The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXIX, NO. 4 • AUGUST 2014

Stock Options as Lotteries

BRIAN H. BOYER and KEITH VORKINK*

ABSTRACT

We investigate the relationship between ex ante total skewness and holding returns on individual equity options. Recent theoretical developments predict a negative relationship between total skewness and average returns, in contrast to the traditional view that only coskewness is priced. We find, consistent with recent theory, that total skewness exhibits a strong negative relationship with average option returns. Differences in average returns for option portfolios sorted on ex ante skewness range from 10% to 50% per week, even after controlling for risk. Our findings suggest that these large premiums compensate intermediaries for bearing unhedgeable risk when accommodating investor demand for lottery-like options.

RECENT RESEARCH SHOWS that standard rational asset pricing models have difficulty explaining many of the basic empirical facts about the aggregate stock market, the cross-section of average returns, and individual trading behavior. Furthermore, experimental economists find that individuals deviate from standard utility theory when making choices in the face of uncertainty (see, e.g., Kahneman and Tversky (1979)). As a result, many researchers have turned their attention to the asset pricing implications of models that depart from the standard representative agent/expected utility framework.

One prominent departure considers investors who prefer skewness or lottery-like features in asset return distributions, and how these preferences influence asset prices in equilibrium.[1] These newer models posit that *total skewness*, including idiosyncratic skewness, is priced because investors optimally choose to underdiversify. Asset returns in these models have a strong negative relationship with total skewness. In stark contrast, the prevailing view is that only

*Boyer and Vorkink are with The Marriott School of Management, Brigham Young University. We acknowledge financial support from the Harold F. and Madelyn Ruth Silver Fund and Intel Corporation. Vorkink notes support from a Ford research fellowship. We thank Turan Bali, Nick Barberis, Josh Coval, Jefferson Duarte, Danling Jiang, Chris Jones, Don Lien, Francis Longstaff, Grant McQueen, Todd Mitton, Lasse Pedersen, Josh Pollet, Tyler Shumway, Grigory Vilkov, seminar participants at Brigham Young University, Florida State, UC Irvine, UCLA, and the University of Michigan, and conference participants at the 2012 Adam Smith Asset Pricing Conference and the 2012 Western Finance Association Meetings for helpful comments and suggestions. We also thank Greg Adams and Troy Carpenter for research support.

[1] This literatures includes the endogenous probabilities model of Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007), the heterogeneous skewness preference model of Mitton and Vorkink (2007), and the cumulative prospect theory model of Barberis and Huang (2008).

DOI: 10.1111/jofi.12152

coskewness with the market is value relevant (Kraus and Litzenberger (1976) and Harvey and Siddique (2000)).[2]

The individual equity options market offers an ideal arena to study these competing views of skewness preference on asset prices for three reasons. First, the implicit leverage in an option contract combined with a nonlinear payoff creates unusually dramatic lottery-like features in option returns. The ex ante return skewness of option contracts can easily be more than 10 times higher than equity return skewness. Second, cross-sectional variation in ex ante skewness is relatively straightforward to identify among options, both for the investor and the econometrician. Third, the skewness of individual equity options is largely idiosyncratic. Since the moments of index options are predominantly systematic, index options are poorly suited to differentiate between the effects of total skewness and coskewness on prices.[3]

Our findings strongly suggest that total skewness is priced. Portfolios of short-term options with high ex ante skewness lose about 10% to 50% per *week* on average. Portfolios of otherwise similar options with low ex ante skewness earn average weekly returns close to zero. We find a statistically significant and economically large effect of total skewness preference on option prices in both call and put option markets and across maturities ranging from one week to about three months after controlling for the influence of risk and other characteristics following Duarte and Jones (2007) and Broadie, Chernov, and Johannes (2009). We base these findings on a simple ex ante measure of option skewness that we develop and use in our empirical tests. The magnitude and robustness of the negative relationship between total skewness and returns suggest that skewness preference may be of *first-order* importance in the pricing of securities with extreme lottery-like features.

Recent papers find that total skewness is priced in stocks. This literature also concludes, however, that estimating ex ante skewness for stock returns is quite difficult because the correct set of predictive instruments is not known. Lagged skewness in particular is a poor instrument for ex ante skewness since low probability events that largely determine estimates of the third moment are not persistent.[4] In contrast, our measure of ex ante option return skewness is simple to construct and demonstrates that most of the cross-sectional

[2] Work on skewness preferences predates the articles cited above. Arditti (1967) and Scott and Horvath (1980) show that well-behaved utility functions include a preference for positive skewness. Rubinstein (1973) develops a model in which expected returns are a linear function of higher comoments between returns and future wealth. Simkowitz and Beedles (1978) and Conine and Tamarkin (1981) show that agents that have skewness preference may prefer underdiversified portfolios in equilibrium in contrast to standard representative agent equilibrium holdings.

[3] Dierkes (2009) and Polkovnichenko and Zhao (2013) report empirical evidence suggesting that skewness preference influences index option prices.

[4] For further discussion, see Boyer, Mitton, and Vorkink (2010), who use a set of stock characteristics to forecast stock return skewness in a rolling cross-sectional regression framework. Zhang (2005) uses estimates of cross-sectional skewness within stock peer groups to forecast future stock return skewness. Conrad, Dittmar, and Ghysels (2013) obtain estimates of implied risk-neutral stock return skewness from the cross-section of equity options. Bali, Cakici, and Whitelaw (2010) use the maximum daily return as a measure of lottery potential.

variation in ex ante skewness for individual option returns, holding maturity fixed, can be explained by just two variables: moneyness and underlying asset return volatility. Moneyness is directly observable, and underlying asset return volatility is relatively straightforward to estimate. We also show that option return skewness is largely unaffected by the ex ante skewness of the underlying stock return.

Our findings also contribute generally to the literature in the following three ways. First, because we analyze the full cross-section of both call and put options on individual equities, our results extend the findings of Coval and Shumway (2001) and Ni (2009) to broaden our understanding of average option returns. Second, our results support the case for demand-based option pricing as in Garlaneau, Pedersen, and Poteshman (2009) by showing that one important source of demand in option markets is skewness preference, and that this demand has an economically significant effect on prices. Third, our results contribute to the vast literature on the relation between option prices and moneyness.[5] A stylized fact of this literature is that out-of-the-money options are overvalued relative to standard models. Ni (2009) adds to this literature by showing that out-of-the-money call options earn low average returns. In this paper, we show that ex ante skewness unrelated to moneyness is priced in both call and put securities. In contrast, after controlling for our measure of ex ante skewness, we find that the relationship between option returns and moneyness documented by Ni (2009) largely disappears. Our results suggest that investor demand for lottery-like assets combined with limits-to-arbitrage in the form of market-maker hedging costs may help explain the well-documented relation between moneyness and option prices.

We test whether state variables commonly used in asset pricing can explain the incredibly low average option portfolio returns we document, including the excess market return, excess returns on a zero-Δ index straddle, and the coskewness factor of Harvey and Siddique (2000). We find that average returns of the *underlying stocks* can be largely explained by return covariation with the excess market return. Average *option* returns, however, cannot be explained by return covariation with any of the state variables we consider.

We confirm our findings in Fama-MacBeth (1973) regressions that allow us to jointly control for the influence of a variety of risk factors and other characteristics, as well as in double-sorted portfolio tests that enable us to control for characteristics while allowing for nonlinearities in the pricing relationships. Our main results hold after controlling for two different measures of coskewness, the bid-ask spread, volume, and even moneyness.[6]

Empirical work in option pricing typically relies on the estimation of fully specified parametric models. Option returns are more straightforward to

[5] Whaley (2003) and Bates (2003) provide summaries of this literature. Whaley (2003), in particular, argues that researchers should consider supply and demand effects in option markets to understand the relationship between option prices and moneyness.

[6] The two measures of coskewness we control for include an ex ante measure of coskewness (similar to our ex ante measure of total skewness) and return covariation with the squared excess market return as in Harvey and Siddique (2000).

interpret economically than the pricing errors of such models because returns represent the actual gains or losses to an investor on purchased securities. Several others have also noted the advantages of analyzing average (risk-adjusted) option returns.[7] For example, Duarte and Jones (2007), who analyze equity options using Fama-MacBeth (1973) regressions, argue that many parametric option pricing models impose a highly rigid structure on both risk premia and the relative riskiness of different option contracts in a manner that can lead to misleading conclusions. Further, the feasibility of imposing realistic parametric assumptions on the entire cross-section of underlying assets is questionable.

Of course, there are obvious issues to consider when applying standard asset pricing metrics to option returns given their nonnormality and nonlinearity. Broadie, Chernov, and Johannes (2009) apply standard asset pricing methods to option returns but anchor hypothesis tests at appropriate null values by comparing estimated parameters to those obtained using artificial data generated under formal option pricing models. Following their procedure, we first simulate data under the usual Black-Scholes (1973) assumptions and then again under the jump diffusion model of Merton (1976). In both simulations we impose the null that skewness is not priced. We then apply the same standard asset pricing methods to the simulated data as we do using the actual data. These simulations inform us regarding how often properties such as the nonnormality and nonlinearity of option returns can lead to results as extreme as those found in the actual data. We find the answer to be virtually never: the results we estimate using the actual data look quite abnormal relative to results simulated under these two models. In fact, our simulation exercise leads to the same conclusions we arrive at using standard empirical methods, namely, that total skewness is priced in the cross-section of individual equity option returns.

While investors appear willing to pay substantial premiums for the lottery-like characteristics of individual equity options, we find that the losses of option buyers are *not* passed on as gains to investors who write options. We find that investors who write lottery-like options near the bid earn risk-adjusted returns that are generally insignificant from zero and do not vary systematically with ex ante skewness. This helps explain why the remarkably low average returns on options with high ex ante skewness are not arbitraged away and can persist in equilibrium. We conjecture that the ability of intermediaries to effectively hedge short positions in individual options deteriorates with the ex ante skewness of the option.[8] High ask prices therefore compensate intermediaries for bearing the unhedgeable risk of writing options with high ex ante skewness while bid prices are more closely aligned to the textbook no-arbitrage relations with the stock. Garleanu, Pedersen, and Poteshman's (2009) model of option

[7] For example, see Coval and Shumway (2001), Bondarenko (2003), Driessen, Maenhout, and Vilkov (2009), Duarte and Jones (2007), Broadie, Chernov, and Johannes (2009), Goyal and Saretto (2009), and Frazzini and Pedersen (2011).

[8] Intermediaries cannot perfectly hedge their option positions because of the impossibility of trading continuously, jumps in the underlying, stochastic volatility, and transaction costs. Hedging individual option positions can be especially difficult because of greater short-sale constraints, lower liquidity, and the lack of a viable futures market.

pricing illustrates that demand pressure on an option's price is related to the variance of the unhedgeable part of the option.[9] Building on this work, we begin to uncover sources of such demand pressure.

Our findings do not appear to be merely driven by restrictions in supply by intermediaries. In a small data set of intraday transaction prices and quotes, we find that nearly half of all trades in options with high ex ante skewness occur near or at the ask price. These findings corroborate our interpretation of earlier results, that a strong preference for total skewness exists among option investors. Barberis and Huang (2008, p. 2066), for example, study the implications of cumulative prospect theory for asset pricing motivated by observation that cumulative prospect theory "... captures attitudes to risk in experimental settings very effectively," but also cautions that "there is no guarantee" that cumulative prospect theory "will help us understand investor behavior in financial markets." Our study of the individual equity options market suggests that perhaps people do exhibit preference for skewness, or at a minimum, that we should further consider the implications of models in which total skewness is priced to help us understand other asset-pricing phenomena.

The rest of the paper is organized as follows. Section I introduces our ex ante skewness measure. In Section II we form option portfolios and report their average returns. Section III presents results on average portfolio returns after controlling for risk and other option characteristics. Section IV investigates the returns from writing options at the bid price. Section V offers concluding remarks.

I. Ex Ante Skewness

To understand whether differences in the lottery-like characteristics of options help explain cross-sectional variation in their expected returns, we make the simplifying assumption that skewness is a proxy for the lottery-like characteristics of options consistent with much of the lottery-preference literature (e.g., Brunnermeier and Parker (2005), Mitton and Vorkink (2007), and Barberis and Huang (2008)). We construct closed-form ex ante skewness measures for the physical distribution of option returns by integrating the appropriate PDF under the assumption that stock prices are lognormal.

The lognormal assumption does not perfectly characterize the distribution of the underlying stocks. We make this assumption because it allows for a simple approach to estimate the physical ex ante skewness of an option contract that uses only information available to an investor at the time of purchase and because of its familiarity to others in the finance profession. Integrating the truncated lognormal PDF to obtain closed-form moments for options is relatively simple (Lien (1985)). As such, our method to derive option moments should be straightforward for readers to understand and less prone to accusations of "cherry picking" assumptions.

[9] Bollen and Whaley (2004) provide empirical evidence that net buying pressure influences option prices.

In the Internet Appendix, we explore the limits of the lognormal assumption for our analysis.[10] In particular, we account for ex ante underlying stock skewness (both positive and negative) that the lognormal PDF is unable to represent. We derive ex ante stock skewness similar to Boyer, Mitton, and Vorkink (2010) and find that cross-sectional variation in ex ante underlying stock skewness explains little of the variation in realized option skewness. We also find that accounting for ex ante underlying stock skewness even further strengthens our pricing results. In light of these findings, the lognormal assumption appears to be conservative. We report these results in the Internet Appendix, and further discuss the drivers of cross-sectional variation in option return skewness below. The critical issue for our asset pricing tests is whether our measure actually predicts realized skewness in option returns. In Section II.A, we demonstrate that it does.

