	29.76	32.01
$Skew^{BKM}$ 3-1	4.35	4.11	4.96	4.48		6.37	8.32	7.09	7.26		11.58	10.08	3.37	8.34
	(5.19)	(4.63)	(5.23)	(5.41)		(7.17)	(8.05)	(5.84)	(7.82)		(9.54)	(7.60)	(2.33)	(7.64)

A3: $Kurt^{BKM}$

Vol^{BKM} 1	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$	Vol^{BKM} 2	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$	Vol^{BKM} 3	$Skew^{BKM}$ 1	$Skew^{BKM}$ 2	$Skew^{BKM}$ 3	Avg. $Skew^{BKM}$
$Kurt^{BKM}$ 1	12.33	13.45	16.28	14.02		16.50	18.89	23.15	19.51		23.13	24.38	31.02	26.18
$Kurt^{BKM}$ 2	12.86	13.94	17.16	14.65		16.67	19.94	24.82	20.48		26.07	24.74	31.78	27.53
$Kurt^{BKM}$ 3	12.07	14.52	17.77	14.79		17.78	20.87	26.50	21.72		26.41	27.79	32.77	28.99
$Kurt^{BKM}$ 3-1	-0.26	1.07	1.49	0.77		1.28	1.99	3.36	2.21		3.28	3.42	1.75	2.81
	(-0.50)	(2.14)	(1.93)	(1.69)		(1.95)	(3.11)	(3.41)	(3.83)		(3.68)	(4.60)	(1.80)	(5.72)

Table A1: Tri-Variate Dependent Sort Portfolios - Alternative Sort Order - continued

Panel B: *NonPar* Sample

B1: Vol^{NonPar}

$Kurt^{NonPar}$ 1	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
Vol^{NonPar} 1	14.72	13.02	14.04	13.92
Vol^{NonPar} 2	21.54	18.22	21.55	20.44
Vol^{NonPar} 3	29.11	26.61	30.87	28.86
Vol^{NonPar} 3-1	14.39	13.59	16.83	14.94
	(11.47)	(9.36)	(16.12)	(12.40)

$Kurt^{NonPar}$ 2	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
	14.55	13.25	13.57	13.79
	19.68	17.55	19.47	18.90
	26.83	24.74	28.87	26.81
	12.28	11.50	15.29	13.02
	(8.83)	(9.23)	(13.96)	(10.83)

$Kurt^{NonPar}$ 3	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
	12.89	13.79	13.46	13.38
	22.34	20.44	22.86	21.88
	31.20	28.98	32.35	30.84
	18.31	15.19	18.89	17.46
	(13.33)	(12.71)	(22.62)	(16.77)

B2: $Skew^{NonPar}$

Vol^{NonPar} 1	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
$Skew^{NonPar}$ 1	12.93	13.81	12.01	12.92
$Skew^{NonPar}$ 2	13.53	14.06	13.93	13.84
$Skew^{NonPar}$ 3	13.85	14.03	13.67	13.85
$Skew^{NonPar}$ 3-1	0.92	0.23	1.66	0.93
	(1.60)	(0.38)	(2.41)	(1.50)

Vol^{NonPar} 2	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
	18.18	18.10	19.78	18.69
	19.14	19.37	20.83	19.78
	20.75	20.86	22.69	21.43
	2.57	2.76	2.91	2.74
	(4.63)	(4.80)	(5.01)	(5.48)

Vol^{NonPar} 3	$Kurt^{NonPar}$ 1	$Kurt^{NonPar}$ 2	$Kurt^{NonPar}$ 3	Avg. $Kurt^{NonPar}$
	27.42	26.07	29.52	27.67
	27.99	26.91	29.65	28.18
	30.60	30.02	32.49	31.04
	3.18	3.96	2.97	3.37
	(4.77)	(6.68)	(3.54)	(5.90)

B3: $Kurt^{NonPar}$

Vol^{NonPar} 1	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Skew^{NonPar}$
$Kurt^{NonPar}$ 1	13.05	13.42	13.84	13.43
$Kurt^{NonPar}$ 2	13.58	14.00	14.23	13.94
$Kurt^{NonPar}$ 3	12.24	13.90	13.66	13.27
$Kurt^{NonPar}$ 3-1	-0.81	0.48	-0.17	-0.17
	(-2.14)	(1.34)	(-0.43)	(-0.53)

