Stock Options as Lotteries

Brian H. Boyer and Keith Vorkink[1]

This Version: December 16, 2011

[1]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, Francis Longstaff, Josh Pollet, Tyler Shumway, and seminar participants at Brigham Young University, Florida State, and the University of Michigan for helpful comments and suggestions. We also thank Greg Adams and Troy Carpenter for research support. Contact Information: Both authors are from the Marriott School of Management, 640 TNRB, Brigham Young University, Provo, UT 84602. Boyer: 801-422-7641, bhb@byu.edu. Vorkink: 801-422-1765, keith_vorkink@byu.edu.

ABSTRACT

We find strong evidence of a negative cross-sectional relationship between ex-ante total skewness and risk-adjusted returns on individual equity options, consistent with the predictions of recent theoretical asset-pricing models. The alphas of option portfolios with high ex-ante skewness in some cases are less than -50 percent per *week*, even though the alphas of the underlying stocks are insignificant from zero. We demonstrate that the negative relationship between ex-ante skewness and option returns is not subsumed by moneyness. Simulations further indicate that our findings are also robust to various statistical features of option returns such as non-normality, non-linearity, and peso problems. Our results suggest that the ability of intermediaries to effectively hedge short positions in individual options deteriorates with ex-ante skewness. Intermediaries are therefore compensated for bearing unhedgable risk when accomodating the relatively high investor demand for lottery-like options.

I. Introduction

Research by financial economists over the last few decades 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. Additional evidence from experimental economists suggests that individuals deviate from standard utility theory when making choices in the face of uncertainty (see for example Kahneman and Tversky, 1979). As a result, many have turned their attention to the asset pricing implications of models that depart from the standard representative-agent/expected-utility framework.

One prominent theme in this literature is that investors exhibit a preference for skewness, or lottery-like features in asset return distributions, and that such preferences can influence asset prices in equilibrium. In particular, the endogenous probabilities model of Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007), the heterogeneous skewness preference model of Mitton and Vorkink (2006), and the cumulative prospect theory model of Barberis and Huang (2008), all predict that skewed assets have abnormally low expected returns. Earlier models predict that *co-skewness* with the market is priced (Kraus and Litzenberger (1976) and Harvey and Siddique (2000)). In contrast, the recent models mentioned above posit that *total* skewness, including idiosyncratic skewness, is priced because investors seeking lottery-like assets optimally choose to hold underdiversifed portfolios.[1]

The stock market proved to be the initial testing ground for these new models. Zhang (2005), Boyer, Mitton, and Vorkink (2010) and Conrad, Dittmar and Ghysels (2010) indeed provide evidence that stocks with high ex-ante skewness earn abnormally low risk-adjusted returns. While empirical asset pricers commonly use equities as test assets in their research, options may offer more fertile ground to better clarify our understanding of skewness preference and its corresponding influence on asset prices for two reasons. First, the enormous implicit leverage in an option contract combined with its nonlinear payoff structure creates skewness in option returns impossible to replicate in the underlying equity market given realistic market

[1] Work on skewness preferences pre-dates the articles cited above. Arditti (1967) and Scott and Horvath (1980) show that well-behaved utility functions include a preference for positive skewness. 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.

frictions. Second, cross-sectional variation in skewness is much easier to identify among options than among stocks, both for the investor and the econometrician.

We construct a simple ex-ante option return skewness measure by integrating the appropriate PDF for option returns under the assumption that stock prices are lognormal. The option return PDF depends only on the first two moments of the underlying stock return, the strike price, the option price, and the expiration date of the option. Under the assumption of stock price lognormality this measure estimates the true option holding period return skewness. More importantly we empirically test whether the measure predicts realized skewness in option returns. Our findings indicate that, in fact, our ex-ante skewness measure strongly predicts realized option return skewness. We also find that cross-sectional variation of skewness in option returns is dramatically higher than that in stocks.[2] Most, but not all, of the cross-sectional variation in our ex-ante skewness measure appears to be driven by differences in moneyness.

We therefore investigate the relationship between total ex-ante skewness and average returns in the cross section of individual equity options. We focus on individual equity options rather than index options for two primary reasons. First, individual equity options exhibit greater cross-sectional variation in expected skewness than index options. Second, since individual equity options are more difficult to hedge than index options, their prices are likely to respond to demand pressure arising from non-standard preferences. If competitive intermediaries can hedge perfectly, then option prices must be consistent with no arbitrage; options are merely levered positions in the stock. In reality, however, even intermediaries cannot hedge their option positions perfectly 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. Garleanu, Pedersen, and Poteshman's (2009) model of option pricing illustrates that demand pressure on an option's price is related to the variance of the unhedgeable part of the option.[3] Building on this work, we begin to uncover sources of such demand pressure. Our results indicate that skewness preference causes both calls and

[2]See Boyer, Mitton, and Vorkink (2010) or Conrad, Dittmar, and Ghysels (2010) for empirical estimates of skewness for equities.

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

puts with lottery-like characteristics to be over-valued relative to the underlying assets on which they are written, and may be of *first-order* importance in the pricing of securities with substantial skewness such as options.

Following early empirical asset pricing research on index options markets (see Coval and Shumway, (2001), and Jones (2006)), we employ traditional portfolio sorts and Fama-MacBeth (1973) regressions rather than estimate the parameters of a fully specified parametric model. Recent studies that apply similar techniques to individual equity options include Duarte and Jones (2007), who estimate Fama-Mcbeth regressions on a cross section of stock option portfolios, and Broadie, Chernov and Johannes (2009), who estimate alphas for index options. Both of these recent papers acknowledge and address a number of potential concerns regarding the use of standard empirical methods with options including non-normality, non-linearity, peso problems, and measurement error. Following this literature, we make an effort to carefully address the robustness of our findings to these issues.

We find that the average returns on portfolios of highly-skewed options are both statistically and economically lower than the returns on portfolios of options with less skewness. The spread in average returns across skewness-sorted portfolios is on the order of 10% per *week* and in some cases greater than 60% per *week*. These results are found in both call and put option markets. We find that the strong negative relationship between average returns and skewness holds across a number of maturities ranging from one week through five months.

Having found such dramatic spreads in average returns, we then investigate if our findings can be explained by cross-sectional differences in risk or other option characteristics. We estimate CAPM alphas using two different approaches and find the spread in alphas across skewness-sorted portfolios of options to be on the order of 10% to 50% per week, even though the CAPM alphas of the underlying stock are insignificant from zero. We also find in Fama-McBeth regressions a negative and significant relationship between the cross section of option returns and our measure of ex-ante skewness that persists after including market, volatility risk, and momentum betas as explanatory variables along with other option characteristics, including volume, bid-ask spread, volatility smirk (Pan (2002) and Xing, Zhang, and Zhao (2011)), and even moneyness (Ni (2007)). We also use conditional double sorts to control for the influence of these characteristics and find that significant spreads in alpha remain across our ex-ante skewness-sorted portfolios after doing so. We then reverse the order of our sorting procedure and find that after first controlling for ex-ante skewness, alpha spreads across *moneyness*-sorted portfolios lose their significance. Hence, although moneyness is a very important determinant of our ex-ante skewness measure, our findings are not subsumed by any option characteristic related to moneyness.

We then address issues regarding the application of standard empirical methods to option returns. We first investigate whether the substantial deviation of option return distributions from normality invalidates the use of asymptotic inference. To do this we estimate bootstrapped p-values for our measured alpha spreads and find that our conclusions regarding significance do not change. We then investigate whether peso problems or nonlinearities might be driving our results. In particular, we calibrate a simulation similar to that of Broadie, Chernov and Johannes (2009) in which we impose the condition that skewness preference has no effect on option prices. We then estimate alphas in exactly the same manner as we do using our real data sample, and investigate how often we can generate results through our simulation as extreme as those found using the actual data. We find the answer to be virtually zero, suggesting these other issues cannot explain our findings.