A. Ex Ante Skewness under Lognormality

We define our measure of ex ante skewness for option i over horizon t to T as

$$sk_{i,t:T} = \frac{E_t\left[R_{i,t:T} - \mu_{i,t:T}\right]^3}{\left[\sigma_{i,t:T}\right]^3}, \tag{1}$$

where $R_{i,t:T}$ denotes option i's return, $E_t[\cdot]$ denotes the expectation given information known at time t, $\mu_{i,t:T} = E_t[R_{i,t:T}]$, and $\sigma_{i,t:T} = (E_t[R^2_{i,t:T}] - \mu^2_{i,t:T})^{1/2}$. By rewriting equation (1) in terms of its raw moments,

$$sk_{i,t:T} = \frac{E_t\left[R^3_{i,t:T}\right] - 3E_t\left[R^2_{i,t:T}\right]\mu_{i,t:T} + 2\mu^3_{i,t:T}}{\left[E_t\left[R^2_{i,t:T}\right] - \mu^2_{i,t:T}\right]^{1.5}}, \tag{2}$$

we see that only the first three raw moments of the option return are required to calculate $sk_{i,t:T}$.

To understand how we calculate these raw moments, note that the return from holding a call option to maturity, $R^c_{i,t}$, is simply

$$R^c_{i,t:T} = \frac{(S_{i,T} - X_i)^+}{C_{i,t}}, \tag{3}$$

where $(\cdot)^+$ is the $max(0,\cdot)$ function, $S_{i,T}$ is the value of the underlying asset at maturity, X_i is the exercise price, and $C_{i,t}$ is the call premium at time t. Equation (3) indicates that the j^{th} raw moment for call option i can be written as

$$E_t\left[\left(R^c_{i,t:T}\right)^j\right] = E_t\left[\left(\frac{S_{i,T} - X_i}{C_{i,t}}\right)^j |S_{i,T} > X_i\right] P_t(S_{i,T} > X_i), \tag{4}$$

[10] The Internet Appendix may be found in the online version of this article.

where $P_t(\cdot)$ indicates the probability given information as of time t. Assuming that $S_{i,T}$ is distributed lognormally, equation (4) illustrates that the raw moments for a call option are a function of the raw moments of a truncated lognormal distribution. Lien (1985) derives the moments of a truncated lognormal distribution that we use to construct $sk_{i,t:T}$ for any option contract. We further demonstrate how to construct our expected skewness measure, $sk_{i,t:T}$, in the Appendix.

B. Option Characteristics and Skewness

We provide plots to understand how different option characteristics influence our expected skewness measure, $sk_{i,t:T}$. Figure 1 plots $sk_{i,t:T}$ as a function of moneyness, $X_i/S_{i,t}$, for both call and put options and for a number of maturities. This figure illustrates that a strong relationship exists between moneyness and ex ante skewness. Options trading out-of-the-money offer substantially more skewness than in-the-money options, especially as maturity decreases. The ex ante skewness of short-term, out-of-the-money options is well over 10, several times higher than the ex ante skewness of equity returns (see Boyer, Mitton, and Vorkink (2010) and Conrad, Dittmar, and Ghysels (2013)). One other observation from Figure 1 is that put options can offer skewness opportunities that are at least as large as their corresponding call options.

In Figure 2, we plot the relationship between $sk_{i,t:T}$ and the annualized volatility of the underlying stock return $\left(\sigma_i^s\right)$. Panels A and B of Figure 2 plot the relationship for options trading at a moneyness level of 0.9, corresponding to in-the-money call options and out-of-the-money put options. We see that the volatility of the underlying can have a strong impact on skewness, but that the magnitude of the relationship is influenced by both maturity and moneyness. In Panel A, we see that higher underlying stock volatility results in slightly higher skewness for in-the-money call options. However, in Panel B the relationship flips for out-of-the-money put options: higher underlying stock volatility leads to much *lower* skewness. Panels C and D of Figure 2 plot the relationship for a moneyness level of 1.1 corresponding to out-of-the-money call options and in-the-money put options. Similar to out-of-the-money put options, the relationship between volatility and skewness is strong and negative for out-of-the-money call options: higher underlying stock volatility leads to much *lower* skewness in Panel C. We observe essentially no relationship between volatility and skewness for in-the-money put options in Panel D.

Figures 1 and 2 also shed light on the relationship between maturity and skewness. Skewness generally decreases with maturity for out-of-the money options, but increases with maturity for in-the-money options.

II. Empirical Results

A. Option Portfolio Formation

We obtain data for options written on common stock, including end-of-day closing bid and ask quotes, underlying asset values, open interest, and trading

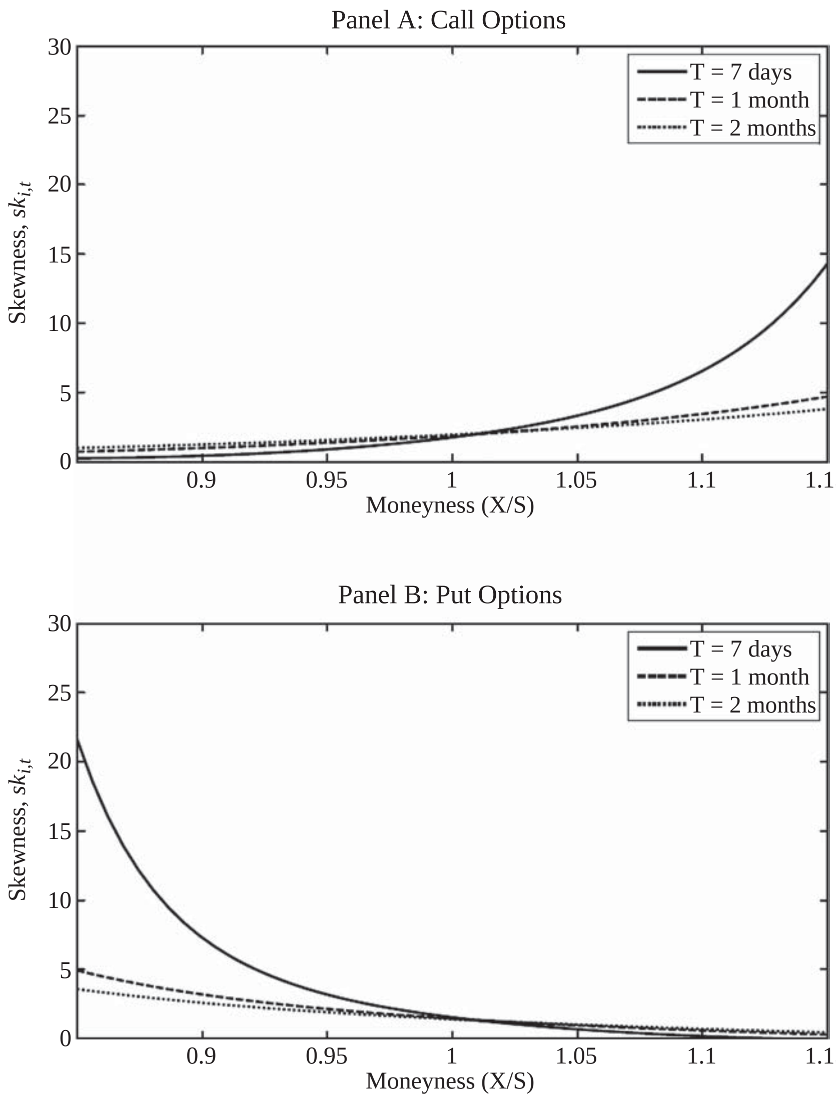

Figure 1. Option return skewness against moneyness. This figure plots option holding return skewness against moneyness (X/S) assuming the stock return volatility = 0.4, annualized expected return on the stock = 8%, risk-free rate = 5%. Panel A reports return skewness for a call option, while Panel B reports skewness for a put option.

volume, from the Ivy Optionmetrics database and create option portfolios on the first trading date of each month and on the second Friday of each month, one week before options expire. Before creating our portfolios, we first screen out records that may contain errors and quotes that may not be tradable. This procedure, detailed in the Appendix, eliminates options from each portfolio using information observable on or before the corresponding formation date.

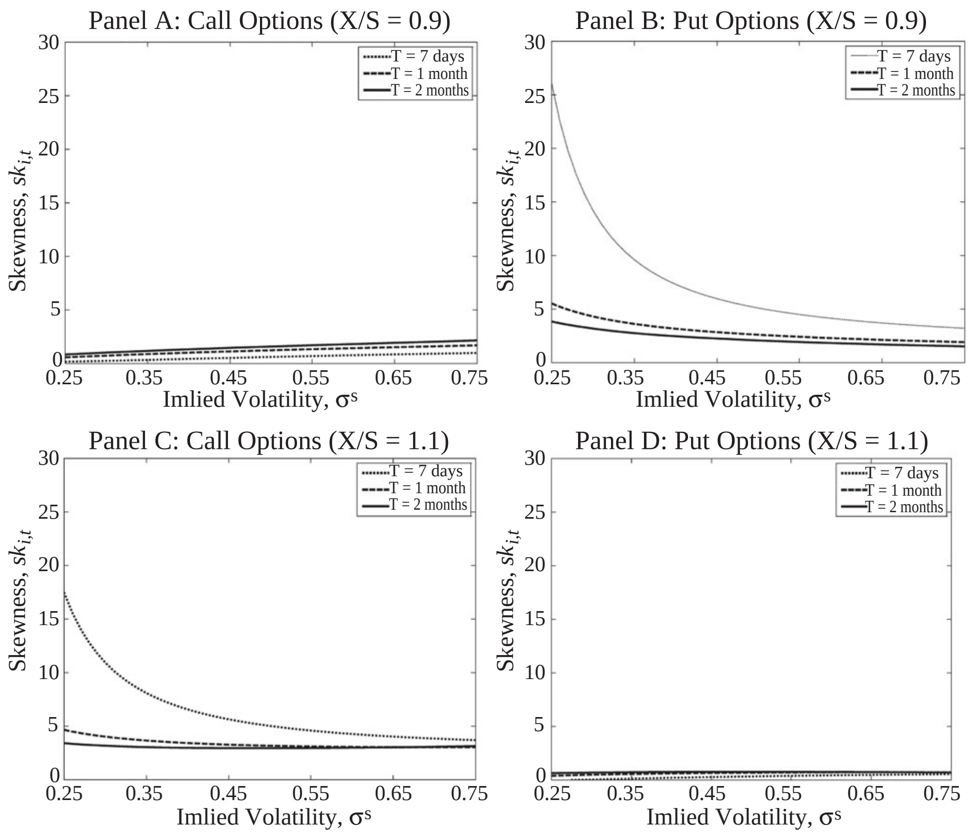

Figure 2. Option return skewness against volatility. This figure plots option holding return skewness against implied volatility, σ^s, assuming the annualized expected return on the stock is 8% and the risk-free rate is 5%. Panel A reports return skewness for in-the-money call options (X/S = 0.9). Panel B reports return skewness for out-of-the-money put options (X/S = 0.9). Panel C reports return skewness for out-of-the-money call options (X/S = 1.1). Panel D reports return skewness for in-the-money put options (X/S = 0.9).

For example, we screen out options that do not trade on the formation date, options that have zero open interest on the trading day immediately prior to the formation date, and options that have excessive bid-ask spreads. Portfolio formation dates extend from February 1, 1996, through October 9, 2009.[11] We also eliminate options that expire after December 2009.

For our analysis we also need the underlying asset value on each option's expiration date. We observe this value in Ivy for approximately 99.4% of our screened data. After filling in as many missing values as possible using CRSP stock prices, we observe underlying asset values on expiration dates for 99.9%

[11] The Ivy database currently begins January 4, 1996, and ends October 30, 2009. Since we cannot observe open interest on the trading date immediately prior to the first trading date of January 1996, we exclude this formation date from our sample.

of our observations. The other 0.01% are unobservable due to events such as mergers and delistings. We also eliminate these few records from our data even though this information is not directly observable on the portfolio formation dates.[12]

Panel A of Table I presents the number of option quotes we observe on portfolio formation dates for each year, as well as the number of quotes for which we can observe the underlying asset value at expiration. In 2007, for example, we observe 194,822 option quotes across the 24 portfolio formation dates for the year, and the corresponding underlying asset values at expiration for 194,402 of these quotes in the Ivy database. We are able to locate another 10 underlying asset values at expiration in CRSP, implying that we observe the corresponding underlying asset values at expiration for 99.8% of the original quotes (194,412). In 2009, we pull numerous underlying asset values from CRSP because our Ivy database ends October 30, 2009, implying that we must turn to CRSP to get underlying asset values at expiration for options that expire at the end of 2009. The far right column in Panel A of Table I gives the number of unique underlying assets in our data each year.

Each month we include options that fit into one of three expiration bins and then within each expiration bin we rank options into ex ante skewness quintiles. The first expiration bin contains options that expire in one week. Since options expire on the third Friday of each month, we form these bins on the second Friday of each month. We do not create portfolios of any other maturity on these dates. The second and third expiration bins contain options that on average expire in 18 and 48 days, respectively. We form these two bins on the first trading date of the month of expiration and the month prior.[13] We do not investigate the returns of options with longer expirations due to low trading volume.