Vol^{NonPar} 2	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Skew^{NonPar}$
	17.94	19.19	20.75	19.29
	18.21	19.21	21.22	19.55
	19.84	20.66	22.68	21.06
	1.90	1.46	1.93	1.76
	(4.10)	(3.16)	(5.17)	(4.92)

Vol^{NonPar} 3	$Skew^{NonPar}$ 1	$Skew^{NonPar}$ 2	$Skew^{NonPar}$ 3	Avg. $Skew^{NonPar}$
	27.22	28.05	30.42	28.57
	26.66	26.53	30.48	27.89
	29.71	29.49	32.07	30.42
	2.48	1.43	1.65	1.86
	(3.80)	(2.97)	(3.05)	(5.76)

Table A2: Tri-Variate Dependent Sort Portfolios - Two Month Samples

Each month, all stocks in the sample (BKM sample in Panel A, $NonPar$ sample in Panel B) are grouped into portfolios based on tri-variate dependent sorts of the risk-neutral moments (BKM-based in Panel A, nonparametric in Panel B) calculated using two-month options. All stocks in the samples are first sorted into three portfolios based on the first sort variable. Each of these portfolios is then sorted into three portfolios based on the second variable. Finally, each of the resulting portfolios is sorted into two (for the BKM sample) or three (for the $NonPar$ sample) portfolios based on the third sort variable. For the first two sorts, the 30% of stocks with the lowest values of the sort variable are put in portfolio one, the next 40% are put in portfolio two, and the stocks with the highest values are put in portfolio three. For the BKM sample, for the third sort, the 50% of stocks with the lowest values of the sort variable are put into portfolio one and the remaining 50% are put into portfolio two. For the $NonPar$ sample, for the third sort, the 30% of stocks with the lowest values of the sort variable are put in portfolio one, the next 40% are put in portfolio two, and the stocks with the highest values are put in portfolio three. The table below presents the time-series average of the monthly equal-weighted average expected returns (ER) for each of the portfolios. The first sort variable, along with the corresponding portfolio number, is presented in the upper left of each table. Portfolios of the second sort variable are represented by columns. Portfolios of the third sort variable are represented by rows. The portfolio row labeled “2-1” for the BKM (“3-1” for the $NonPar$ sample) presents the time series average of monthly differences between portfolio two (three) and portfolio one of the third sort variable, for the given sort variable one and sort variable two portfolios. The t-statistic testing the null hypothesis that the average difference between portfolio two (three) and portfolio one of the third sort variable is equal to zero, adjusted following Newey and West (1987) using six lags, is presented in parentheses. The columns labeled “Avg.” present the average expected return of the three sort variable two portfolios for the given sort variable one and sort variable three portfolio. Panels A1 and B1 present results of portfolio analyses designed to examine the relation between volatility (BKM-based measure in Panel A1, nonparametric measure in Panel B1) and expected returns after controlling for skewness and kurtosis, by sorting first on skewness, then on kurtosis, and finally on volatility. Panels A2 and B2 sort on kurtosis, volatility, then skewness, and therefore examine the relation between skewness and expected returns. Panels A3 and B3 examine the relation between kurtosis and expected returns by sorting first on skewness, then on volatility, and finally on kurtosis.