Investors, therefore, appear willing to pay substantial premiums for the lottery-like characteristics of individual equity options. As is standard, our proxy for "true" option prices for our main results is the midpoint of closing bid and ask prices. We also find that bid-ask spreads significantly increase with skewness. Hence, from the perspective of an investor who purchases options near the ask, the average return spread between options with high and low skewness is even more dramatic than those we document. The losses of option buyers however, 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. From these results we conjecture that the ability of intermediaries to effectively hedge short positions in individual options deteriorates with the ex-ante skewness of the option. High ask prices therefore compensate intermediaries for bearing the unhedgeable risk of writing options while bid prices are more closely aligned with the text-book no arbitrage relations with the stock. Writing options with high skewness, of course, involves taking on a position with a very small chance of incurring extreme losses: a position where jump or volatility risk may be especially difficult to hedge. Hence, the precise features that attract some investors to lottery-like options may also act as a limit to arbitrage for the writer of that option. On the other hand, since potential losses on long positions are limited to the premium, these positions likely entail less unhedgeable jump or volatility risk.

Our findings however, do not appear to be merely driven by restrictions in supply by intermediaries. We find that option trading volume and open interest are significantly *increasing* in ex-ante skewness despite the extraordinary premiums investors must pay to hold lottery-like options. Further, in a small sample of data where we actually observe option transaction prices, we find that nearly half of all trades occur near or at the ask. Our findings therefore indicate that a strong preference among investors for skewness exists, consistent with the theoretical models mentioned above that depart from the standard representative-agent/expected-utility framework.

As mentioned above, others document evidence for skewness preference among stocks. While these papers support our findings, they also illustrate the challenge of the econometrician (and investor) to determine which stocks have lottery potential. Zhang (2005) uses estimates of cross-sectional skewness within stock peer groups to forecast future skewness. Boyer, Mitton, and Vorkink (2010) use a set of stock characteristics to forecast skewness in a rolling cross-sectional regression framework. Bali, Cakici, and Whitelaw (2010) use the maximum daily return as a measure of lottery potential. Conrad, Dittmar, and Ghysels (2010) obtain estimates of implied risk-neutral stock return skewness from the cross section of equity options.

Others report empirical evidence consistent with skewness preference using index options. Dierkes (2009) and Polkovnichenko and Zhao (2010) find that implied probability weighting functions under rank dependent utility extracted from S&P 500 index options are inverse-S shaped. Option traders in aggregate, therefore, behave as if they overweight the probability of extreme rare events, consistent with the modeling features of rank dependent utility (and prospect theory) meant to capture preference for lottery-like gambles.

Other researchers have studied the properties of individual option returns. Driessen, Maenhout and Vilkov (2009) find that correlation risk exposure helps explain the cross section of individual option returns. Goyal and Saretto (2009) investigate the cross section of individual equity option returns as they relate to volatility risk premiums. Perhaps the paper most closely related to ours is Ni (2009), who investigates the return properties of call options across moneyness and underlying (for a fixed maturity). She finds that out-of-the-money call option returns are low and conjectures that her findings may be due to skewness preference. Our paper is less about identifying an asset pricing anomaly, as in Ni (2009), and more about testing and assessing the magnitude of skewness-preferences in individual equity options. Further, we find that the negative relationship between option returns and ex-ante skewness persists even after controlling for moneyness.

The rest of the paper is organized as follows. Section II illustrates how to construct our ex-ante skewness measure. Section III shows how we construct option portfolios for use in our empirical tests and presents results on the overall average returns of these portfolios. Section IV presents results on average portfolio returns after controlling for risk and other option characteristics, and also investigates the influence of various statistical issues on our findings. Section V investigates the returns from writing options at the bid price. Section VI offers concluding remarks.

II. 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 an appropriate proxy for the lottery-like characteristics of options consistent with much of the behavioral literature (e.g., Brunnermeier and Parker (2005), Barberis and Huang (2007), and Mitton, and Vorkink (2006)). Ex-ante skewness is unobservable for any security and must be estimated. Zhang (2005) estimates skewness in stock returns using industry cross-sectional estimates of skewness. Boyer, Mitton, and Vorkink (2010) derive estimates of stock return skewness using firm characteristics in a predictive regression framework. Conrad, Dittmar and Ghysels (2010) use the cross section of a firm's option prices to derive a model-free estimate of risk-neutral skewness for the underlying stock.[4] We construct closed form,

[4]Conrad, Dittmar and Ghysels' (2010) approach to measuring skewness in stocks is advantageous in that it provides a model-free, forward-looking measure of skewness. However, interpretation of their measure

ex-ante skewness measures for the physical distribution of option returns by integrating the appropriate PDF under the assumption that stock prices are lognormal.[5]

A. Ex-Ante Skewness under Lognormality

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

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

where $R_{i,t:T}$, $\mu_{i,t:T}$ and $\sigma_{i,t:T}$ denote option i's return, expected return and standard deviation over the same horizon, respectively. By rewriting equation (1) in terms of its raw moments,

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

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 $(.)^+$ is the $max(0,.)$ 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. Assuming that $S_{i,T}$ is distributed lognormally, equation (3) indicates the raw moments for a call option are a function of the

is confounded by the fact that risk-neutral probabilities are a product of marginal utilities and physical probabilities.

[5] Our ex-ante skewness measure estimates the true expected skewness of option returns when stock prices are lognormally distributed. Clearly this distributional assumption is violated empirically. However, we also use this approach because it is simple and because it uses only information available to an investor at the time of option selection. The critical issue for our asset-pricing tests is whether our measure predicts realized skewness in option returns. In section 3, we show that this is the case.

raw moments of a truncated lognormal distribution. In particular, the j^{th} raw moment for call option i can be written

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

Lein (1985) derives the moments of a truncated lognormal distribution which 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 Appendix A.

B. Option Characteristics and Skewness

We construct plots to understand how different option characteristics influence our expected skewness measure, $sk_{i,t:T}$. Figure 1, which 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, 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 (2010)). 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 Figures 2 and 3 we plot the relationship between $sk_{i,t:T}$ and return volatility (σ). Figure 2 plots the relationship for options trading at a moneyness level of 0.9, corresponding to out-of-the-money put options and in-the-money call options. We see that volatility can have a strong impact on skewness, but that the magnitude of the relationship is influenced by both maturity and moneyness. In Figure 2 we see that higher return volatility results in slightly higher skewness for in-the-money call options. However, the relationship flips for out-of the money put options: higher return volatility leads to much *lower* skewness. Figure 3 plots the relationship for a moneyness level of 1.1 corresponding to in-the-money put options and out-of-the-money call 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 return volatility leads to much *lower* skewness. We observe essentially no relationship between volatility and skewness for in-the-money put options in Figure 3.

Figures 1 through 3 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.

III. 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 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 or quotes that may not be tradable. This procedure, detailed in Appendix B, eliminates options from each portfolio using information observable on or before the corresponding formation date. 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, or options that have excessive bid-ask spreads. Portfolio formation dates extend from February 1, 1996 through October 9, 2009.[6] 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 98.5 percent 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 about 99.6 percent of our observations. The other 0.4 percent 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.[7]

[6] 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.

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

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 354,402 option quotes across the 24 portfolio formation dates for this year, and the corresponding underlying asset values at expiration for 351,516 of these quotes. We are able to locate another 125 underlying asset values at expiration in CRSP, implying that we observe the corresponding underlying asset values at expiration for 99.2 percent of the original quotes (351,641). In 2009 we pull numerous underlying asset values from CRSP because our Ivy database ends October 30, 2009. For options that expire the last quarter of 2009 we must turn to CRSP to get underlying asset values at expiration. The far right column in Panel A of Table I gives the number of unique underlying assets in our data each year.