Next, on each portfolio formation date we sort options within each expiration bin into ex ante skewness quintiles. To estimate ex ante skewness as illustrated by equations (1) through (4), we need estimates of the expected return and volatility for every underlying asset and formation date in our sample. We use six months of daily data immediately prior to each formation date to estimate these moments.[14] Other variables needed to compute the skewness of the option include the underlying stock price, time to maturity, strike, and price of the option on the formation date, all of which are readily obtained from the Ivy

[12] This is the only screen that relies on information observable after the portfolio formation dates.

[13] Given irregular calendar intervals between the first trading date of each month and option expiration dates, the exact maturities for portfolios in the second and third expiration bins vary slightly across time. For expositional clarity later, however, we simply refer to each maturity bin by the average number of days to expiration. For example, we refer to options in the second expiration bin simply as "options that expire in 18 days."

[14] We also estimate stock moments using a window of five years of daily data prior to each formation date and use these as inputs for our measures of ex ante skewness. We find that this has little impact on our results. See the Internet Appendix for further details.

Table I

Number of Option Quotes

This table reports summary statistics for individual equity options taken from the Ivy Database that survive our data filter as described in Appendix B. Panel A displays the total number of option quotes each year, the source for the closing prices at expiration (S_T), and the number of unique underlying assets. On each portfolio formation date we then sort options into ex ante skewness quintiles where ex ante skewness is defined by equations (1) through (4). Panel B reports for each maturity the average number of options in each ex ante skewness quintile, the average number of unique underlying assets across skewness quintiles ("Unique Underlying"), and the average number of skewness quintiles spanned by a single underlying asset ("Underlying Span").

Panel A: Number of Option Quotes

Year	Screened Data	S_T from Ivy	S_T from CRSP	S_T Observable	Unique Underlying
1996	37,695	37,695	0	37,695	1,094
1997	54,806	54,805	1	54,806	1,440
1998	67,527	67,515	4	67,519	1,679
1999	91,415	91,386	0	91,386	1,817
2000	152,511	152,509	0	152,509	1,914
2001	105,854	105,838	0	105,838	1,864
2002	94,856	94,835	0	94,835	1,954
2003	94,203	94,165	0	94,165	1,917
2004	108,917	108,825	0	108,825	2,147
2005	125,908	125,691	7	125,698	2,250
2006	160,236	160,017	14	160,031	2,430
2007	194,822	194,402	10	194,412	2,613
2008	221,945	221,616	0	221,616	2,543
2009	169,600	161,586	7,880	169,466	2,347
Total	1,680,295	1,670,885	7,916	1,678,801	
% of Total		99.44%	0.47%	99.91%	

Panel B: Average # of Securities

Skew Quintile	Days to Expiration		
	7	18	48
Calls			
Low	276	438	449
2	277	439	450
3	277	439	450
4	277	439	450
High	276	439	450
Unique Underlying	729.59	962.87	934.42
Underlying Span	1.69	1.93	1.89
Puts			
Low	230	342	306
2	230	342	307
3	230	342	307
4	230	342	307
High	230	342	306
Unique Underlying	589.51	743.26	637.56
Underlying Span	1.72	1.94	1.92

database. If on any given date there are less than 10 options within an ex ante skewness/expiration bin, we exclude this bin from the analysis for this date.

Panel B of Table I illustrates how often we observe the same underlying asset across different skewness bins. Among put options with seven days to maturity, for example, our sample contains on average 230 options per ex ante skewness bin and 590 unique underlying assets per portfolio formation date. The same underlying asset is observed on average across 1.72 different skewness bins. The ex ante screens described earlier prevent us, in many cases, from observing options written on a broad cross-section of strikes for the same underlying asset on the same portfolio formation date. To verify that our results are not driven by differences in stock characteristics, we create another set of option portfolios for which the set of underlying assets is identical across ex ante skewness bins and across contract type (call/put) for each maturity bin and formation date. These results are reported in Section III.A.

Panel A of Table II reports the average, over time, of the median ex ante skewness measure, $sk_{i,t:T}$, across all options in each portfolio at each formation date. Within each expiration group, skewness increases across the skewness quintiles by construction. The variation in expected skewness across these quintiles is large, especially among short-term options. For example, among call options that expire in seven days, expected skewness ranges from 0.40 to 24.94. In comparison, the typical skewness for a stock varies from around zero up to three (see, e.g., Boyer, Mitton, and Vorkink (2010)).

We next investigate the ability of our expected skewness measure to forecast subsequent return skewness, and, to do so, we adopt two approaches, a time-series test and a cross-sectional test. For our first test we estimate the time-series skewness of each option portfolio. For each ex ante skewness/expiration bin, we calculate the equally weighted hold-to-expiration returns for each formation date. This provides a time series of portfolio returns that we use to estimate a skewness estimate. We report these estimates in Panel B of Table II. The bottom two rows in this panel test for differences in the skewness estimates across the low and high ex ante skewness portfolios. We compute the standard error for this difference by Generalized Method of Moments (GMM) using the approach of Newey and West (1987) to account for both cross-sectional and time-series dependence. In this panel, we observe that portfolio skewness increases monotonically across ex ante skewness bins for a given maturity bin. This relationship is consistent for both call and put options and supports our ex ante skewness measure as a strong predictor of subsequent return skewness. While the differences between the high and low ex ante skewness bins are statistically significant, the magnitudes are muted relative to the skewness results of Panel A. This is likely the result of two effects. First, by forming portfolios, we diversify away much of the idiosyncratic skewness of the individual options. In addition, our time series is relatively short and, given that skewness emphasizes small probability events, our estimates may be inefficient, especially for out-of-the-money options.

For our second test, we estimate skewness in the cross-section, following Zhang (2005). Given that there are many more options than time periods, we

Table II

Ex Ante and Ex Post Skewness

On each portfolio formation date we sort options into ex ante skewness quintiles, where ex ante skewness is defined by equations (1) through (4). We then calculate the median ex ante skewness for each quintile. Panel A reports the time-series average of these medians, which increases monotonically across quintiles by construction. Panel B reports the time-series skewness of each portfolio. The last two rows of Panel B report the difference in portfolio skewness across the low and high ex ante skewness quintiles, and the t-statistic for this difference. This t-statistic is computed by GMM to account for cross-sectional dependence using the approach of Newey and West (1987) to account for intertemporal dependence. Panel C reports the average cross-sectional skewness for these same portfolios. The last two rows of Panel C report differences across the high and low skewness quintiles along with Newey-West (1987) t-statistics.

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Panel A: Average Ex Ante Skewness						
Low	0.40	0.55	0.86	0.24	0.31	0.42
2	1.03	1.18	1.51	1.00	1.12	1.27
3	1.82	1.93	2.20	1.91	2.03	2.15
4	3.36	3.11	3.23	3.75	3.77	3.65
High	24.94	7.31	6.27	15.78	13.52	10.04
Panel B: Portfolio Skewness						
Low	0.07	−0.30	0.38	0.38	0.62	1.28
2	0.57	0.16	0.76	0.77	1.20	1.86
3	1.09	0.71	0.96	1.35	1.76	2.80
4	1.82	1.37	1.17	2.09	2.70	3.94
High	2.68	1.64	1.48	2.71	4.55	7.01
Low − High	−2.61	−1.93	−1.10	−2.33	−3.93	−5.73
(t-stat)	−(4.92)	−(7.14)	−(3.24)	−(6.34)	−(5.15)	−(5.42)
Panel C: Average Cross-Sectional Skewness						
Low	0.86	0.99	1.56	0.95	1.07	1.61
2	1.52	2.03	2.84	1.89	2.35	2.54
3	2.95	3.47	3.96	3.61	3.88	3.65
4	5.04	5.46	5.50	6.00	6.13	5.20
High	9.11	9.58	8.23	10.08	10.24	8.37
Low − High	−8.29	−8.62	−6.73	−9.13	−9.19	−6.75
(t-stat)	−(25.66)	−(23.72)	−(21.44)	−(29.75)	−(27.24)	−(20.75)

should be better able to capture small probability events that relate to skewness in the cross-section than when using time-series estimates. This approach relies on the observation that the average cross-sectional skewness for a given bin is positively related to the average time-series idiosyncratic skewness of the options in that bin. In Panel C of Table II, we report the time-series average of the cross-sectional skewness estimates within each skewness/expiration bin. These results provide additional evidence that our expected skewness measure, $sk_{i,t:T}$, does a good job as a forecast. The average cross-sectional skewness increases across the skewness quintiles for each maturity group. Rows labeled "(t-stat)" in this panel test for a significant difference in average cross-sectional skewness across the bottom and top skewness quintiles. We derive these t-statistics using the approach of Newey and West (1987).

We examine the empirical relationship between each input and our ex ante skewness measure in the Internet Appendix. In cross-sectional regressions, holding maturity fixed, we find that about 92% of the variation in ex ante skewness for our sample can be explained by moneyness alone. After controlling for moneyness, the next most important input is underlying asset volatility. Accounting for both moneyness and volatility enables us to explain 97% of the cross-sectional variation in ex ante skewness. While moneyness plays an important role in characterizing an option's ex ante skewness, other option characteristics are also important and we make use of variation in ex ante skewness unrelated to moneyness in our tests later in the paper.

B. Option Characteristics and Portfolio Returns

In Table III, we report summary statistics on liquidity for each ex ante skewness/expiration bin. In Panel A of Table III, we report the average bid-ask spread, where we define the bid-ask spread as the difference between the closing bid and ask prices on portfolio formation dates scaled by their midpoint. We find average option bid-ask spreads to be large and monotonically increasing with our measure of ex ante skewness holding maturity fixed. For options with the shortest maturity, the average bid-ask spread for the low skewness quintile is about 7%, and for the high skewness quintile about 75% to 100%. Such wide spreads make it very difficult for outside investors to arbitrage away the overvaluations we document in this paper. As is standard when computing option returns, our proxy for "true" option prices is the midpoint of the bid-ask spread. Given the particularly large bid-ask spreads of option contracts, this proxy may be subject to considerable measurement error, especially for options that are highly skewed. However, as Blume and Stambaugh (1983) show, this measurement error induces an *upward* bias in computed returns because of Jensen's inequality. Hence, if anything, our estimated expected returns are too high, especially for options that are highly skewed. Moreover, our use of long-horizon returns (hold-to-expiration) rather than daily returns should attenuate the effects of measurement error in our study.

In Panel B of Table III, we report summary statistics on average daily volume per contract, and in Panel C we report the average total dollar volume for each ex ante skewness quintile. In general, we observe that high ex ante skewness options have more trading volume relative to lower ex ante skewness options. For example, among call options with seven days to maturity in the low (high) skewness quintiles, we observe an average of 182 (319) contracts traded per security per day, where each contract is for delivery of 100 shares of stock. Hence, options with high skewness are actively traded, despite their comparatively high bid-ask spreads. Average daily total dollar volume, as reported in Panel C, across call options in the low (high) skewness bins is on the

Table III

Liquidity

This table reports additional summary statistics for the options that survive the data filter outlined in Appendix B. For Panels A and B, we first measure the average characteristic (either bid-ask spread or volume) across options within each ex ante skewness quintile on each portfolio formation date, and then report the time-series average of this measure. Panel A reports the average bid-ask spread, defined as *(ask-bid)/midpoint* for the portfolio formation date, Panel B reports average trading volume defined as the number of contracts traded on the portfolio formation date. For Panel C, we first measure the total dollar volume across options within each ex ante skewness quintile on each portfolio formation date, and then report the time-series average of this measure. Total dollar volume is the sum of closing *price* × *volume* on the portfolio formation date across all options within each ex ante skewness quintile. Each panel reports results separately for calls and puts, as well as differences in each characteristic across the high and low skewness quintiles for each maturity. We also report Newey-West (1987) standard errors for these differences.

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Panel A: Average Bid-Ask Spreads						
Low	0.07	0.06	0.06	0.07	0.07	0.07
2	0.13	0.11	0.10	0.14	0.12	0.10
3	0.23	0.19	0.14	0.25	0.20	0.13
4	0.46	0.34	0.20	0.47	0.35	0.19
High	1.01	0.84	0.48	0.93	0.77	0.41
Low − High	−0.94	−0.78	−0.42	−0.86	−0.70	−0.34
(st. error)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Panel B: Average Daily Volume per Contract						
Low	182.70	139.39	89.56	160.29	157.39	96.58
2	342.48	264.05	139.70	290.57	223.87	134.49
3	488.52	371.36	170.56	413.04	312.30	152.45
4	483.47	362.87	175.63	392.38	291.13	145.77
High	318.59	247.20	145.51	253.60	180.14	108.35
Low − High	−135.89	−107.81	−55.95	−93.31	−22.75	−11.77
(st. error)	(14.72)	(13.12)	(8.18)	(8.72)	(12.77)	(5.16)
Panel C: Average Daily Total Dollar Volume (Millions)						
Low	52.27	48.67	30.20	25.76	50.61	26.06
2	29.87	47.03	25.09	20.07	25.29	13.66
3	22.18	33.87	18.76	17.54	23.96	12.37
4	9.62	15.54	11.69	8.52	12.35	9.06
High	2.78	4.06	4.81	2.58	3.27	3.69
Low − High	49.49	44.61	25.39	23.18	47.34	22.37
(st. error)	(2.30)	(10.50)	(11.68)	(7.81)	(6.33)	(3.65)

Table IV
Average Weekly Returns

This table reports the average holding-period returns for individual equity option portfolios taken from the Ivy database over the period 1996 to 2009. The portfolios are constructed by sorting on ex ante skewness as in equations (1) to (4) and the returns are holding-period returns to expiration as in equation (3) for calls, using the midpoint of the bid and ask prices as the proxy for price. The final two rows report differences in average returns across the high and low skewness quintiles along with Newey-West (1987) t-statistics that test whether these differences are equal to zero. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Call Options: Days to Expiration			Put Options: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Low	1.87	0.22	0.83	−5.38**	−0.90	0.02
2	1.34	0.83	1.03	−8.51**	−0.74	−0.33
3	−0.78	0.97	1.01	−15.52***	−2.24	−1.00
4	−3.92	0.56	0.09	−31.78***	−4.67	−1.77
High	−35.25***	−8.76***	−2.58***	−59.98***	−13.73***	−3.16
Low − High	37.11***	8.98***	3.40***	54.60***	12.83***	3.18*
(t-stat)	(7.56)	(4.07)	(5.05)	(14.13)	(3.92)	(1.94)

order of \$52 million (\$2.8 million). Unlike contract volume, dollar volume is decreasing in ex ante skewness because options with high skewness are less expensive. However, dollar volume for options with high ex ante skewness is still relatively high and comparable to that of the smallest size decile of stocks that trade on the NYSE. In the Internet Appendix, we investigate open interest and find patterns very similar to those of Panels B and C of Table III.