Table A2: Tri-Variate Dependent Sort Portfolios - Two Month Samples - continued

Panel A: Two Month BKM Sample

A1: Vol_{2M}^{BKM}

$Skew_{2M}^{BKM}$ 1	$Kurt_{2M}^{BKM}$ 1	$Kurt_{2M}^{BKM}$ 2	$Kurt_{2M}^{BKM}$ 3	Avg. $Kurt_{2M}^{BKM}$	$Skew_{2M}^{BKM}$ 2	$Kurt_{2M}^{BKM}$ 1	$Kurt_{2M}^{BKM}$ 2	$Kurt_{2M}^{BKM}$ 3	Avg. $Kurt_{2M}^{BKM}$	$Skew_{2M}^{BKM}$ 3	$Kurt_{2M}^{BKM}$ 1	$Kurt_{2M}^{BKM}$ 2	$Kurt_{2M}^{BKM}$ 3	Avg. $Kurt_{2M}^{BKM}$
Vol_{2M}^{BKM} 1	14.11	13.16	12.28	13.19		17.24	16.24	15.15	16.21		22.23	21.33	19.07	20.88
Vol_{2M}^{BKM} 2	18.87	19.68	21.14	19.90		23.88	23.53	23.29	23.57		30.07	30.60	30.21	30.29
Vol_{2M}^{BKM} 2-1	4.75	6.52	8.87	6.71		6.64	7.29	8.14	7.36		7.84	9.27	11.14	9.42
	(3.73)	(6.27)	(7.04)	(8.04)		(8.40)	(9.63)	(7.52)	(11.46)		(6.61)	(8.79)	(9.82)	(11.35)

A2: $Skew_{2M}^{BKM}$

$Kurt_{2M}^{BKM}$ 1	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}	$Kurt_{2M}^{BKM}$ 2	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}	$Kurt_{2M}^{BKM}$ 3	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}
$Skew_{2M}^{BKM}$ 1	15.70	20.69	25.45	20.61		13.84	16.46	23.39	17.90		11.14	14.70	23.51	16.45
$Skew_{2M}^{BKM}$ 2	19.74	27.36	32.66	26.59		16.55	22.99	29.18	22.91		13.82	18.30	26.69	19.60
$Skew_{2M}^{BKM}$ 2-1	4.04	6.67	7.21	5.97		2.71	6.53	5.79	5.01		2.68	3.59	3.17	3.15
	(5.86)	(7.77)	(4.55)	(8.38)		(4.37)	(6.19)	(4.31)	(6.95)		(5.23)	(3.18)	(2.27)	(3.82)

A3: $Kurt_{2M}^{BKM}$

$Skew_{2M}^{BKM}$ 1	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}	$Skew_{2M}^{BKM}$ 2	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}	$Skew_{2M}^{BKM}$ 3	Vol_{2M}^{BKM} 1	Vol_{2M}^{BKM} 2	Vol_{2M}^{BKM} 3	Avg. Vol_{2M}^{BKM}
$Kurt_{2M}^{BKM}$ 1	11.62	16.10	21.82	16.51		14.90	19.64	24.71	19.75		18.52	24.87	30.97	24.78
$Kurt_{2M}^{BKM}$ 2	10.91	15.49	23.84	16.75		14.78	19.09	26.31	20.06		18.68	26.12	34.57	26.46
$Kurt_{2M}^{BKM}$ 3-1	-0.71	-0.61	2.02	0.23		-0.12	-0.55	1.60	0.31		0.16	1.26	3.61	1.67
	(-1.26)	(-0.66)	(1.29)	(0.33)		(-0.19)	(-0.65)	(1.83)	(0.66)		(0.25)	(1.13)	(2.80)	(2.56)

Table A2: Tri-Variate Dependent Sort Portfolios - Two Month Samples - continued

Panel B: Two Month $NonPar$ Sample

B1: Vol_{2M}^{NonPar}

	$Skew_{2M}^{NonPar}$ 1				$Skew_{2M}^{NonPar}$ 2				$Skew_{2M}^{NonPar}$ 3			
	$Kurt_{2M}^{NonPar}$ 1	$Kurt_{2M}^{NonPar}$ 2	$Kurt_{2M}^{NonPar}$ 3	Avg. $Kurt_{2M}^{NonPar}$	$Kurt_{2M}^{NonPar}$ 1	$Kurt_{2M}^{NonPar}$ 2	$Kurt_{2M}^{NonPar}$ 3	Avg. $Kurt_{2M}^{NonPar}$	$Kurt_{2M}^{NonPar}$ 1	$Kurt_{2M}^{NonPar}$ 2	$Kurt_{2M}^{NonPar}$ 3	Avg. $Kurt_{2M}^{NonPar}$
Vol_{2M}^{NonPar} 1	15.06	15.10	13.49	14.55	13.71	12.87	13.24	13.27	13.96	13.53	13.78	13.75
Vol_{2M}^{NonPar} 2	22.26	20.94	23.28	22.16	18.92	17.21	19.07	18.40	21.24	19.43	24.47	21.71
Vol_{2M}^{NonPar} 3	30.54	28.10	31.36	30.00	27.43	23.84	27.36	26.21	32.17	29.07	34.70	31.98
Vol_{2M}^{NonPar} 3-1	15.48	13.00	17.87	15.45	13.72	10.97	14.12	12.94	18.22	15.54	20.93	18.23
	(11.62)	(10.35)	(16.40)	(13.23)	(9.63)	(10.71)	(11.59)	(10.62)	(14.20)	(13.56)	(21.61)	(17.03)