On each portfolio formation date we separate options into 40 portfolios. We first divide options among eight expiration bins and then within each expiration bin we divide options among 5 skewness bins. 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 formation dates. The second through eighth expiration bins contains options that on average expire in 18, 48, 78, 108, 138, 168 and 198 days. We form these bins on the first trading date of each month, m. The options in these bins will expire on the third Friday of month m, $m+1$, $m+2$, $m+3$, $m+4$, $m+5$, and $m+6$, respectively.[8] We eliminate options with longer expirations due to low trading volume.

On each portfolio formation date we then sort options within each expiration bin into 5 ex-ante skewness quintile bins. To estimate expected skewness as discussed in equation (2), 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. Other variables needed to compute the skewness of the option

[8]Given irregular calendar intervals between the first trading date of each month and option expiration dates the exact maturities for portfolios in the second through eight expiration bins vary slightly across time. For clarity in writing below 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."

include the underlying stock price, time to maturity, strike, and price of the option on the formation date. All of these are readily obtained from the Ivy 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 reports the number of options on average across time within each of our 40 bins. For example, there are on average 276 call options in the lowest skewness quintile bin for options that expire in 7 days.

Rows labeled "Unique Underlying" and "Underlying Span" in Panel B of Table I illustrate how often we observe the same underlying asset across different skewness bins. Among call options with 138 days to maturity, for example, we observe 188 options on average per skewness bin, or 940 options total. These options are written, on average, on 355 unique underlying assets. The same underlying asset, however, is on average observed across only 1.72 different skewness bins. The ex-ante screens mentioned above prevent us from observing options written on a broad cross section of strikes for the same underlying asset on the same portfolio formation date.

Panel A of Table II reports the average, across 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 7 days, expected skewness ranges from 0.40 to 24.94. In comparison, the typical skewness for a stock varies from around 0 up to 3 (see, for example Boyer, Mitton, and Vorkink (2010)).

In unreported results we examine the influence of moneyness and underlying asset volatility on the cross-sectional variation in skewness documented in Panel A of Table II using a double sorting exercise similar to Ang, Hodrick, Xing, and Zhang (2006, 2008).[9] After controlling for moneyness, the spread in ex-ante skewness for options across the first and fifth skewness quintiles drops by about 90 percent for short dated options, and by about 30 percent for longer

[9] On each portfolio formation date we first sort options of a given maturity into 5 portfolios based on a characteristic, either moneyness or volatility. Then within each characteristic-sorted portfolio, we sort options into five ex-ante skewness portfolios. We then average the ex-ante skewness measure across each of the five characteristic-sorted portfolios separately for each of the five ex-ante skewness sorts, thereby creating five portfolios similar in terms of the characteristic while maximizing the cross-sectional variation in ex-ante skewness.

dated options. In contrast, after controlling for underlying volatility we find that these spreads drop at most by about 15 percent. Hence, cross-sectional variation in moneyness appears to be the primary influence behind our ex-ante skewness measure across options. Even so, some variation in ex-ante skewness remains even after controlling for moneyness.[10]

We next verify that our expected skewness measure actually does a good job forecasting return skewness. Empirically estimating skewness from the time-series of option returns is challenging, especially for out-of the money options, since small probability events are often not observed within a short period of time. We therefore choose to follow Zhang (2005) and empirically estimate skewness in the cross section. Since there are many more options than time periods, it is easier to capture small probability events in the cross section. It can be shown that the average cross-sectional skewness for a given bin is positively related to the average idiosyncratic skewness of the options in that bin.

We calculate the return for each option assuming it is held to expiration, as given by equation (3) for call options. In Panel B of Table II we report the time-series average of the cross-sectional skewness estimates across returns within each skewness/expiration bin. These results provide some evidence that our expected skewness measure, $sk_{i,t:T}$, does a good job as a forecast.[11] 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. These differences are all highly significant. Since our returns overlap for options with 48 or more days to maturity, these standard errors are adjusted for autocorrelation using the approach of Newey and West (1987).

B. Option Characteristics and Portfolio Returns

Table III reports summary statistics on some additional characteristics for options within each of our skewness/expiration portfolios. In Panel A we report the average bid-ask spread, defined as the difference between the closing bid and ask prices on portfolio formation dates

[10] These results and all others discussed in this paper not reported in the tables are available upon request.

[11] We also find qualitatively similar results when we use the portfolio time series skewness as our realized skewness measure.

scaled by their midpoint. In Panel B we report average trading volume, defined as the average number of contracts traded per option on portfolio formation dates. And in Panel C we report the average open interest per contract on the day prior to portfolio formation dates. We also report the standard error for the difference in each characteristic across the bottom and top skewness quintiles, calculated using the approach of Newey and West (1987), in part to account for overlapping observations of some expiration bins.

The bid-ask spreads of some option contracts are very large, and is in fact monotonically increasing with our ex-ante skewness measure for all expiration bins, but especially for options with shorter maturities. Differences in bid-ask spreads across the high and low skewness quintiles are highly significant for short-dated options. As is standard when computing option returns, our proxy for "true" option prices when calculating returns is the midpoint of the bid-ask spread. The results given by Panel A of Table III suggest that 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. Later we also investigate the return properties when we define the price at either the bid or the ask. 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 see that volume is significantly higher among options in the high skewness bins than among those in the low skewness bins for options with shorter maturities. This table illustrates that options with high skewness are actively traded, despite their relatively higher bid-ask spreads, and offers some initial evidence regarding investor preference for such contracts. In Panel C of Table III we see that open interest is monotonically increasing in skewness at all maturities for calls and at shorter maturities for puts. Moreover, open interest is significantly higher for options in the high skewness bins at all maturities for calls, and at shorter maturities for puts. These results support the findings of Panel B and further demonstrate investor preference for options with lottery-like characteristics.

Using hold-to-expiration returns calculated as illustrated by equation (3), we then calculate equally-weighted option portfolio returns for each maturity/skewness bin. Our hold-to-expiration returns ignore the possibility of early exercise. This simplification however, should have little impact 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 II. 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.[12]

Average portfolio returns, across time, are reported in Table IV. In each case returns are scaled to be weekly. This table provides some initial evidence of the influence of skewness preference on option 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 (Table II). For example, among call options that will expire in 7 days, the average weekly return is monotonically decreasing from 1.87 percent for the low skewness bin to -35.25 percent 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 puts. Among puts that will expire in 7 days, returns are again monotonically decreasing, this time from -5.38 percent for the low skewness bin to -59.98 percent 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 some expiration bins. Spreads in average returns across the high and low skewness portfolios decline in value at longer horizons, but the spread is always positive. For options at longer maturities average returns are not always monotonically decreasing, however, any observed non-monotonicity is statistically insignificant.

Results may be stronger for short-dated puts because short put positions are likely to be more difficult for intermediaries to hedge than comparable short call positions given short-

[12] In unreported tables, we adjust our returns for the possibility of early exercise, and show that doing so does not change our findings. Our results also hold after excluding any option written on an underlying asset that paid any kind of distribution between the portfolio formation date and the expiration date.

sale constraints on the stock.[13] As Garleanu, Pedersen, and Poteshman (2009) show, demand pressure on option prices is related to the variance of the unhedgeable part of the option.