We report time-series averages of portfolio returns for each ex ante skewness/maturity bin in Table IV. In each case returns are scaled to be weekly. This table provides initial evidence that skewness preference influences prices in equilibrium. The returns decrease dramatically across skewness bins for every maturity group, especially among short-term options where we observe the most cross-sectional variation in ex ante skewness (Panel A of Table II). For example, among call options that expire in seven days, the average weekly return is monotonically decreasing from 1.87% for the low skewness bin to −35.25% for the high skewness bin. The paired t-statistic for the difference is 7.56. These results are within the range of average returns reported by Ni (2009). We find even more dramatic results for put options. Among put options that expire in seven days, returns are again monotonically decreasing, this time from −5.38% for the low skewness bin to −59.98% for the high skewness bin. The paired t-statistic for this difference is 14.13. Standard errors for Table IV are calculated using the approach of Newey and West (1987), in part to account for overlapping observations of options with 48 days to maturity. While the average difference in spreads between the low and high skewness portfolios decreases as maturity increases, it is positive and significant in all cases.

Our returns ignore the possibility of early exercise. This simplification should have little impact, however, on our *relative* results. Ignoring the possibility of early exercise biases downward the returns of options that become optimal to exercise early. The likelihood of optimal exercise increases with moneyness. But options that are in-the-money tend to be less skewed as discussed in Section I. Therefore, ignoring early exercise should, if anything, tend to bias downward the returns of in-the-money, less skewed options. The point of our paper is to show that such options earn higher risk-adjusted returns than out-of-the-money skewed options. In the Internet Appendix we adjust our returns for the possibility of early exercise similar to Pool, Stoll, and Whaley (2008) and show that doing so has little impact on our results.

In summary, the magnitude in the return differential between high- and low-skewed options is remarkable for short-dated options. These results indicate that individual equity option investors give up average returns on the order of 50% weekly for exposure to the lottery opportunities that options with high ex ante skewness offer. Later, we investigate what other factors influence this relationship and determine that most of this return differential can be attributed to skewness preference.

III. Controls for Risk and Other Characteristics

The traditional asset pricing framework maintains that assets earn low expected returns only if they pay off high in states when the marginal utility of investors is high. In this section, we try to explain the incredibly low average returns of Table IV by the return comovement with state variables commonly used in the asset pricing literature. In addition to a simulation exercise, we also explore the ability of various firm- and option-level characteristics to explain the low average returns. First, we estimate the pricing errors of linear factor models. Second, we run two simulations, one under the Black-Scholes (1973) paradigm and another under the jump diffusion model of Merton (1976) to test the robustness of our linear pricing model results to assumptions underlying the empirics. Third, we estimate Fama-MacBeth (1973) cross-sectional regressions that allow us to simultaneously control for a variety of factor loadings and option characteristics. Fourth, we use a double-sorting exercise that allows for a nonlinear relationship between returns and characteristics. All methods yield similar results. We find a negative significant relationship (both economically and statistically) between ex ante skewness and average option returns after controlling for both comovement and characteristics.

We feature results that control for coskewness as a test of the prevailing view that only coskewness is priced. Recent research suggests that total skewness is priced in equities (see footnote 4). Option markets, however, offer a richer environment to explore the extent and manner in which skewness preference influences asset prices given the enormous skewness accessible through option markets and the ease, relative to stocks, of determining which options offer the greatest lottery-like payoffs.

We also feature results after controlling for moneyness to separate our findings from the extensive literature on the relation between moneyness and option prices. The discussion in Section I.B and Figures 1 and 2 shows that out-of-the-money call and put options have particularly high ex ante skewness. However, a well-known stylized fact already established in the options pricing literature is that out-of-the-money options are overvalued relative to standard theoretical models. More recently, Ni (2009) shows that out-of-the-money call options, in particular, earn low average returns. In this paper we show that ex ante skewness unrelated to moneyness is priced. In contrast, after controlling for our measure of ex ante skewness, we find that the relationship between option returns and moneyness documented by Ni (2009) largely disappears. Hence, investor demand for lottery-like assets may help explain the well-documented relation between moneyness and prices.

A. Pricing Errors of Linear Factor Models

Can the low option returns documented in Table IV be explained by their comovement with state variables? Here we explore this question by investigating the pricing errors of linear factor models. Specifically, we regress the excess return of each ex ante skewness portfolio on the excess returns of zero-investment portfolios over the same time period,

$$r_{p,t:T} - r_{f,t:T} = \alpha_p + \sum_i \beta_{i,p} f_{i,t:T} + e_{p,t}, \tag{5}$$

where $r_{p,t:T}$, $r_{f,t:T}$, and $f_{i,t:T}$ represent the net returns on the option portfolio, the risk-free asset, and zero-investment portfolio i from t to T, respectively.

We begin by considering a single state variable, namely, the excess market return. We examine the ability of this single state variable to explain both the returns of the option portfolios of Table IV and the underlying assets of these options. We report the intercepts from estimating this one-factor model for option portfolios in Panel A of Table V.[15] Perhaps not surprisingly, these intercepts, or CAPM α's, look similar to the average returns in Table IV. Capital Asset Pricing Model (CAPM) α's are generally decreasing across skewness quintiles and spreads in CAPM α across the low and high ex ante skewness quintiles are quite significant, both economically and statistically, with t-statistics in the range of 4–12. We calculate standard errors for Table V via GMM using the approach of Newey and West (1987), in part to account for the overlapping observations of options with 48 days to maturity. In the Internet Appendix we report CAPM α's using each portfolio's instantaneous β and find similar results.[16]

In Panel B of Table V we report the CAPM α's for the portfolios of underlying stocks for the options in each ex ante skewness bin. We compute returns for each underlying asset across the same holding periods as our option returns, and take the equally weighted average across stocks in a given maturity/ex ante skewness bin to get stock portfolio returns for each date. We then regress excess stock portfolio returns on excess market returns over time as in

[15] We report β's for the various portfolios in the Internet Appendix.

[16] The instantaneous β for a call option is defined as $\Delta_t \frac{S_t}{C_t} \beta_{S,t}$, where Δ_t is the option's Δ and $\beta_{S,t}$ is the underlying stock's β with respect to the market.

Table V

CAPM Pricing Errors

Panel A reports CAPM pricing errors as in equation (5) for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Portfolios are formed by sorting on ex ante skewness as in equations (1) to (4) and returns are holding-period returns to expiration as in equation (3) for calls, using the midpoint of the bid and ask prices as the proxy for price. Panel B reports CAPM pricing errors for the underlying stocks. We obtain stock CAPM pricing errors by regressing stock portfolio excess returns on excess market returns over the same time horizon as we do for the option portfolios in Panel A. In the final rows of each panel we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM t-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% significance levels is indicated, respectively, by *, **, and ***.

Panel A: Option CAPM Pricing Errors						
	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Low	−1.20	−0.01	0.37	−2.42**	−0.79	0.41
2	−3.44*	0.53	0.43	−3.56**	−0.52	0.26
3	−6.90**	0.62	0.32	−9.30***	−1.93	−0.27
4	−10.71**	0.17	−0.61	−25.59***	−4.27**	−0.93
High	−40.15***	−9.10***	−3.22***	−55.68***	−13.37***	−2.12
Low − High	38.95***	9.09***	3.58***	53.27***	12.58***	2.53
(t-stat)	(9.00)	(4.27)	(5.36)	(12.73)	(4.43)	(1.42)
Panel B: Underlying Stock CAPM Pricing Errors						
Low	−0.02	0.00	0.05	−0.13	−0.10	−0.21***
2	−0.15	−0.03	0.00	−0.20*	−0.06	−0.12**
3	−0.22*	−0.06	−0.06	−0.25*	−0.02	−0.05
4	−0.23*	−0.06	−0.13**	−0.23*	−0.01	0.02
High	−0.03	−0.04	−0.21***	−0.13	0.01	0.08
Low − High	0.01	0.05	0.26***	−0.01	−0.11	−0.29**
(t-stat)	(0.08)	(0.44)	(2.71)	−(0.04)	−(0.89)	−(2.53)

equation (5) and report the intercepts of these regressions. Remarkably, in contrast to the results given in Panel A, the CAPM α's of the underlying stocks of short-dated options are generally insignificantly different from zero, and do not vary systematically across the ex ante skewness bins. In particular, the CAPM α spread across high and low ex ante option skewness quintiles is insignificantly different from zero for the 7- and 18-day maturity bins. Short-maturity options written on individual stocks therefore appear to be nonredundant securities from the simple perspective of the CAPM.

For options with 48 days to maturity, the underlying CAPM α spreads are significant in Table V. In the Internet Appendix we show that these significant spreads are caused by momentum. After controlling for the past six-month return using a double-sort procedure, virtually all CAPM α's and all spreads in CAPM α for the *underlying stock* portfolios become insignificantly different from zero. For short-term *option* portfolios, however, we still find a significant cross-sectional relationship between returns and ex ante skewness even after controlling for momentum (see Section III.D). Hence, while underlying asset characteristics appear capable of explaining the average returns for longer term options, they cannot explain the average returns of short-term options.

To further illustrate that the CAPM mispricing we document for short-term options in Table V is unrelated to the characteristics of the underlying assets, we repeat the analysis of Table V using option portfolios for which the set of underlying assets is identical across ex ante skewness bins and contract type (call/put) for options with the same maturity. To maximize sample size for this investigation, we focus only on options in the high and low ex ante skewness quintiles.

On a given formation date we classify options with a given maturity into one of four groups: call in high quintile (CH), call in low quintile (CL), put in high quintile (PH), and put in low quintile (PL). For each underlying asset, we count the number of option contracts within each of these four groups and then identify the group with the least number of contracts. For example, on May 1, 2001, our sample contains 14 options written on Applied Materials Inc. that mature on May 18 of the same year: four calls in the low quintile, three calls in the high quintile, two puts in the low quintile, and five puts in the high quintile. The group with the least number of contracts, therefore, is PL, which has two contracts. We then force the number of option contracts written on a given underlying asset to be the same across all four groups. For the example using Applied Materials Inc. this involves eliminating options from CH, CL, and PH until all groups have only two option contracts, the same as PL. We select option contracts to eliminate from each group with independent uniform probability. By conducting this exercise for every portfolio formation date, we develop a sample in which the set of underlying assets is identical across ex ante skewness bins and contract type (call/put) for options of the same maturity.[17]

We report the results of this exercise in Table VI. Here we see that the CAPM α spreads for call and put options, given in Panels A and B, respectively, are quite similar to those reported in Panel A of Table V. In Panel B of Table VI we report the CAPM α's of the underlying stocks for each bin. For every maturity, not only is the CAPM α spread across the high and low ex ante skewness bins zero by construction, but the CAPM α's for each stock portfolio are also all insignificantly different from zero. These results provide clear evidence that the large differences in CAPM α documented in Table V are not driven by differences in underlying stock characteristics, including differences in risk or distributional properties.

While the results of Tables V and VI indicate that shorter term individual stock options are not redundant, these options may still earn low average returns because they covary with other state variables orthogonal to the market return. Other work suggests that the relevant state variable is nonlinear in the market return and that coskewness is the appropriate pricing measure (see Kraus and Litzenberger (1976) and Harvey

[17] The average number of contracts per maturity/skewness bin in the revised sample is on the order of 45 to 65 with a minimum imposed of 10.

Table VI

CAPM Pricing Errors Holding Underlying Assets Fixed

This table reports CAPM pricing errors as in Table V with the exception that the underlying assets are held constant across ex ante skewness quintiles, and across contract type (call/put) for options with the same maturity. On a given formation date we classify options with a given maturity into one of four groups: call in high quintile (*CH*), call in low quintile (*CL*), put in high quintile (*PH*), and put in low quintile (*PL*). For each underlying asset, we count the number of option contracts within each of these four groups, and then identify the group with the least number of contracts. We then force the number of option contracts written on a given underlying asset to be the same across all four groups by eliminating contracts from groups that have more than the minimum with independent uniform probability. By conducting this exercise for every portfolio formation date, we develop a sample in which the set of underlying assets is identical across ex ante skewness bins and contract type (call/put) for options of the same maturity. Panel A reports CAPM pricing errors as in equation (5) for the individual equity option portfolios. Panel B reports CAPM pricing errors for the underlying stocks. We obtain stock CAPM pricing errors by regressing stock portfolio excess returns on excess market returns over the same time horizon as we do for the option portfolios in Panel A. In the final row of Panel A we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM t-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Pricing errors for stocks in Panel B across the high and low ex ante skewness quintiles and across contract type are identical by construction.