B2: $Skew_{2M}^{NonPar}$

	$Kurt_{2M}^{NonPar}$ 1				$Kurt_{2M}^{NonPar}$ 2				$Kurt_{2M}^{NonPar}$ 3			
	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}
$Skew_{2M}^{NonPar}$ 1	13.56	19.13	28.58	20.42	13.38	17.73	25.88	19.00	12.42	20.77	29.44	20.88
$Skew_{2M}^{NonPar}$ 2	13.90	20.24	29.01	21.05	13.27	18.51	25.41	19.06	14.21	22.03	30.58	22.27
$Skew_{2M}^{NonPar}$ 3	14.39	21.66	32.59	22.88	13.70	19.65	28.60	20.65	14.31	24.70	35.28	24.76
$Skew_{2M}^{NonPar}$ 3-1	0.84	2.53	4.01	2.46	0.32	1.92	2.72	1.66	1.89	3.92	5.84	3.88
	(1.36)	(4.75)	(6.06)	(5.97)	(0.52)	(3.24)	(3.51)	(3.36)	(3.06)	(5.17)	(6.06)	(6.13)

B3: $Kurt_{2M}^{NonPar}$

	$Skew_{2M}^{NonPar}$ 1				$Skew_{2M}^{NonPar}$ 2				$Skew_{2M}^{NonPar}$ 3			
	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}	Vol_{2M}^{NonPar} 1	Vol_{2M}^{NonPar} 2	Vol_{2M}^{NonPar} 3	Avg. Vol_{2M}^{NonPar}
$Kurt_{2M}^{NonPar}$ 1	14.35	21.23	30.28	21.96	13.19	18.19	26.80	19.40	13.64	20.66	32.05	22.11
$Kurt_{2M}^{NonPar}$ 2	15.33	21.50	29.08	21.97	13.15	17.92	24.65	18.57	13.76	20.53	30.56	21.61
$Kurt_{2M}^{NonPar}$ 3	13.73	22.92	31.29	22.64	13.20	18.68	27.29	19.73	13.33	22.82	34.36	23.50
$Kurt_{2M}^{NonPar}$ 3-1	-0.62	1.68	1.00	0.69	0.01	0.49	0.49	0.33	-0.30	2.16	2.31	1.39
	(-1.73)	(3.57)	(1.58)	(2.56)	(0.03)	(1.57)	(1.21)	(1.40)	(-0.93)	(5.44)	(3.96)	(5.09)

Table A3: Fama-MacBeth Cross-Sectional Regressions - Two Month Samples
The table below presents the results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER) on combinations of the two-month risk-neutral moments and controls. The columns whose names begin with BKM ($NonPar$) contain results for the BKM ($NonPar$) sample. Each month, a cross-sectional regression of expected returns is performed on all data points in the sample. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series average of the cross-sectional regression coefficients. Newey and West (1987) t-statistics, adjusted for six lags, testing the null hypothesis that the average coefficient is equal to zero are in parentheses. The last two rows present the average adjusted R-squared values and the average number of cross-sectional observations.