Even though we observe large differences in skewness between the high- and low-skewness quintiles for long maturities in Table II, we observe little pricing differences in these longer maturities in Table IV. One potential explanations is that the lottery-like characteristics of long-dated options do not actually materialize until the option gets closer to maturity. In addition, there is uncertainty as to whether long dated options will actually end up a lottery. To investigate this hypothesis regarding the skewness of long-dated options, we present the results of a simulation exercise in Figure 4. We study a theoretical call option with six months to maturity, struck at 140, written on an underlying asset with an initial value of 100, annualized volatility of 20 percent and an annualized expected return of 15 percent. This option has an ex-ante skewness of 12.47, in the range of longer-dated options in our data as shown in Panel A of Table II. We price this option under Black-Scholes assuming the annualized risk-free rate is 3 percent. We then simulate 1,000 paths of the underlying asset over the life of the option, and value the option at the beginning of each week for each sample path. We next construct returns from buying the option at the beginning of each week and selling it at the beginning of the following week for each sample path. This gives us a sample of 1,000 weekly returns for each of the 24 weeks until the option expires. We empirically estimate the skewness for each of these weekly returns and save these 24 skewness estimates. We then repeat this exercise 5,000 times to estimate the empirical distribution of skewness for each of the 24 weeks. Figure 4 displays the average skewness measure for each week along with percentile bands.

Figure 4 provides two key insights. First, the skewness of a one-week, buy-to-sell, long-dated call option is low. In Figure 4, the average skewness over the first week is only 1.92, much lower than the ex-ante skewness of the option over the entire 6 month holding period (12.47 as mentioned above). Second, as the option approaches maturity, not only does the average skewness increase, but the *volatility* of skewness increases dramatically. Over the last week of the option, the 1^{st} percentile estimate of skewness is only 8.59 while the 99^{th} percentile

[13] Note that at shorter maturities, cross-sectional variation in skewness is actually smaller for puts than for calls in Panel A of Table II. Hence, the stronger pricing differences in Table IV for puts are not driven by higher differences in skewness.

estimate is 31.61. In other words, sometimes a long dated out-of-the-money option eventually becomes an in-the-money short dated option and offers very little skewness, while other times it remains out-of-the-money and offers even higher skewness as it approaches maturity.[14] If an investor is seeking lottery-like characteristics in options, they are much better off choosing a short dated out-of-the-money option with known lottery prospects, than holding a long-dated out-of-the-money option and hoping the contract continues to remain out-of-the money as it approaches maturity. This may help explain why the influence of skewness preference on prices does not appear to be as strong on long-dated options in Table IV. As well, options with longer maturities are likely to be easier for intermediaries to hedge then options with shorter maturities, causing prices of longer-dated options to be more closely determined by no-arbitrage relations with the stock.[15]

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 10-30 percent weekly for exposure to the skewness opportunities that these securities offer. Subsequently we investigate what other factors influence this relationship and determine that most of this return differential can be attributed to skewness preference.

IV. Controls for Risk and Other Characteristics

We estimate alphas for our skewness quintile portfolios by standard OLS regression and consider the statistical properties of these regressions below. We also estimate alphas for these portfolios using their instantaneous betas. We find that both methods of estimating alpha provide similar results suggesting that skewness preference has a considerable influence on option prices. In addition to construction of alphas, we also estimate Fama-Mcbeth (1973) cross-sectional regressions that allow us to simultaneously control for a variety of option characteristics. We also find in the context of these regressions that the relationship between

[14] We have created similar figures for put options.

[15] Outside investors cannot profit from the average run-up in skewness as options approach maturity since they will be sold back to intermediaries in the future near the bid. As mentioned in the introduction, bid prices of lottery-like options do not appear abnormally high relative to the CAPM. We discuss this in further detail below.

skewness and expected option returns is negative and significant, both economically and statistically. Finally, we control for the effect of option characteristics using a double-sorting exercise and again find strong evidence for the influence of skewness preference on option prices independent of these other characteristics.

A. Alpha

We first estimate alpha using standard market model regressions. Specifically, we regress the excess return of each ex-ante skewness portfolio on the excess market return over the same time period,

$$r_{p,t:T} - r_{f,t:T} = \alpha_p + \beta_{p,r}^{mkt}(r_{m,t:T} - r_{f,t:T}) + e_t, \tag{5}$$

where $r_{p,t:T}$ is the portfolio return over the horizon $t:T$, $r_{m,t:T}$ is the corresponding market return, $r_{f,t:T}$ is the risk-free return over the same horizon, and $\beta_{p,r}^{mkt}$ corresponds to the portfolio regression beta.

We report the alphas from estimating the one-factor model given in equation (5) for call and put option portfolios in Panel A of Tables V and VI respectively.[16] The results here are dramatic. CAPM alphas are generally decreasing across skewness quintiles similar to the average returns in Table V. For example, among call options that will expire in 7 days (Panel A of Table V), the alpha is monotonically decreasing from -1.20 percent per week for the low skewness portfolio to -40.15 percent per week for the high skewness portfolio. The t-statistic for the difference is 9.00. We find the difference in alpha across the high and low skewness quintiles to be significant among call options at all maturities. Again, results are somewhat stronger for put options at shorter maturities in Table VI. Among put options that will expire in 7 days, (Panel A of Table VI) the alpha is monotonically decreasing from -2.42 percent per week for the low skewness portfolio to -55.68 percent per week for the high skewness portfolio. The t-statistic for the difference is 12.73. Options with 18 days to maturity also exhibit significantly different alphas for put options. Similar to Table IV, alphas are not

[16]In unreported results we find that betas take on a "hump-shape" across skewness quintiles within each expiration group for both calls and puts. For example, among call options that expire in seven days, the beta for the low skewness quintile is 16.69, then increases to about 20 for the second and third skewness quintiles, and then declines to 9.87 for the high skewness quintile. This non-monotonicity in betas arises because underlying assets do not span all bins.

always monotonically decreasing for options with higher maturities, but any estimated non-monotonicity is statistically insignificant. Standard errors for Tables V and VI are calculated via GMM using the approach of Newey and West (1987), in part to account for overlapping observations of some expiration bins.

In Panel B of Tables V and VI we present alpha estimates using each portfolio's instantaneous beta. On each portfolio formation date, t, we first calculate the instantaneous beta of each option in the portfolio,

$$\beta_t^{mkt} = \Delta_t \frac{S_t}{C_t} \beta_{S,t}^{mkt}, \tag{6}$$

where Δ_t is the option's delta and $\beta_{S,t}^{mkt}$ is the underlying stock's beta with respect to the market estimated using six months of daily data prior to the portfolio formation date. On each portfolio formation date, t, we then estimate the portfolio instantaneous beta, $\beta_{p,t}^{mkt}$, as an equally-weighted average of all the instantaneous betas of options within the portfolio. The instantaneous beta may especially be an appropriate measure for portfolios with short maturities. We use deltas provided in the Ivy Optionmetrics database that are constructed using the Cox, Ross, and Rubinstein (1979) binomial tree for American options. We then calculate the alpha for each portfolio as

$$\alpha = \frac{1}{N} \sum_t \left[r_{p,t:T} - r_{f,t:T} - \beta_{p,t}^{mkt} (r_{m,t:T} - r_{f,t:T}) \right], \tag{7}$$

where N corresponds to the number of months in the data. Standard errors for the average alpha estimates are constructed using Newey-West (1987) methods to account for the overlapping observations of some portfolios. Results using instantaneous betas in Panel B of Tables V and VI are very similar to the regression betas given in Panel A of these same tables. Both call and put option portfolios with low maturities have significantly different alphas between the high and low skewness quintile portfolios.