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Panel A: Option CAPM Pricing Errors						
Low	0.21	−0.01	−0.41	−2.54*	−1.01	0.09
High	−39.27***	−14.03***	−4.15***	−54.49***	−16.79***	−2.45
Low − High	39.48***	14.02***	3.74***	51.95***	15.78***	2.54
(t-stat)	(4.76)	(4.00)	(3.02)	(6.22)	(4.50)	(1.00)
Panel B: Underlying Stock CAPM Pricing Errors						
Low	0.02	0.03	−0.09	0.02	0.03	−0.09
High	0.02	0.03	−0.09	0.02	0.03	−0.09
Low − High	0.00	0.00	0.00	0.00	0.00	0.00

and Siddique (2000)). This view stands in contrast to recent models, discussed in the introduction, predicting that total skewness is priced. In addition, index options are often considered nonredundant because they insure the holder against changes in systematic volatility and/or systematic jumps (see, e.g., Pan (2002), Bakshi and Kapadia (2003a, Bakshi and Kapadia 2003b), and Duarte and Jones (2007)). We analyze options on individual stocks for which much of the variation is idiosyncratic. Further, we find strong results among call options, which do not insure against downward jumps. Hence, models with volatility or jump risk premia are unlikely to explain our findings. Nevertheless, we now examine whether coskewness or volatility risk can explain the low average returns documented in Table IV.

To investigate the ability of coskewness and volatility risk to explain our results, we estimate the intercepts of a linear pricing model with three state variables: the excess market return, the zero-investment coskewness portfolio of Harvey and Siddique (2000), and the excess return on a zero-Δ S&P 500 index straddle. Harvey and Siddique (2000) find that their zero-investment coskewness portfolio is priced in the cross-section of equity returns and considerably reduces the time-series pricing errors of standard linear factor models. Coval and Shumway (2001) find that zero-Δ straddles earn significantly negative returns and Ang et al. (2006) find that excess straddle returns represent a priced risk factor in the cross-section of equities.

To construct returns on the zero-investment coskewness portfolio, we use five years of monthly data to estimate coskewness for every common stock in the CRSP universe as defined in equation (A2) of Harvey and Siddique (2000). At the beginning of each month, we then rank stocks based on their past historical coskewness and use the 30% with the most negative coskewness to create a value-weighted portfolio. We then compound the subsequent daily returns of this portfolio over the appropriate option holding period (from t to T) and subtract the corresponding risk-free return to construct factor realizations.

To construct zero-Δ straddle returns, we choose the closest-to-the-money put and call options on the S&P 500 each day in our sample and form long positions in each such that the Δ of the portfolio is zero. We then compound daily straddle returns over the appropriate option holding period (from t to T) and subtract the corresponding risk-free return to construct factor realizations.

We report intercept estimates for the three-factor model in Table VII. While the pricing errors reported in this table and their spreads are somewhat smaller in absolute terms relative to the CAPM intercepts of Table V, the results indicate that the low average option returns documented in Table IV cannot be explained by either coskewness or volatility risk. For options that mature in seven days, the pricing error spreads in Table VII are still 35.31% for call options and 49.88% for put options with t-statistics of 7.45 and 10.28. Total skewness appears to be priced in the individual equity options market.

In summary, we do not find evidence that the low average option returns documented in Table IV can be explained by their comovement with common state variables. We further investigate the ability of market risk, volatility risk, and coskewness to explain the returns of option portfolios sorted on ex ante skewness in Fama-MacBeth regressions and double sorts below. These methods also enable us to investigate the influence of various characteristics on option returns.

B. Simulation Exercise

We next investigate whether more robust models of stock return dynamics can generate the patterns in individual stock options we observe in the data. Broadie, Chernov, and Johannes (2009) discuss some of the concerns regarding the empirical analysis of option returns and allege that standard methods to compute pricing errors for options can be misleading. We address four of the

Table VII

Pricing Errors, Three-Factor Model

This table reports pricing errors as in equation (5) for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Portfolios are formed by sorting on ex ante skewness as given in equations (1) to (4) and returns are holding-period returns to expiration as in equation (3) for calls, using the midpoint of the bid and ask prices as the proxy for price. Here we report pricing errors for a three-factor model where the three factors are the excess market return, the return on the zero-investment coskewness portfolio of Harvey and Siddique (2000), and the excess return on a zero-Δ S&P 500 index straddle. In the final rows of each panel we report differences in pricing errors across the high and low skewness quintiles along with GMM t-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Low	−1.37	0.09	0.52	−2.24**	−0.96*	0.41
2	−3.07	1.00	0.70	−2.57	−0.52	0.30
3	−5.75*	1.42	0.65	−6.92**	−1.49	−0.12
4	−8.21*	1.36	−0.34	−21.53***	−3.25	−0.62
High	−36.69***	−7.89***	−3.00***	−52.13***	−12.07***	−1.37
Low − High	35.31***	7.98***	3.52**	49.88***	11.11***	1.78**
(t-stat)	(7.45)	(3.78)	(5.57)	(10.28)	(3.95)	(2.04)

prominent concerns about using standard empirical analysis of option returns in our simulation exercise: nonnormality, nonlinearity, nonadditivity, and the tendency of option returns to suffer from peso problems in finite samples. First, option returns deviate substantially from normality and the small-sample distributions of standard CAPM α estimates may not conform with asymptotic inference. Second, the nonlinear relation between option and stock returns is likely to cause $e_{p,t}$ in the regression given by equation (5) in the paper to be correlated with the pricing factors ($f_{i,t:T}$), thereby causing OLS estimates of α to be biased and inconsistent. Third, because returns are nonadditive, expectations and β's do not scale linearly with time.[18] This implies, for example, that if stock prices follow a geometric Brownian motion and Merton's (1971) continuous-time CAPM holds, then the CAPM cannot hold over discrete horizons. Estimates of α may therefore be unduly influenced by the particular horizon over which we choose to measure returns. Finally, finite samples of option returns may lead to peso problems; they may lack certain important extreme rare events correctly anticipated by option investors ex ante but not reflected in our estimates of α measured ex post.

Following Broadie, Chernov, and Johannes (2009), we run two simulations, one under the Black-Scholes (1973) paradigm and another under the jump

[18] While log-returns are additive and are a satisfactory approximation for simple stock returns, they may not be a satisfactory approximation for the returns of options held to maturity as noted by Coval and Shumway (2001). The log-return of any option expiring worthless is negative infinity, and all moments for the log-return of any option are either positive or negative infinity.

diffusion model of Merton (1976). We simulate under the Black-Scholes assumptions as a base case. We simulate under the Merton (1976) jump-diffusion assumptions as this model can generate more flexible distributions in the underlying returns than the lognormal assumption. In addition, the Merton jump diffusion model is a relatively tractable model that can be applied to a variety of options across a large cross-section of underlyings at each point in time.

We calibrate both simulations to match the moments and size of our original data and in both simulations impose the null that skewness is *not* priced. These simulations allow us to determine how often we might expect to observe results as extreme as those we find in the original data using the same empirical methods because of either statistical issues or peso problems. We find that the answer is virtually never. The results we estimate using the actual data look quite abnormal relative to both of the models we simulate. In fact, our simulation exercise leads us to the same conclusions that we arrive at using standard empirical methods. This consensus may be attributable to the fact that we simulate portfolios of options written on a broad cross-section of stocks rather than on a single underlying index. Similarly, Broadie, Chernov, and Johannes (2009) find that concerns surrounding the extreme statistical nature of option returns can be largely alleviated by analyzing option portfolios. Given that our simulation exercise does not alter our interpretation of results, for the sake of brevity we report all details and results of our simulation exercise in the Internet Appendix.

C. Fama-MacBeth

To further assess the influence of ex ante skewness on option returns, we conduct cross-sectional regressions following the approach of Fama and MacBeth (1973). We find a strong economic and statistical relation between average returns and ex ante skewness in the cross-section that persists even after including in these regressions portfolio β's and other option characteristics that may influence expected returns.

On each portfolio formation date, we sort each option within a given maturity bin into one of 100 bins based on ex ante skewness and then calculate the equally weighted portfolio return for each ex ante skewness bin.[19] For each date t, we then estimate the following cross-sectional regression across portfolios with the same maturity horizon:

$$r_{p,t:T} = \gamma_{0,t} + \gamma_{1,t}\mathcal{R}^{skew}_{p,t} + \phi_t'\mathbf{Z}_{p,t} + \varepsilon_{p,t}, \tag{6}$$

where $r_{p,t:T}$ is the equally weighted net return for portfolio p observed over the horizon from t to T, $\mathcal{R}^{skew}_{p,t}$ is the ex ante skewness portfolio rank for portfolio p (from one to 100), and $\mathbf{Z}_{p,t}$ is a vector of control characteristics and factor loadings for portfolio p.

[19] For each period, we exclude portfolios that do not have at least 10 options, as we do in forming portfolios for our time-series results earlier. We also exclude time periods that do not have at least 30 portfolios with sufficient options. Our results are robust to these choices.

We use $\mathcal{R}^{skew}_{p,t}$ instead of average portfolio skewness on the right side of our regressions because the cross-sectional distribution of average portfolio skewness is itself quite positively skewed with an extremely high standard deviation that complicates the economic interpretation of our results (see footnote 22). For consistency, we use average ranks of the other characteristics as control variables in $\mathbf{Z}_{p,t}$, although our results are robust to the use of ranks for our controls. We calculate these average characteristic ranks by independently sorting each option on a given portfolio formation date with a given maturity into 100 bins based on each control characteristic. We then average the control characteristic rank across all options within each of the 100 skewness bins. The control characteristics we consider include moneyness ($X_i/S_{i,t}$), volume (total contracts traded on the portfolio formation date), bid-ask spread (scaled by the midpoint), and volatility smirk as in Xing, Zhang, and Zhao (2010).[20] We also include each portfolio's market β, volatility risk β, momentum β, and coskewness β. These factor loadings are all estimated by regression as in equation (5) using the market excess return, the excess return on a zero-Δ S&P 500 straddle, the standard momentum factor obtained from Ken French's website, and the squared market excess return as right-side variables, respectively.[21]

We include moneyness in our regressions to separate our findings from those of Ni (2009). We include volume and the bid-ask spread in our regressions to investigate the influence of liquidity on our pricing results. We include the volatility smirk to control for asymmetries in the return distribution of the underlying stock. The volatility smirk is unique among the characteristics we consider in the Fama-MacBeth regressions in that it is the same for all options with the same underlying and maturity. We include the momentum β in our analysis given that momentum helps to explain the underlying asset returns (see the Internet Appendix). We include the volatility risk β to investigate whether risk factors unique to index option markets can explain our results. We include the coskewness β to verify whether our results can be explained by traditional models of coskewness or if they are more consistent with new models that suggest total skewness is priced.

In Table VIII, we report the time-series averages of the γ and ϕ coefficients from equation (6), along with Newey-West (1987) t-statistics. Panel A reports results for call options while Panel B reports results for put options. In the interest of brevity, we report results only for options that expire in 18 days. The top row in each panel of Table VIII reports the cross-sectional pricing of ex ante skewness. The coefficient on expected skewness is negative and highly significant in all cases. For example, in column 10 of Panel A, we report results including all controls we consider, and we see that the average coefficient on

[20] We calculate the volatility smirk for all options written on asset i for portfolio formation date t as the volume-weighted average implied volatility across all puts for which $0.80 < X_i/S_{i,t} < 0.95$ minus the volume-weighted average implied volatility across all calls for which $0.95 < X_i/S_{i,t} < 1.05$.

[21] Alternatively, we control for the influence of coskewness by including the average ex ante coskewness rank for each option in $Z_{p,t}$, where ex ante coskewness is calculated as in the Appendix under the lognormal assumption. Doing so gives similar results.