	$BKM1$	$NonPar1$	$BKM2$	$NonPar2$
Vol_{2M}^{BKM}	0.31		0.19	
	(14.47)		(6.89)	
$Skew_{2M}^{BKM}$	7.74		3.84	
	(9.76)		(5.76)	
$Kurt_{2M}^{BKM}$	0.84		0.38	
	(5.16)		(2.74)	
Vol_{2M}^{NonPar}		0.39		0.27
		(21.53)		(14.87)
$Skew_{2M}^{NonPar}$		0.25		0.11
		(8.65)		(5.42)
$Kurt_{2M}^{NonPar}$		0.11		0.05
		(4.87)		(3.26)
β			2.41	2.28
			(2.76)	(3.47)
$IdioVol$			0.06	0.01
			(2.36)	(1.01)
$CoSkew$			-0.11	-0.10
			(-2.65)	(-2.25)
$CoKurt$			0.01	0.01
			(1.32)	(0.66)
$Size$			0.82	0.55
			(3.02)	(3.10)
BM			1.04	0.20
			(1.45)	(0.62)
$Illiq$			393.98	184.67
			(4.73)	(5.30)
Rev			-0.39	-0.48
			(-18.62)	(-34.38)
Mom			-0.04	-0.04
			(-4.95)	(-9.45)
$Earn$			52.77	26.80
			(5.48)	(7.32)
$AnlystCov$			-1.48	-1.37
			(-3.58)	(-9.24)
LTG			0.31	0.25
			(7.36)	(11.94)
Intercept	10.28	3.87	-3.48	-0.69
	(10.89)	(4.48)	(-1.17)	(-0.30)
$Adj.\ R^2$	0.14	0.14	0.28	0.26
n	109	1014	88	794

Table A4: Regressions - Systematic and Unsystematic Components - Risk-Neutral Beta

The table below presents the results of Fama and MacBeth (1973) regressions of price target-based expected returns (ER) on combinations of the decomposed components of BKM-based risk-neutral moments and controls. Decomposition of the risk-neutral moments is done using risk-neutral beta. Risk-neutral beta is taken to be the squared root of the slope coefficient from a regression of the implied variance of the stock on the implied variance of the market. Each month, a cross-sectional regression of expected returns is performed on all data points in the sample. All independent variables are winsorized at the 0.5% level on a monthly basis. The table presents the time-series average of the cross-sectional regression coefficients. Newey and West (1987) t-statistics, adjusted for six lags, testing the null hypothesis that the average coefficient is equal to zero are in parentheses. The last two rows present the average adjusted R-squared values and the average number of cross-sectional observations.

	(1)	(2)	(3)	(4)	(5)	(6)
Var_S^{BKM}	60.85	40.57			47.29	41.38
	(8.97)	(5.86)			(8.02)	(5.90)
Var_U^{BKM}			35.36	11.99	18.83	10.16
			(12.40)	(5.24)	(7.91)	(3.77)
$Skew_S^{BKM}$	26.41	13.49			19.02	12.02
	(8.74)	(4.76)			(6.48)	(4.09)
$Skew_U^{BKM}$			6.63	2.65	6.62	2.69
			(9.64)	(6.47)	(10.15)	(6.33)
$Kurt_S^{BKM}$	9.70	6.09			5.13	4.83
	(3.31)	(3.24)			(3.20)	(3.51)
$Kurt_U^{BKM}$			0.62	0.19	0.74	0.22
			(6.86)	(3.07)	(7.06)	(3.65)
$IdioVol$		0.11		0.16		0.05
		(6.40)		(8.76)		(2.51)
$CoSkew$		-0.10		-0.09		-0.11
		(-1.61)		(-1.37)		(-1.68)
$CoKurt$		0.00		0.00		0.00
		(1.07)		(1.09)		(1.25)
$Size$		0.29		0.34		0.34
		(1.36)		(1.79)		(1.67)
BM		1.23		1.62		1.37
		(2.23)		(2.72)		(2.32)
$Illiq$		304.98		306.83		290.54
		(3.54)		(3.62)		(3.50)
Rev		-0.52		-0.49		-0.48
		(-24.54)		(-24.79)		(-24.17)
Mom		-0.04		-0.04		-0.04
		(-6.41)		(-6.22)		(-6.53)
$Earn$		30.86		29.06		30.99
		(5.73)		(5.22)		(6.27)
$AnlystCov$		-1.64		-1.54		-1.60
		(-5.11)		(-5.29)		(-5.24)
LTG		0.26		0.26		0.26
		(10.23)		(10.18)		(10.56)
Intercept	20.73	10.78	15.69	7.07	19.14	11.31
	(16.74)	(4.14)	(19.65)	(3.18)	(15.38)	(4.31)
Adj. R^2	0.08	0.25	0.09	0.24	0.13	0.25
n	195	162	195	162	195	162