In Panel C of Tables V and VI we present alpha estimates for the portfolios of underlying stocks for the options in each ex-ante skewness bin. We compute stock returns across the same holding periods as our option returns, and take an equally weighted average across stocks in a given bin to get stock portfolio returns. We then regress excess stock portfolio returns on excess market returns across time as in equation (5). We present the intercept of these regressions in Panel C of Tables V and VI. In contrast to results given in Panels A and B, the alphas of the underlying stocks of short-dated options are generally insignificant from zero, and do not appear to vary systematically across the ex-ante skewness bins. For example in Panel C of Table V, the difference in stock alphas across the low and high ex-ante skewness bins for options that expire in 7 days is only 1 basis point per week with a $t-$ statistic of 0.08.

The alphas of underlying stocks for longer-dated options in Panel C of Tables V and VI are sometimes negative and significant, in particular for calls with high ex-ante skewness (which are generally out-of-the-money) and for puts with low ex-ante skewness (which are generally in-the-money). Upon further investigation, we find that in general, the value of the underlying stocks in these bins fall dramatically *prior* to the portfolio formation date.[17] This causes the difference between the strike price of an option written on one of these stocks and the value of the underlying stock itself to be exceptionally high, and call (put) options written on these stocks to be classified in the high (low) skewness bins. Further, given the well-known relation between past and future performance in equity markets (Jegadeesh and Titman 2001), loser stocks in these bins continue to underperform on a risk-adjusted basis going forward.

Below, we show that our main results regarding option alphas are robust to controlling for past stock returns and loadings on the standard momentum factor. However, the alphas of stock portfolios, even at longer horizons, become insignificant from zero after controlling for past returns. In any case, the alphas of underlying stock portfolios for short term options that expire in 7 or 18 days do not appear to be affected by momentum. Options written on these portfolios provide some of our strongest evidence suggesting that investor preference for skewness impacts equilibrium option prices.

The results of Tables V and VI therefore indicate that individual stock options with high ex-ante skewness are not only over-valued on a risk-adjusted basis, but are also greatly over-valued relative to their underlying stocks, inconsistent with standard no-arbitrage option pricing models based on the notion that options are redundant securities. The enormous implicit leverage in an option contract with high ex-ante skewness combined with its nonlinear

[17] In unreported results we find that past returns of underlying stocks for call options with high ex-ante skewness are significantly lower than past returns of stocks with low ex-ante skewness. We also find that past returns of underlying stocks for put options with low ex-ante skewness are significantly lower than past returns of underlying stocks for puts with high ex-ante skewness.

payoff structure creates skewness impossible to replicate in the underlying equity market. Our results indicate *investors* are willing to pay substantial premiums for such lottery-like characteristics. Our results further suggest that the ability of *intermediaries* to effectively hedge short positions in individual options deteriorates with ex-ante skewness, and that intermediaries are compensated for bearing the unhedgeable risk of writing lottery-like options. This unhedgeable risk may be related to the potential of being entirely wiped out by short option positions; the precise features that attract skewness preferring investors to options may in themselves also act as a limit to arbitrage.

Other work suggests that options are non-redundant because they insure the holder against changes in systematic volatility and/or systematic jumps (e.g., Bakshi and Kapadia (2003a, 2003b) and Pan (2002)). Our measure of total ex-ante skewness, however, is largely a forecast of *idiosyncratic* skewness. Further, we find strong results among individual stock calls, which do not insure against downward jumps. Hence, option pricing models in which systematic volatility or jumps are priced cannot easily explain our findings.

To further investigate the relation of systematic volatility risk to our results we estimate alphas for a pricing model with two factors: the market return and the return on a zero-delta S&P 500 index straddle. For each day in our sample, we choose the put and call on the S&P 500 closest to being at-the money, and choose long positions in each such that the delta of the portfolio is zero. We then calculate factor realizations by aggregating these straddle returns over the appropriate option holding period. The second factor accounts for volatility risk as in Ang, Hodrick, Xing and Xang (2006), but has virtually no impact on our results.

Volatility risk is not likely to explain the cross-sectional variation across ex-ante skewness portfolios because of the relation between an option's exposure to volatility and its skewness. Vega, or the option price sensitivity to volatility is high for options that are at the money and asymptotes to zero as moneyness either increases or decreases. High-skewed options with low returns are also options that are likely to have near zero vegas, while at-the-money options will have high vegas and little ex-ante skewness. Consequently, volatility risk pricing would predict that our high-skewed (low vega) options will have higher returns than at-the-money options with lower ex-ante skewness and high vega. We further investigate the ability of volatility risk to explain cross-sectional variation in returns across skewness quintiles in Fama-McBeth regressions and double sorts below.

B. Fama-Mcbeth

To further assess the pricing effects of ex-ante skewness, 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 portfolio betas and other option characteristics in these regressions that may influence expected returns.

On each portfolio formation date we sort each option within a given maturity bin into 100 bins based on ex-ante skewness and calculate the equally-weighted portfolio return for each ex-ante skewness bin.[18] For each date t we then estimate the following cross-sectional regression across portfolios with the same maturity horizon:

$$r_{p,t:T} = \gamma_{0,t} + \gamma_{1,t}\mathcal{R}^{skew}_{p,t} + \boldsymbol{\phi}'_t\mathbf{Z}_{p,t} + \varepsilon_{p,t}, \tag{8}$$

where $r_{p,t:T}$ is the equally-weighted 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 0 to 99), and $\mathbf{Z}_{p,t}$ is a vector of control characteristics and factor loadings for portfolio p.

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 exceedingly high standard deviation that complicates the economic interpretation of our results. (See footnote 20.) For consistency, we use average ranks of the other characteristics as control variables in $\mathbf{Z}_{p,t}$ although we get similarly significant results if we instead use average characteristics. We calculate these average characteristic ranks by independently sorting each option on a given portfolio formation date and within a given maturity bin into 100 bins based on some control characteristic. We then average the control characteristic rank across all options within each of the 100 skewness bins. The control characteristics

[18] 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 above. We also exclude time periods that do not have at least 30 portfolios with sufficient options. We find our results to be robust to these choices.

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 Pan (2002).[19] We also include each portfolio's market beta, volatility risk beta, and momentum beta. Market beta is the regression beta as given in equation (5). The volatility risk beta for portfolio p is obtained by regressing the returns of portfolio p on contemporaneous returns of a zero-delta S&P 500 straddle as described above at the end of the previous section. The momentum beta for portfolio p is obtained by regressing the returns of portfolio p on contemporaneous returns of the momentum factor obtained from Ken French's website. We include the momentum beta in our analysis because the evidence in Panel C of Tables V and VI suggest the underlying stocks of some option portfolios load on this factor.

We include moneyness in our regressions to investigate whether a relation exists between skewness and expected option returns unrelated to moneyness. Coval and Shumway (2001) establish a relationship between moneyness and average index option returns, and Ni (2009) investigates the relationship between moneyness and the average returns of call options on individual stocks. From Section II and Figures 1-3, we know that our ex-ante skewness measure is strongly related to moneyness. 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. The volatility smirk is unique among the characteristics we consider in that it is the same for all options with the same underlying and maturity.

In Table VII, we report the time-series averages of the γ and $\boldsymbol{\phi}$ coefficients from equation (8), along with Newey West (1987) t-statistics. Panel A reports results for calls while Panel B reports results for puts. In the interest of brevity, we report results only for options that expire in 18 days. The top row in each panel of Table VII 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 9 of Panel A the average coefficient on ex-ante skewness is -0.426 with a t-statistic of -4.43. This implies that increasing the skewness rank of a portfolio

[19] 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 $0.95 < X_i/S_{i,t} < 1.05$.

by 1 is associated with a 43 basis point decline in expected returns.[20] Again, we find slightly stronger results for puts. In column 9 of Panel B the average coefficient on ex-ante skewness is -0.571 with a t-statistic of -4.19.