Table VIII

Fama-McBeth Regressions: 18 Days to Maturity

This table reports the time-series average of cross-sectional regression parameters following Fama and MacBeth (1973) using individual equity options taken from the Ivy database over the period 1996 to 2009. Each month we construct 100 portfolios by sorting options on ex ante skewness as given in equations (1) to (4) and regress these portfolio returns on a set of risk controls and other portfolio characteristics. Risk controls include β^{mkt}, which corresponds to a regression market β as defined by equation (5) in the paper, β^{mom}, which corresponds to a regression momentum β on the momentum factor provided by Ken French, β^{vol}, the volatility risk β of the option portfolio obtained by regressing portfolio returns on returns of a zero-Δ index straddle, and β^{csk}, the coskewness β of the option portfolio obtained by regressing portfolio returns on squared excess market returns. We also include ex ante skewness, $sk_{t:T}$, as an explanatory variable in our cross-sectional regressions, measured as is the ex ante skewness rank of the portfolio, which can take a value from zero to 99. To control for other characteristics, we first independently sort options into 100 bins by moneyness, volume, spread, and smirk as defined in the paper. We then measure the average characteristic rank across options within each of the 100 skewness-sorted portfolios for each characteristic, and use these average rank measures as additional explanatory variables in our cross-sectional regressions. Newey-West (1987) t-statistics are in parentheses. In Panel A, we report results for portfolios of call options with 18 days to maturity. In Panel B, we report analogous results for portfolios of put options. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Call Options

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$sk_{t:T}$	−0.097***									−0.411***
	−(3.23)									−(4.07)
β^{mkt}		0.804***								2.107***
		(3.03)								(7.06)
β^{mom}			−0.059							0.128
			−(0.11)							(0.24)
β^{vol}				−17.668***						2.426
				−(6.69)						(1.02)
β^{csk}					−0.208***					−0.016
					−(5.36)					−(0.38)
X/S						−0.098***				0.258***
						−(3.06)				(2.58)
Volume							0.209***			0.008
							(3.41)			(0.21)
Spread								−0.134***		−0.068
								−(3.62)		−(1.25)
Smirk									0.005	−0.029
									(0.14)	−(1.17)

(Continued)

Table VIII—*Continued*

Panel B: Put Options										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$sk_{t:T}$	−0.142***									−0.437***
	−(2.81)									−(3.46)
β^{mkt}		0.194								−1.151***
		(0.66)								−(3.29)
β^{mom}			3.538***							0.448
			(5.46)							(0.79)
β^{vol}				−2.052						4.130*
				−(1.19)						(1.91)
β^{csk}					−0.019					−0.040*
					−(1.44)					−(1.79)
X/S						0.144***				−0.242*
						(2.71)				−(1.89)
Volume							0.139			0.067*
							(1.45)			(1.79)
Spread								−0.189***		−0.080
								−(2.87)		−(1.56)
Smirk									−0.184***	−0.017
									−(4.92)	−(0.78)

ex ante skewness is -0.411 with a t-statistic of -4.07. This implies that increasing the ex ante skewness of a portfolio of call options from the top of the bottom quintile to the bottom of the top quintile is associated with a 25% decline in average weekly returns (-0.411×60), comparable to the results of Table IV.[22] In column 10 of Panel B, the average coefficient on ex ante skewness for put options is -0.437 with a t-statistic of -3.46.

The results of Table VIII indicate that a relationship exists between ex ante skewness and expected option returns unrelated to loadings on the four risk factors and the other portfolio characteristics we consider. Of particular note, a relationship between ex ante skewness and expected option returns exists that is unrelated to moneyness. Used in isolation without other controls, the average coefficient on moneyness is negative for call options and positive for put options and highly significant, indicating that out-of-the-money options earn low average returns. When ex ante skewness is included in the regressions, however, the sign on moneyness flips, suggestive of the high positive correlation between these two variables. That the sign on ex ante skewness remains the same when moneyness is included indicates that the negative association between average option returns and our ex ante skewness measure is not subsumed by any option characteristic related to moneyness. Skewness unrelated to moneyness appears to be priced.

To further explore this issue, we conduct the same analysis using the average returns from *moneyness*-sorted portfolios as left-side variables in our cross-sectional regressions. As right-side variables we use the average ex ante skewness rank across these portfolios and the actual moneyness rank of each portfolio. In isolation, the average coefficients on each of these variables are again highly significant and of the expected sign. However, when used together, the average coefficients on *both* variables lose their significance. That is, in skewness-sorted portfolios moneyness cannot trump our ex ante skewness measure, but in moneyness-sorted portfolios skewness causes moneyness to lose its significance. Again, this exercise illustrates the ability of our ex ante skewness measure to explain the cross-section of option returns above and beyond moneyness as documented by Ni (2009).

Table VIII also provides evidence that the low average option returns we document cannot be easily explained by option coskewness. The results are more consistent with new total skewness models. Used in isolation without other controls, the coskewness β is negative and significant for call options, consistent with theory, but insignificant for put options. When ex ante skewness is included in the regressions, the coskewness β is negative for both call and put options, but is significant at the 10% level only for put options. The coefficient on total ex ante skewness, however, remains negative and significant, again suggesting that total skewness is priced.

[22] When average skewness is used as the sole explanatory variable, the coefficient is around -0.35 with t-statistics in the range of 2 to 3. This result is difficult to interpret economically, however, since the cross-sectional standard deviation of average skewness across portfolios is about 22,000.

D. Double Sorts

Fama-MacBeth (1973) regressions impose linearity on the structure between ex ante skewness, returns, and characteristics. In this section, we control for the influence of characteristics using double-sorted portfolios. Following the methodology in Ang et al. (2006, 2008), on each portfolio formation date we first sort options of a given maturity into deciles based on some characteristic. Then, within each characteristic-sorted decile, we rank options into two ex ante skewness bins. We next average the returns across options with the same ex ante skewness rank across all characteristic deciles, thereby creating the returns for two (equally weighted) portfolios similar in terms of the given characteristic but different in terms of their ex ante skewness.[23] After creating two such portfolios for each formation date in our sample, we estimate and compare their CAPM α's. We choose to examine CAPM α's given the considerable discrepancy we find in such pricing errors for options versus their underlying assets (see Tables V and VI). This approach also allows us to easily report results across different option maturities.

We conduct this exercise using moneyness (strike price scaled by underlying asset price) and a measure of ex ante coskewess (similar to our measure of ex ante skewness) as control variables. We report results controlling for moneyness in Panel A of Table IX, where we see that the difference in CAPM α's remains large and statistically significant. For call options with seven days to maturity, the CAPM α spread is 8.81% per week (t-statistic of 4.93) while, for the analogous put options, the spread is 9.70% per week (t-statistic of 4.05). In Panel B of Table IX, we report the results of an exercise where we reverse the order of sorting. We first sort into deciles based on our ex ante skewness measure and then, within each decile, rank options into two moneyness bins. We then average the returns for options with the same moneyness rank across all ex ante skewness deciles, thereby creating two portfolios similar in terms of ex ante skewness but different in terms of their moneyness. After controlling for ex ante skewness, we find the spread in CAPM α's across out-of-the-money options and in-the-money options to be quite small. In fact, for most maturity bins the differences are not statistically significant.[24] These findings again indicate that our results are not entirely subsumed by an explanation related to option moneyness. In particular, after controlling for our measure of ex ante skewness, the relationship between moneyness and expected returns documented by Ni (2009) virtually disappears.

[23] We find that the ten-two sorting combination is especially helpful in disentangling the effects of variables that are highly correlated, such as moneyness and skewness, because it helps eliminate cross-sectional variation in the control characteristic across the two conditionally sorted skewness portfolios. Other sorting combinations give similar pricing results, but also produce portfolios with greater cross-sectional variation in the control characteristic, thereby complicating the interpretation.

[24] We show in the Internet Appendix that CAPM α spreads across portfolios *unconditionally* sorted on moneyness are similar to those of the ex ante skewness portfolios of Tables V and VII.

Table IX

Double Sorts on Moneyness

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. In Panel A, we adopt a double sort procedure to net out the influence of moneyness. For a given portfolio formation date, we first sort options by moneyness (X/S) into 10 portfolios and then within each moneyness decile sort options into two portfolios by ex ante skewness. We then average the one-period returns across all moneyness-sorted portfolios to create returns of two portfolios with similar levels of moneyness but different skewness. In Panel B, we reverse this procedure, and first sort options by ex-ante skewness into 10 bins, and then within each ex ante skewness bin sort options by moneyness into two bins. We then average the one-period returns across all ex ante skewness-sorted portfolios to create returns of two portfolios with similar levels of skewness but different moneyness. We obtain CAPM pricing errors by regressing option portfolio returns on excess market returns as in equation (5). In the final rows of each panel, we report differences in CAPM pricing errors across the two conditionally sorted portfolios along with Newey-West (1987) t-statistics. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Controlling for Moneyness

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Rank	7	18	48	7	18	48
Low	−8.05***	0.54	0.25	−14.43***	−1.63	0.35
High	−16.86***	−3.64***	−1.32**	−24.13***	−6.70***	−1.40*
Low − High	8.81***	4.17***	1.57***	9.70***	5.07***	1.76***
(t-stat)	(4.93)	(3.73)	(2.58)	(4.05)	(4.66)	(2.68)

Panel B: Controlling for Ex Ante Skewness

	Calls: Days to Expiration			Puts: Days to Expiration		
Moneyness Rank	7	18	48	7	18	48
Low	−10.73***	−1.61	−0.58	−20.32***	−3.60**	0.07
High	−14.20***	−1.50	−0.51	−18.29***	−4.74***	−1.13**
Low − High	3.48*	−0.11	−0.07	−2.04	1.14	1.20**
(t-stat)	(1.91)	−(0.09)	−(0.12)	−(0.91)	(1.01)	(2.41)

We report results controlling for ex ante coskewness in Panel A of Table X. We estimate ex ante coskewness at the individual option level under the assumption that stock returns are lognormal. Using the results of Lien (1985), we obtain an ex ante estimate of the coskewness measure of Harvey and Siddique (2000) for each option, denoted as β^{skd}, as follows:

$$\beta^{skd}_{i,t:T} = \frac{E_t\left[\epsilon_{i,t:T}\,\epsilon^2_{M,t:T}\right]}{\sqrt{E_t\left[\epsilon^2_{i,t:T}\right]}E_t\left[\epsilon^2_{M,t:T}\right]}, \tag{7}$$

where t and T represent the portfolio formation date and expiration date of the option, $\epsilon_{i,t:T}$ is the component of the option return (from t to T) orthogonal to the market return, and $\epsilon_{M,T}$ is the deviation of the market return

Table X

Double Sorts on Ex Ante Coskewness

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. In Panel A, we adopt a double sort procedure to net out the influence of ex ante coskewness. For a given portfolio formation date, we first sort options by ex ante coskewness (as given in Section A.2) into 10 portfolios and then within each ex ante coskewness decile sort options into two portfolios by ex ante skewness. We then average the one-period returns across all ex ante coskewness-sorted portfolios to create returns of two portfolios with similar levels of coskewness but different total skewness. In Panel B, we reverse this procedure, and first sort options by ex ante skewness into 10 bins, and then within each ex ante skewness bin sort options by ex ante coskewness into two bins. We then average the one-period returns across all ex ante skewness-sorted portfolios to create returns of two portfolios with similar levels of skewness but different coskewness. We obtain CAPM pricing errors by regressing option portfolio returns on excess market returns as in equation (5). In the final rows of each panel, we report differences in CAPM pricing errors across the two conditionally sorted portfolios along with Newey-West (1987) t-statistics. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Controlling for Ex Ante Coskewness

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Rank	7	18	48	7	18	48
Low	−2.36	0.89	0.38	−4.42**	−0.86	0.08
High	−22.50***	−3.98**	−1.46**	−34.03***	−7.47***	−1.13
Low − High	20.14***	4.87***	1.84***	29.61***	6.60***	1.21
(t-stat)	(8.79)	(4.51)	(4.73)	(10.68)	(4.07)	(1.26)

Panel B: Controlling for Ex Ante Skewness

	Calls: Days to Expiration			Puts: Days to Expiration		
Coskew Rank	7	18	48	7	18	48
Low	−15.90***	−2.83**	−0.85*	−21.03***	−3.96***	−0.31
High	−9.09***	−0.29	−0.23	−17.59***	−4.38***	−0.74
Low − High	−6.81***	−2.54**	−0.62	−3.44	0.42	0.43
(t-stat)	−(2.59)	−(2.14)	−(1.38)	−(1.34)	(0.33)	(0.66)

(over t to T) from its expected value. We estimate the ex ante moments of these residuals assuming the option's underlying stock return and the market return are jointly lognormal in the same manner that we estimate ex ante skewness. Our measure of ex ante coskewness is a function of moneyness, maturity, option price, stock price, and the first two moments of stock and market returns including the covariance. We provide additional details in the Appendix.

In Table X, we see that controlling for ex ante coskewness has a relatively small impact on our results. In Panel A the CAPM α spread for seven-day call options is 20.14% per week (t-statistic of 8.79) while for seven-day put options the spread is as high as 29.61% per week (t-statistic of 10.68). Hence, CAPM α spreads are somewhat smaller than those in Table V, where we sort unconditionally on ex ante skewness. The results of Table X, however, are not consistent with models that suggest only coskewness is priced.

We again conduct a conditional sort exercise where we reverse the order of sorting and report the CAPM α's of these conditionally sorted portfolios in Panel B of Table X. After controlling for ex ante skewness, we find that α spreads across ex ante coskewness portfolios are generally insignificant and small compared to those of Panel A. If anything, short maturity call options with *lower* coskewness earn *lower* returns, holding total skewness fixed, contrary to the traditional coskewness pricing models.[25] The results of Table X not only provide empirical support for new models that suggest total skewness is priced, but also further highlight the unique ability of our ex ante skewness measure to explain the cross-section of option returns since our measure of ex ante coskewness is a function of the same inputs as our measure of ex ante skewness.

In the Internet Appendix we also conduct this double-sort exercise using as control variables each of the four characteristics considered in our Fama-MacBeth regressions (moneyness, volume, bid-ask spread, and volatility smirk), the past six-month underlying stock return, option vega, and each of the inputs into our measure of ex ante skewness (stock price, stock volatility, option price, and stock expected return). We control for the past six-month underlying stock return as a control for momentum. We use vega as a proxy for an option's sensitivity to volatility risk. We also individually control for each input into our measure of ex ante skewness to verify that our pricing results are not unduly driven by a single input that may proxy for some other priced risk or characteristic. Our findings remain after controlling for each of these other variables. The low average returns we document cannot be easily explained by liquidity effects, volatility smirk, momentum, volatility risk, or any single input to our ex ante skewness measure.