The results of Table VII indicate that a relation exists between ex-ante skewness and expected option returns unrelated to loadings on the three risk factors and the other four portfolio characteristics we consider. Specifically, there exists a relationship between ex-ante skewness and expected option returns unrelated to moneyness. Used in isolation without other controls, the average coefficient on moneyness is negative for calls and positive for puts 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.

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 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 options returns above and beyond moneyness.

[20] When average skewness is used 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.

C. Double Sorts

Fama-Mcbeth regressions impose linearity on the structure between ex-ante skewness and returns. In this section we explore the relationship between ex-ante skewness and average option returns after controlling for the influence of other characteristics by examining alphas of double-sorted portfolios. This approach also allows us to easily report results across different option maturities. Following the methodology in Ang, Hodrick, Xing, and Zhang (2006, 2008), on each portfolio formation date we first sort options of a given maturity into ten portfolios based on some characteristic. Then for each characteristic-sorted portfolio, we sort options into two ex-ante skewness portfolios. We then equal-weight the returns across each of the ten characteristic-sorted portfolios separately for each of the two ex-ante skewness sorts, thereby creating two portfolios similar in terms of the given characteristic but different in terms of their ex-ante skewness.[21] After creating two such portfolios for each formation date in our sample, we then estimate and compare their alphas.

We conduct this exercise for each of the four characteristics considered in our Fama-McBeth regressions, namely, moneyness, volume, bid-ask spread, and volatility smirk, as well as option vega, and the past six-month underlying stock return. We use vega as a proxy for an option's sensitivity to volatility risk rather than try to estimate volatility risk betas at the individual option level. We control for the past six-month underlying stock return as a control for momentum. The results of this exercise for each characteristic except moneyness are reported in Table XIII. Results for moneyness are reported in Table IX. All results in these two tables suggest that variation in any of the five characteristics cannot explain the alpha spread between high- and low-skewness equity options. In Table XIII the difference in alphas across the high- and low- skewness portfolios remains as high as 39 percent per week (for put options in Panel C where we control for the volatility smirk) and remains *at least* as high as 15 percent per week (for call options in Panel D where we control for the bid-ask spread).

[21] 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.

Differences in alphas for short-term options are highly significant. In addition, in every panel we find somewhat stronger results for puts than for calls.

In Table IX, the difference in alphas also remains large and statistically significant after controlling for moneyness. For short-dated call options the spread in alphas is as high as 8.81 percent per week (t-statistic of 8.81) while for short-dated puts the spread is as high as 9.70 percent per week (t-statistic of 4.05). In this table we also conduct a conditional sort exercise where we reverse the order of sorting. We first sort into 10 portfolios based on our ex-ante skewness measure and then sort into 2 portfolios based on moneyness. We report the alphas of these portfolios in Panel B of Table IX. After controlling for ex-ante skewness we find the spread in alphas across out-of-the-money options and in-the-money options to be quite small. In fact, for short-maturity options the differences are not statistically significant.[22]

In Table X we report alphas of the underlying stocks after controlling for the lagged six-month return using the double-sort methodology. In this table, virtually all alphas are insignificant from zero, confirming that the reason many of the stock alphas in Panel C of Tables V and VI are non-zero is because sorting stocks based on the ex-ante skewness of the options written on them is akin to a noisy sort on past returns, or momentum. A comparison of the results of Table IX to those of Panel E of Table XIII provides further evidence that individual stock options with high ex-ante skewness are not only over-valued on a risk-adjusted basis, but are also greatly over-valued relative to their underlying stocks.

D. Estimating Option Alphas

In this section we consider four potential hazards in using standard regression methods to estimate and test the significance of option alphas: non-normality, non-linearity, non-additivity, and peso problems. First, because option returns deviate substantially from normality, the small-sample distributions of our alpha estimates may not conform with asymptotic inference. Second, the non-linear relation between option and stock returns is likely to cause e_t in the regression given by (5) to be correlated with $r_{m,t:T}$, thereby causing OLS estimates of alpha to be somewhat biased and inconsistent. Third, because returns are non-additive, expectations

[22] In unreported results, we find the differences in average returns and alphas across portfolios *unconditionally* sorted on moneyness to be similar to those of the ex-ante skewness portfolios of Tables V and VII.

and betas do not scale linearly with time.[23] This implies, for example, that if stock prices follow geometric brownian motion and Merton's (1971) continuous-time CAPM holds then the CAPM cannot hold over discrete horizons. Estimates of alpha may therefore be unduly influenced by the particular horizon over which we choose to measure returns. And fourth, our particular sample may lack important certain extreme rare events correctly anticipated by option investors ex-ante, but not reflected in our estimates of alpha measured ex-post (peso problems).

To account for the non-normality of option returns, we estimate bootstrapped p-values for our regression alpha estimates. To do this, we create non-overlapping samples for options that expire in 7, 18 and 48 days, by forming portfolios every other month. We then sample portfolio returns in the time series with replacement to create a new sample of the same size as the original and estimate alphas using this new sample. We then repeat this procedure 10,000 times. In Panel A of Table XI we report the estimated alphas using the non-overlapping data sample, asymptotic t-statistics, and boot-strapped p-values for spreads in alpha across the high and low skewness portfolios. We calculate p-values as the fraction of bootstrapped samples for which the difference in alpha is less than zero. These p-values are consistent with the reported t-statistics. Hence, our results remain after accounting for the non-normality of option returns.

To investigate whether non-linearity, non-additivity, or peso problems can explain our results, we conduct a simulation exercise similar to Broadie, Chernov, and Johannes (2009). We simulate a Black-Scholes world in which Merton's (1971) continuous-time CAPM holds, and calibrate the simulation to match the ex-ante moments and size of our sample of non-overlapping option returns created for the bootstrap exercise above. In particular, we use annualized estimated stock return volatilities and betas using six months of daily data prior to the portfolio formation dates as our instantaneous second moments and assume that instantaneous expected stock returns are given by the CAPM with an annualized risk premium of five percent. We price options using the Black-Scholes model and estimate regression alphas

[23] 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 (2000). 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.

for option returns over discrete horizons exactly as we do for our results in Table XI. We repeat the exercise 1000 times.

The objective of our simulation is to determine how often, in a world in which preference for skewness has no impact on prices, can we generate results as extreme as those reported in Table XI. Although true instantaneous alphas are zero by construction, the estimated alphas will be non-zero for two reasons. First, the estimated alphas are somewhat biased given the non-linear relation between simulated option and market returns. Second, the CAPM holds instantaneously in the simulated data while we estimate alphas over discrete horizons. Finally, the simulation also allows us to investigate how often we might expect to observe samples with peso problems that can generate results as extreme as those of Table XI.

The results of this simulation are given in Panel B of Table XI. Rows marked "p-value" in Panel B report the fraction of simulated samples that provide spreads in alpha at least as extreme as those found in Panel A. All are virtually zero. The only exception is for puts with 48 days to expiration. Hence, non-linearity, non-additivity, and peso problems do not appear adequate to explain our results.

In unreported results we conduct a similar simulation after removing any quandries associated with non-additivity. In particular, instead of pricing options under Black-Scholes, we price options assuming the CAPM holds over the exact discrete horizon over which we estimate alpha: we discount the expected cash flow of the option under lognormality using the CAPM equation, where the true beta of the option is derived by integrating the appropriate bivariate distribution for option and market returns following Lien (1985). For this simulation we find the estimated alphas to be very close to zero, suggesting any bias arising from non-linearity is trivial. These results are consistent with Duarte and Jones (2007) who also find evidence that non-linearities have little effect on the statistical properties of regressions using option returns.

V. Alphas From Writing Options

The returns we calculate to produce the results of Tables V through VIII use the mid-point of closing bid and ask prices as the proxy for the "true" price. In Panel A of Table III we show that bid-ask spreads are monotonically increasing in skewness at all horizons. Investors who buy options near the ask, therefore, earn even lower returns than we document, particularly when buying options with lottery-like characteristics.

In Table XII we report the average alphas earned across our sample from writing options at the bid price. We obtain these alphas from estimating the one-factor model given in equation (5) using option portfolio returns computed at bid prices. Alphas estimated using instantaneous betas give similar results. Table XII shows that investors who write options with high ex-ante skewness generally earn alphas that are insignificant from zero, and if anything, negative. The premiums investors pay to buy options with high ex-ante skewness are not passed on to investors who write options. The only exception is for put options that expire in seven days. Further, differences in alpha across the high and low skewness quintiles are generally insignificant. The only exceptions are again for call options that expire in 18 days, in which case the alpha 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).

If competitive intermediaries can hedge perfectly, then option prices are simply determined by no arbitrage; options are merely levered positions in the underlying asset and will be priced to earn zero alpha given that the stock earns zero alpha. The results of Table XII suggest that intermediaries are better able to hedge their long positions in lottery-like options than short positions, since estimated alphas using bid prices are more closely aligned with the zero alphas 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, the results of Tables V through VIII 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 data 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 first choose thirty 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 day, 18 day, and 48 day) 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 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 will expire that month (options with 7 days to expiration). We gather the option price for each transaction, as well as the 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 calls and the top quintile of puts ranked by ex-ante skewness on each transaction date. This procedure leaves us with data on 5992 transactions.

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

$$\pi = \frac{trade - bid}{ask - bid} \tag{9}$$

and plot histograms of π in Figure 5. 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 7 days, 50% of all trades occur at the ask and among put options that expire in 7 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 for taking on unhedgeable risk in writing such options.

VI. Conclusion

We find evidence suggesting that the impact of skewness preference on prices and subsequent returns is remarkable in option markets. Investors are willing to compromise as much as 50 percent per *week* in order to gain exposure to options with the greatest lottery potential. In comparison, recent research on the effect of skewness in equities markets have found that lottery-preferring investors are willing to lose on average around 12% per year in order 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, options market 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 enhances 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 lottery prospects of securities may not only inform our understanding of investment demand functions, but that these effects can have a surprisingly large equilibrium impact. 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.

Appendix

A. Expected Skewness Calculations

In this appendix, we demonstrate how our expected skewness measure, $sk_{i,t:T}$ is constructed assuming lognormal stock prices. We make use of Lien's (1985) theorem regarding truncated lognormal distributions. We restate Lien's (1985) theorem 1 below, noting that Lien's theorem applies to bivariate distributions and our use will primarily be univariate:

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

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

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

Lien's (1985) Theorem 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 will 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

$$E\left[R^c_{t:T}\right] = \left[\frac{S_t}{C_t}E\left(\frac{S_T}{S_t}|\frac{S_T}{S_t} > \frac{X}{S_t}\right) - \frac{X}{C_t}\right]P\left(\frac{S_T}{S_t} > \frac{X}{S_t}\right), \tag{10}$$

where S_t is the value of the underlying asset at time $t < T$ and we suppress the subscript i for clarity. Let $r = \ln(S_T/S_t)$, the log return, and define A as $A = \ln(X/S_t)$. Then equation (10) can be written as

$$E\left[R^c_{t:T}\right] = \left[\frac{S_t}{C_t} E\left(e^r | r > A\right) - \frac{X}{C_t}\right] P(r > A). \tag{11}$$

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

$$E\left(e^r | r > A\right) = E\left(e^{z+\tilde{\mu}} | z > A - \tilde{\mu}\right) \tag{12}$$

$$= e^{\tilde{\mu}} E\left(e^z | z > A - \tilde{\mu}\right). \tag{13}$$

A direct application of Lein's (1985) theorem implies that equation (13) can be written

$$E\left(e^r | r > A\right) = \frac{\exp\left[\tilde{\mu} + \frac{\tilde{\sigma}^2}{2}\right] N(\bar{d}_1)}{N(\bar{d}_2)}, \tag{14}$$

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 $P(r > A) = N(\bar{d}_2)$. We can then plug equation (14) into equation (11) to get the first moment of the call option return,

$$E\left[R^c_{t:T}\right] = \frac{S_t}{C_t} \exp\left[\tilde{\mu} + \frac{\tilde{\sigma}^2}{2}\right] - \frac{XN(\bar{d}_2)}{C_t}. \tag{15}$$

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

$$E\left[\left(R^c_{t:T}\right)^2\right] = \frac{S_t^2 \exp\left[2\tilde{\sigma}^2 + 2\mu\right]\left[N\left(\bar{d}_3\right)\right] - 2XS_t \exp\left[\frac{\sigma^2}{2} + \mu\right] N\left(\bar{d}_1\right)}{C_t^2} + \frac{X^2 N\left(\bar{d}_2\right)}{C_t^2} \tag{16}$$

$$E\left[\left(R^c_{t:T}\right)^3\right] = \frac{S_t^3 \exp\left[\frac{9}{2}\tilde{\sigma}^2 + 3\tilde{\mu}\right] N\left(\bar{d}_4\right) - 3XS_t^2 \exp\left[2\tilde{\sigma}^2 + 2\tilde{\mu}\right] N\left(\bar{d}_3\right)}{C_t^3} + \frac{3X^2 S_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(\bar{d}_1\right) - X^3 N\left(\bar{d}_2\right)}{C_t^3}, \tag{17}$$

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

$$E\left[R^p_{t:T}\right] = \frac{XN\left(-\bar{d}_2\right) - S_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(-\bar{d}_1\right)}{P_t} \tag{18}$$

$$E\left[\left(R^p_{t:T}\right)^2\right] = \frac{X^2 N\left(-\bar{d}_2\right) - 2XS_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(-\bar{d}_1\right)}{P_t^2} + \frac{S_t^2 \exp\left[2\tilde{\sigma}^2 + 2\tilde{\mu}\right]\left[N\left(-\bar{d}_3\right)\right]}{P_t^2} \tag{19}$$

$$E\left[\left(R^p_{t:T}\right)^3\right] = \frac{X^3 N\left(-\bar{d}_2\right) - 3X^2 S_t \exp\left[\frac{\tilde{\sigma}^2}{2} + \tilde{\mu}\right] N\left(-\bar{d}_1\right)}{P_t^3} + \frac{3XS_t^2 \exp\left[2\tilde{\sigma}^2 + 2\tilde{\mu}\right] N\left(-\bar{d}_3\right) - S_t^3 \exp\left[\frac{9}{2}\tilde{\sigma}^2 + 3\tilde{\mu}\right] N\left(-\bar{d}_4\right)}{P_t^3}, \tag{20}$$

where P_t is the put premium at time t. Equations (15) through (20) can be used to construct $sk_{i,t:T}$ for both call and put options for any level of moneyness, maturity, stock volatility, and stock expected return.

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 non-zero.
2. *Underlying Asset is Not Common Stock*: Optionmetrics "issue_type" for underlying is non-zero.
3. *AM Settlement*: The option expires at the market open of the last trading day, rather than the close.
4. *Non-standard 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 than $100 per tick.
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 Delta*: The option delta 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.[24]
9. *Extreme price*: The mid-point of the bid and ask price is below 50 percent 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 non-missing daily returns in CRSP over the 6-month period prior to date t_i.

[24] Duarte and Jones (2007) argue that eliminating options that do not have a reported delta or implied voltility in the Ivy Optionmetrics database induces a bias in measuring average returns. We have estimated the alphas based on regression betas 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.