IV. CAPM α's from Writing Options

The returns we calculate to produce all results thus far use the midpoint of closing bid and ask prices as the proxy for the "true" price. In Table III, we show that bid-ask spreads are monotonically increasing in skewness at all horizons. The return spreads we document across ex ante skewness quintiles, therefore, are even larger for investors who buy options near the ask.

In Table XI, we report the CAPM α's earned across our sample from writing options at the bid price. We obtain these α's from estimating the one-factor model given in equation (5) using option portfolio returns computed at bid prices. Table XI shows that investors who write options with high ex ante skewness generally earn CAPM α's that are insignificantly different from zero and sometimes negative. The premiums investors pay to buy options with high ex ante skewness are not passed on to investors who write options. The only high ex ante skewness portfolio with positive CAPM α is put options that

[25] In the Internet Appendix, we report results after unconditionally sorting on ex ante coskewness and find no significant relation between ex ante coskewness and option α's.

Table XI

CAPM Pricing Errors from Writing Options at the Bid

This table reports the estimated CAPM pricing errors for portfolios of individual equity call options taken from the Ivy database over the period 1996 to 2009. The portfolios are constructed by sorting on expected skewness as in equation (4) and the returns are holding-period returns to expiration as in equation (3) for calls, multiplied by −1 to indicate returns from writing options, using the bid price in the denominator. We obtain β's by regressing option portfolio returns on excess market returns as in equation (5). Panel A reports results for calls while Panel B reports results for puts. In the final rows of each panel we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM t-statistics calculated using the approach of Newey and West (1987), which tests whether these differences are equal to zero.

	Calls: Days to Expiration			Puts: Days to Expiration		
Skew Quintile	7	18	48	7	18	48
Low	−2.44***	−1.42***	−0.88**	−1.29	−0.77	−1.00**
2	−3.88**	−2.99***	−1.29**	−4.00**	−2.49***	−1.15**
3	−6.42**	−5.20***	−1.52**	−5.85*	−3.32**	−0.91
4	−15.45***	−9.61***	−1.20	−0.69	−4.26*	−0.69
High	−4.80	−10.26***	−0.78	24.46***	−1.29	−0.73
Low − High	2.35	8.84***	−0.10	−25.75***	0.52	−0.27
(t-stat)	(0.32)	(2.76)	−(0.11)	−(3.84)	(0.14)	−(0.13)

expire in seven days. Further, differences in CAPM α's across the high and low skewness quintiles are generally insignificant. The only exceptions are for call options that expire in 18 days, in which case the CAPM α in the high ex ante skewness portfolio is significantly *lower* (Low minus High equals 8.84), and for put options that expire in seven days (Low minus High equals −25.75).

To the extent that bid-ask spreads represent the cost of holding inventory that cannot be perfectly hedged, the results of Table XI suggest that intermediaries are better able to hedge their long positions in lottery-like options than short positions, since estimated CAPM α's using bid prices for options with high ex ante skewness are more closely aligned with the zero CAPM α's of the underlying assets. Further, the ability of dealers to hedge long positions does not vary with the ex ante skewness properties of the option. On the other hand, results reported previously indicate that dealers cannot easily hedge the risk of incurring extreme losses on their short option positions with high ex ante skewness, and demand compensation to bear such risk.

To further verify that our results indeed provide evidence for skewness preference, and to investigate the extent to which investors actually transact at or near the ask price, we analyze a small set of transaction data gathered from Bloomberg, which provides trade and quote data on every option transaction on every major U.S. exchange in the recent past. Using our screened data, we begin by choosing 30 underlying stocks at random among the top quintile of all stocks ranked by total option trading volume in 2009. We then gather trade and quotes for options with three different maturities (7 days, 18 days, and 48 days) during the months of April, May, and June of 2011. Specifically, on the first trading date of these three months, we pull all transaction data for all options that expire within the same month (options with 18 days to expiration) or

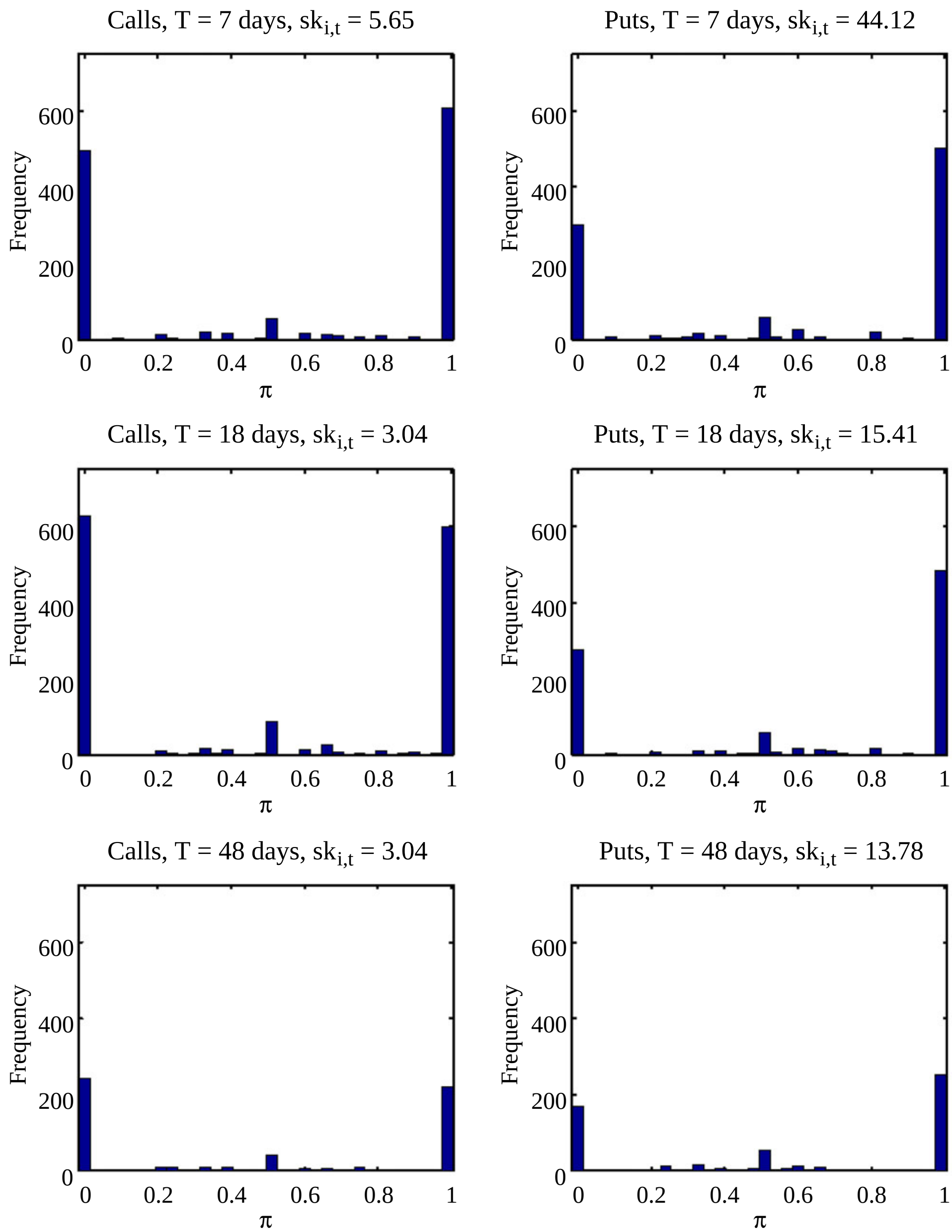

Figure 3. Frequency of trades at bid and ask. This figure reports histograms of $\pi = (Trade - Bid)/(Ask - Bid))$ for end of day option prices on options taken from Bloomberg during April, May, and June 2011. We limit our data on each transaction date to the top ex ante skewness ($sk_{i,t:T}$) quintile for calls and similarly for puts.

expire the following month (options with 48 days to expiration). We also pull all transaction data on the second Friday of each month for all options that expire that month (options with seven days to expiration). We gather the option price for each transaction, as well as the most recent best bid and ask prices quoted at least one second prior to the option transaction time stamp. We then limit our data to the top quintile of call options and the top quintile of put options ranked by ex ante skewness on each transaction date. This procedure leaves us with data on 5,992 transactions.

We then calculate the position of each transaction price relative to the best bid and ask price as

$$\pi = \frac{trade - bid}{ask - bid}, \tag{8}$$

and plot histograms of π in Figure 3. Here we see that options in our sample generally trade right at the ask or bid, with approximately half trading right at the ask. For example, among call options that expire in seven days 50% of all trades occur at the ask, and among put options that expire in seven days 47% of all trades occur at the ask. Hence, many investors appear willing to buy options with high ex ante skewness at or near the ask price despite the high premiums they must pay to intermediaries.

V. Conclusion

We find evidence suggesting that the impact of skewness preference on prices and subsequent returns of individual equity options is large. Our results also lend support to the view that total skewness is more relevant to the pricing of options than coskewness. Investors are willing to compromise as much as 50% per *week* in order to gain exposure to options with the greatest lottery potential. In comparison, recent papers on the effect of skewness in equities markets find that lottery-preferring investors are willing to lose on average around 12% per year to hold stocks offering the greatest lottery potential among equities. The differential impact of skewness preference on equity and options markets is likely driven by at least two factors. First, option markets offer skewness opportunities that are multiples of those offered in the equity market. Second, the precise lottery features that attract skewness-preferring investors to these securities increase the risk that short-sellers, whose positions cannot be completely hedged, will be wiped out, and thus act as a limit-to-arbitrage. Our results suggest that attention to the lottery prospects of securities may deepen our understanding of investor preferences and asset prices in equilibrium. More research is needed to understand how lottery prospects, skewness-preferring investors, and the incentives to arbitrage skewness (sell lottery tickets) by smart or institutional money interact.

Initial submission: December 16, 2011; Final version received: January 17, 2014
Editor: Campbell Harvey

Appendix A: Ex Ante Skewness and Coskewness

In the Appendix, we demonstrate how our ex ante skewness and coskewness measures, $sk_{i,t:T}$ and $\beta^{skd}_{i,t:T}$, are constructed assuming lognormal stock prices. We make use of Lien's (1985) theorem regarding truncated lognormal distributions. We begin by restating Lien's (1985) theorem A.1.

THEOREM A.1: *Let $(u_1, u_2)'$ be a normal random vector with mean $(0,0)'$ and covariance matrix $= [\begin{smallmatrix}\sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2\end{smallmatrix}]$. Then*

$$E(\exp(ru_1 + su_2) \mid u_1 > a) = N\left(\frac{h-a}{\sigma_1}\right)\frac{\exp[-D/2Q]}{N(\frac{-a}{\sigma_1})},$$

where $h = r\sigma_1^2 + s\sigma_{12}$, $D = -Q\left(r^2\sigma_1^2 + 2rs\sigma_{12} + s^2\sigma_2^2\right)$, $Q = \sigma_2^2\sigma_1^2 - \sigma_{12}^2$, and $N(\cdot)$ is the CDF of the normal.

A.1. Ex Ante Skewness

In this section, we show how we construct ex ante skewness measure $sk_{i,t:T}$. To begin, we first note that Lien's (1985) theorem A.1 can be used to derive closed-form solutions for the raw moments of option returns given by equation (4). These raw moments can be substituted into equation (2) to construct $sk_{i,t:T}$. We walk through the solution of equation (4) for the case when $j = 1$. Solving the cases when $j = 2$ or $j = 3$ simply involves more algebra. For $j = 1$, equation (4) can be written as

$$E\left[R^c_{t:T}\right] = \left[\frac{S_t}{C_t}E\left(\frac{S_T}{S_t}|\frac{S_T}{S_t} > \frac{X}{S_t}\right) - \frac{X}{C_t}\right]P\left(\frac{S_T}{S_t} > \frac{X}{S_t}\right), \tag{A1}$$

where S_t is the value of the underlying asset at time $t < T$ and we suppress the subscript i for clarity. Let $\tilde{r} = \ln(S_T/S_t)$, the log stock return, and define A as $A = \ln(X/S_t)$. Then equation (A1) can be written as

$$E\left[R^c_{t:T}\right] = \left[\frac{S_t}{C_t}E\left(e^{\tilde{r}}|\tilde{r} > A\right) - \frac{X}{C_t}\right]P(\tilde{r} > A). \tag{A2}$$

Now assume that $\tilde{r}$ is distributed $N(\tilde{\mu}, \tilde{\sigma}^2)$, where in general $\tilde{\mu}$ can be nonzero. Under this assumption, the stock return, S_T/S_t, is lognormal. Further, define $z = \tilde{r} - \tilde{\mu}$, so that z is distributed $N(0, \tilde{\sigma}^2)$. Then note that

$$E\left(e^{\tilde{r}}|\tilde{r} > A\right) = E\left(e^{z+\tilde{\mu}}|z > A - \tilde{\mu}\right) \tag{A3}$$

$$= e^{\tilde{\mu}}E\left(e^{z}|z > A - \tilde{\mu}\right). \tag{A4}$$

A direct application of Lien's (1985) theorem implies that equation (A4) can be written as

$$E\left(e^{\tilde{r}}|\tilde{r} > A\right) = \frac{\exp\left[\tilde{\mu} + \frac{\tilde{\sigma}^2}{2}\right] N(\bar{d}_1)}{N(\bar{d}_2)}, \tag{A5}$$

where $\bar{d}_1 = \frac{\tilde{\sigma}^2 + ln(\frac{S_t}{X}) + \tilde{\mu}}{\tilde{\sigma}}$ and $\bar{d}_2 = \bar{d}_1 - \tilde{\sigma}$. Note that $P(\tilde{r} > A) = N(\bar{d}_2)$. We can then plug equation (A5) into equation (A2) to get the first moment of the call option return,

$$E\left[R^c_{t:T}\right] = \frac{S_t}{C_t} \exp\left[\tilde{\mu} + \frac{\tilde{\sigma}^2}{2}\right] N(\bar{d}_1) - \frac{X}{C_t} N(\bar{d}_2). \tag{A6}$$

Following this same approach, we calculate the raw holding-period call return moments $E[(R^c_{t:T})^2]$ and $E[(R^c_{t:T})^3]$,

$$E\left[\left(R^c_{t:T}\right)^2\right] = \frac{S_t^2 \exp\left[2\tilde{\sigma}^2 + 2\mu\right]\left[N\left(\bar{d}_3\right)\right] - 2XS_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \mu\right] N\left(\bar{d}_1\right)}{C_t^2} + \frac{X^2 N\left(\bar{d}_2\right)}{C_t^2}, \tag{A7}$$

$$E\left[\left(R^c_{t:T}\right)^3\right] = \frac{S_t^3 \exp\left[\frac{9}{2}\tilde{\sigma}^2 + 3\tilde{\mu}\right] N\left(\bar{d}_4\right) - 3XS_t^2 \exp\left[2\tilde{\sigma}^2 + 2\tilde{\mu}\right] N\left(\bar{d}_3\right)}{C_t^3} + \frac{3X^2 S_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(\bar{d}_1\right) - X^3 N\left(\bar{d}_2\right)}{C_t^3}, \tag{A8}$$

where $\bar{d}_3 = \bar{d}_1 + \tilde{\sigma}$, and $\bar{d}_4 = \bar{d}_1 + 2\tilde{\sigma}$.

The corresponding raw moments for put options are

$$E\left[R^p_{t:T}\right] = \frac{XN\left(-\bar{d}_2\right) - S_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N(-\bar{d}_1)}{P_t}, \tag{A9}$$

$$E\left[\left(R^p_{t:T}\right)^2\right] = \frac{X^2 N\left(-\bar{d}_2\right) - 2XS_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(-\bar{d}_1\right)}{P_t^2} + \frac{S_t^2 \exp\left[2\tilde{\sigma}^2 + 2\tilde{\mu}\right]\left[N\left(-\bar{d}_3\right)\right]}{P_t^2}, \tag{A10}$$

$$E\left[\left(R^{p}_{t:T}\right)^{3}\right] = \frac{X^{3}N\left(-\bar{d}_{2}\right) - 3X^{2}S_{t}\exp\left[\frac{\tilde{\sigma}^{2}}{2} + \tilde{\mu}\right]N\left(-\bar{d}_{1}\right)}{P^{3}_{t}} + \frac{3XS^{2}_{t}\exp\left[2\tilde{\sigma}^{2} + 2\tilde{\mu}\right]N\left(-\bar{d}_{3}\right) - S^{3}_{t}\exp\left[\frac{9}{2}\tilde{\sigma}^{2} + 3\tilde{\mu}\right]N\left(-\bar{d}_{4}\right)}{P^{3}_{t}}, \tag{A11}$$

where P_t is the put premium at time t. Equations (A6) through (A11) can be used to construct $sk_{i,t:T}$ for both call and put options for any level of moneyness, maturity, stock volatility, and expected stock return.

A.2. Ex Ante Coskewness

In this section, we demonstrate how we construct estimates for $\beta^{skd}_{i,t:T}$ as defined in equation (7). Our approach follows that of the prior section's construction of the ex ante skewness measure, $sk_{i,t:T}$. To begin, we define $\epsilon_{i,t:T}$ as

$$\epsilon_{i,t:T} = R_{i,t:T} - \alpha^{LN}_{i,t} - \beta^{LN}_{i,t}(R_{M,t:T}), \tag{A12}$$

where $R_{i,t:T}$ is the simple holding-period option return (either call or put) observed at maturity as in equation (1), $R_{M,t:T}$ is the corresponding market return observed over the same period, and $\alpha^{LN}_{i,t}$, $\beta^{LN}_{i,t}$ are ex ante coefficients defining the linear relationship under the assumption that stock and market returns are jointly lognormal. Using equation (A12), we define the deviation of the market return from its expected value, $\alpha^{LN}_{M,t}$, as

$$\epsilon_{M,t:T} = R_{M,t:T} - \alpha^{LN}_{M,t},$$

where LN superscripts denote the linear relationship under lognormality and time subscripts indicate when variables are observed. Below we drop the LN superscripts for expositional ease when the meaning is clear. The numerator of $\beta^{skd}_{i,t:T}$ defined by equation (7) can then be written as

$$\begin{aligned} E\left[\epsilon_{i}\epsilon^{2}_{M}\right] &= E\left[(R_{i} - \alpha_{i} - \beta_{i}R_{M})(R_{M} - \alpha_{M})^{2}\right] \\ &= E\left[R_{i}R^{2}_{M}\right] - 2\alpha_{M}E[R_{i}R_{M}] + \alpha^{2}_{M}E[R_{i}] + (2\beta_{i}\alpha_{M} - \alpha_{i})E\left[R^{2}_{M}\right] \\ &\quad + \alpha_{i}\alpha^{2}_{M} - \beta_{i}\alpha^{3}_{M} - \beta_{i}E\left[R^{3}_{M}\right], \end{aligned} \tag{A13}$$

and the denominator of $\beta^{skd}_{i,t:T}$ defined by equation (7) can be written as

$$\begin{aligned} \sqrt{E\left[\epsilon^{2}_{i,T}\right]}E\left[\epsilon^{2}_{M,T}\right] &= \left(E\left[R^{2}_{i}\right] + \alpha^{2}_{i} + \beta^{2}_{i}E\left[R^{2}_{M}\right] - 2\alpha_{i}E\left[R_{i}\right] - 2\beta_{i}E\left[R_{i}R_{M}\right]\right. \\ &\quad \left. + 2\beta_{i}\alpha_{i}\alpha_{M}\right)^{1/2} + E\left[R^{2}_{M}\right] - \alpha^{2}_{M}. \end{aligned} \tag{A14}$$

Now define $\beta^{LN}_{i,t:T}$ as

$$\beta^{LN}_{i,t:T} = \frac{E[R_i R_M] - E[R_i]E[R_M]}{E\left[R_M^2\right] - E[R_M]^2} \tag{A15}$$

and $\alpha^{LN}_{i,t:T}$ as

$$\alpha^{LN}_{i,t:T} = E[R_i] - \beta_i E[R_M]. \tag{A16}$$

The numerator and denominator of $\beta^{skd}_{i,t:T}$ given by equations (A13) and (A14) can be seen as functions of $E[R_i^j]$, $E[R_M^j]$, and $E[R_i R_M^j]$ for $j = \{1, 2, 3\}$.

As noted in Section A.1, the log stock return underlying option i is denoted as $\tilde{r}_i = \ln(S_T/S_t)$, with mean $\tilde{\mu}_i$ and variance $\tilde{\sigma}_i^2$, where subscript i references the option and again we note that superscript $\sim$ indicates association with the underlying as opposed to the option. Given this assumption, we can derive option return moments, $E[R_i^j]$ for $j = \{1, 2, 3\}$, from equations (A6) through (A11) for both calls and puts. Further, define $\tilde{r}_M = \ln(R_M)$, the log market return, and assume that $\tilde{r}_M$ is distributed $N(\tilde{\mu}_M, \tilde{\sigma}_M^2)$. We can also calculate $E[R_M^j]$ using the properties of the lognormal distribution,

$$E\left[R_M^j\right] = \exp\left(j\tilde{\mu}_M + \frac{1}{2}j^2\tilde{\sigma}_M^2\right). \tag{A17}$$

Again from Section A.1, we define $A = \ln(X/S_t)$ and let option i be a call option with return R_i^c and price C_t. We can then write $E[R_i^c R_M^j]$ as

$$E\left[R_i^c R_M^j\right] = \left[\frac{S_t}{C_t}E\left(e^{\tilde{r}_i + j\tilde{r}_M}|\tilde{r}_i > A\right) - \frac{X}{C_t}E\left(R_M^j|\tilde{r}_i > A\right)\right]P\left(\tilde{r}_i > A\right). \tag{A18}$$

Let $\tilde{\sigma}_{i,m}$ denote the covariance between the stock underlying option i and the market. Applying the results of Lien (1985), equation (A18) can be written as

$$\begin{aligned} E\left[R_i^c R_M^j\right] = {} & N(\bar{q}_1)\frac{S_t}{C_t}\exp\left[\tilde{\mu}_i + j\tilde{\mu}_M + \frac{(\tilde{\sigma}_i^2 + 2j\tilde{\sigma}_{iM} + j^2\tilde{\sigma}_M^2)}{2}\right] \\ & -N(\bar{q}_2)\frac{X}{C_t}\exp\left[j\tilde{\mu}_M + \frac{j^2\tilde{\sigma}_M^2}{2}\right], \end{aligned} \tag{A19}$$

where $\bar{q}_1 = \frac{\tilde{\sigma}_i^2 + j\tilde{\sigma}_{iM} - A + \tilde{\mu}_i}{\tilde{\sigma}_i}$ and $\bar{q}_2 = \bar{q}_1 - \tilde{\sigma}_i$. If option i is a put option with return R_i^p and price P_t, then we have

$$\begin{aligned} E\left[R_i^p R_M^j\right] = {} & N(-\bar{q}_2)\frac{X}{P_t}\exp\left[j\tilde{\mu}_M + \frac{j^2\tilde{\sigma}_M^2}{2}\right] \\ & -N(-\bar{q}_1)\frac{S_t}{P_t}\exp\left[\tilde{\mu}_i + j\tilde{\mu}_M + \frac{(\tilde{\sigma}_i^2 + 2j\tilde{\sigma}_{iM} + j^2\tilde{\sigma}_2^2)}{2}\right]. \end{aligned} \tag{A20}$$

We estimate $\tilde{\mu}_i$, $\tilde{\sigma}_i^2$, $\tilde{\mu}_M$, $\tilde{\sigma}_M^2$, and $\tilde{\sigma}_{iM}$ using six months of daily data prior to t and use these to estimate $E[R_i^j]$, $E[R_M^j]$, and $E[R_i^c R_M^j]$ for $j = \{1, 2, 3\}$ as defined by equations (A6) through (A11), (A17), (A19), and (A20). We then plug these estimated moments into equations (A13) to (A16) to obtain estimates of ex ante coskewness as defined in equation (7).

Appendix B: Option Database Screening Procedure

We create portfolios on the first trading date of each month. Let t_i be the formation date for portfolio i. We eliminate all options from portfolio i with any of the following characteristics observable in the Ivy database on or before date t_i:

(1) *Underlying Asset Is an Index*: Optionmetrics "index flag" is nonzero.
(2) *Underlying Asset Is Not Common Stock*: Optionmetrics "issue˙type" for underlying is nonzero.
(3) *AM Settlement*: The option expires at the market open of the last trading day, rather than the close.
(4) *Nonstandard Settlement*: The number of shares to be delivered may be different from 100, additional securities and/or cash may be required, and/or the strike price and premium multipliers may be different from \$100 per tick. Optionmetrics "special settlement flag" is nonzero.
(5) *Missing Bid Price*: The bid price on date t_i is 998 or 999. Ivy uses these as missing codes for some years.
(6) *Abnormal Bid-Ask Spread*: The bid-ask spread on date t_i is negative or greater than \$5.
(7) Abnormal Δ: The option Δ on date t_i, as calculated by Ivy, is below -1, above $+1$, or missing.
(8) *Abnormal Implied Volatility*: Implied volatility on date t_i , as calculated by Ivy, is less than zero or missing.[26]
(9) *Extreme Price*: The midpoint of the bid and ask price is below 50% of intrinsic value or \$100 above intrinsic value.
(10) *Duplicates*: Another record exists on date t_i for an option of the same type (call or put), on the same underlying asset, with the same time-to-maturity and same strike price.
(11) *Zero Open Interest*: Open interest on the trading date immediately prior to date t_i is zero.
(12) *No Trade*: The Optionmetrics "last_date" value is before t_i.
(13) *Underlying Price History in CRSP Is Too Short*: The underlying asset does not have at least 100 nonmissing daily returns in CRSP over the six-month period prior to date t_i.

[26] Duarte and Jones (2007) argue that eliminating options that do not have a reported Δ or implied volatility in the Ivy Optionmetrics database induces a bias in measuring average returns. We have estimated the α's based on regression β's for Tables VI and VII after including these observations, and find that our results don't change.

(14) *Expiration Restrictions*: The expiration month is greater than $m_i + 6$, where m_i is the month in which portfolio i is formed, or the option expires after 2009.

Screens 1 and 2 allow us to focus on options written on common stock. We follow Duarte and Jones (2007) in applying screens 3 through 11. Screen number 12 helps exclude stale option quotes from the analysis. We apply screen 13 because we use six months of daily data from CRSP prior to date t_i to estimate moments of underlying assets, and we apply screen 14 because of data limitations.

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Supporting Information

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Appendix S1: Internet Appendix.