Bibliography

Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang. 2008. High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics*, forthcoming.

Arditti, F. D. 1967. Risk and the required return on equity. *Journal of Finance* 22:19-36.

Bali, T., N. Cakici, and R. Whitelaw. 2010. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics.* forthcoming.

Bakshi, G., and N. Kapadia. 2003a. Delta hedged gains and the negative market volatility risk premium. *Review of Financial Studies.* 15:527-566.

Bakshi, G., and N. Kapadia. 2003b. Volatility Risk Premium Embedded in Individual Equity Options: Some New Insights. *Journal of Derivatives.* Fall:45-54.

Bakshi, G., N. Kapadia, and D. Madan. 2003. Stock return characteristics, skew laws, and differential picing of individual equity options. *Review of Financial Studies.* 16: 101-143.

Barberis, N., and M. Huang. 2008. Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 2066-2100.

Bollen, N., and R. Whaley. 2004. Does net buying pressure affect the shape of implied volatility functions?, *Journal of Finance.* 59: 711-753.

Boyer, B., T. Mitton, and K. Vorkink. 2010. Expected idiosyncratic skewness, *Review of Financial Studies.* 23: 169-202.

Brandt, M.W., A. Brav, J. R. Graham, and A. Kumar. 2008. The idiosyncratic volatility puzzle: Time trend or speculative episodes?, *Review of Financial Studies*, forthcoming.

Broadie, M., Chernov, M., and M. Johannes. 2009. Understanding expected option returns. *Review of Financial Studies.* 22: 4493 – 4529.

Brunnermeier, M., C. Gollier, and J. Parker. 2007. Optimal beliefs, asset prices and the preference for skewed returns. *American Economic Review Papers and Proceedings* 97:159-165.

Brunnermeier, M., and J. Parker. 2005. Optimal expectations. *American Economic Review* 95:1092-1118.

Chernov, M. 2007. On the role of risk premia in volatility forecasting. *Journal of Business & Economic Statistics.* 25: 411-426.

Conine, T. E. Jr., and M. J. Tamarkin. 1981. On diversification given asymmetry in returns. *Journal of Finance* 36:1143-1155.

Conrad, J., R. Dittmar, and E. Ghysels. 2009. Ex ante skewness and expected stock returns. Working paper, University of Michigan.

Coval, J. and T. Shumway. 2001. Expected Option Returns. *Journal of Finance*. 56:983-1009.

Dierkes, M. 2009. Option-implied risk attitude under rank-dependent utility. Working paper, University of Münster.

Driessen, J., P. Maenhout, and G. Vilkov. 2009. The price of correlation risk: Evidence from equity options. *Journal of Finance*, 64. 1377-1406.

Duarte, J., and C Jones. 2007. The market price of volatility risk. working paper, USC.

Garleanu, N., Lasse Heje Pedersen, and Alan M. Poteshman. 2009. Demand-based option pricing. *Review of Financial Studies*. 22:4259-4299.

Goyal, A., and A. Saretto. 2009. Cross-section of option returns and volatility. *Journal of Financial Economics*. 94: 310-326.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3-56.

Harvey, C. R., and A. Siddique. 1999. Autoregressive conditional skewness. *Journal of Financial and Quantitative Analysis* 34:465-488.

Harvey, C. R., and A. Siddique. 2000. Conditional skewness in asset pricing tests. *Journal of Finance* 55:1263-1295.

Jones, C. 2006. A nonlinear factor analysis of S&P 500 index Option Returns. *Journal of Finance.* 61: 2325-2363.

Jones,C. 2003.The dynamics of stochastic volatility: Evidence from underlying and options markets. *Journal of Econometrics*. 116: 181–224.

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica*. 47(2): 263-91.

Kapadia, N. 2006. The next Microsoft? Skewness, idiosyncratic volatility, and expected returns. Working paper, Rice University.

Kraus, A., and R. H. Litzenberger. 1976. Skewness preference and the valuation of risky assets. *Journal of Finance.* 31:1085-1100.

Lien, D. 1985. Moments of truncated bivariate log-normal distributions, *Economic Letters.* 19:243-247.

Mitton, T., and K. Vorkink. 2007. Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies* 20:1255-1288.

Newey, W., and K. West. 1987. A simple, positive definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703-708.

Ni, S., 2009. Stock option returns: A puzzle. working paper Hong Kong University of Science and Technology.

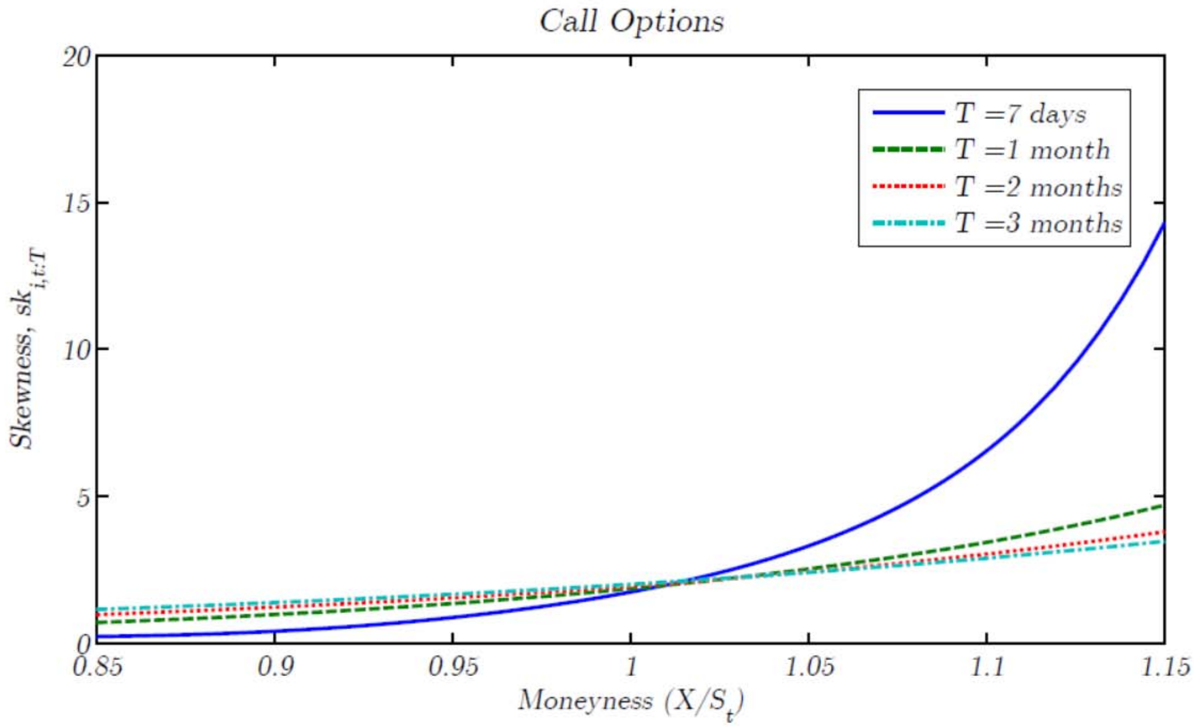
Pan, J. 2002. The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics.* 63:3–50.

Polkovnichenko, V., and F. Zhao. 2010. Probability weighting functions implied by options prices. Working paper, University of Texas at Dallas.

Scott, R. C., and P. A. Horvath. 1980. On the direction of preference for moments of higher order than the variance. *Journal of Finance* 35:915-919.

Simkowitz, M., and W. Beedles. 1978. Diversification in a three-moment world. *Journal of Financial and Quantitative Analysis* 13:927-941.

Zhang, Y. 2005. Individual skewness and the cross-section of average stock returns. Working paper, Yale University.



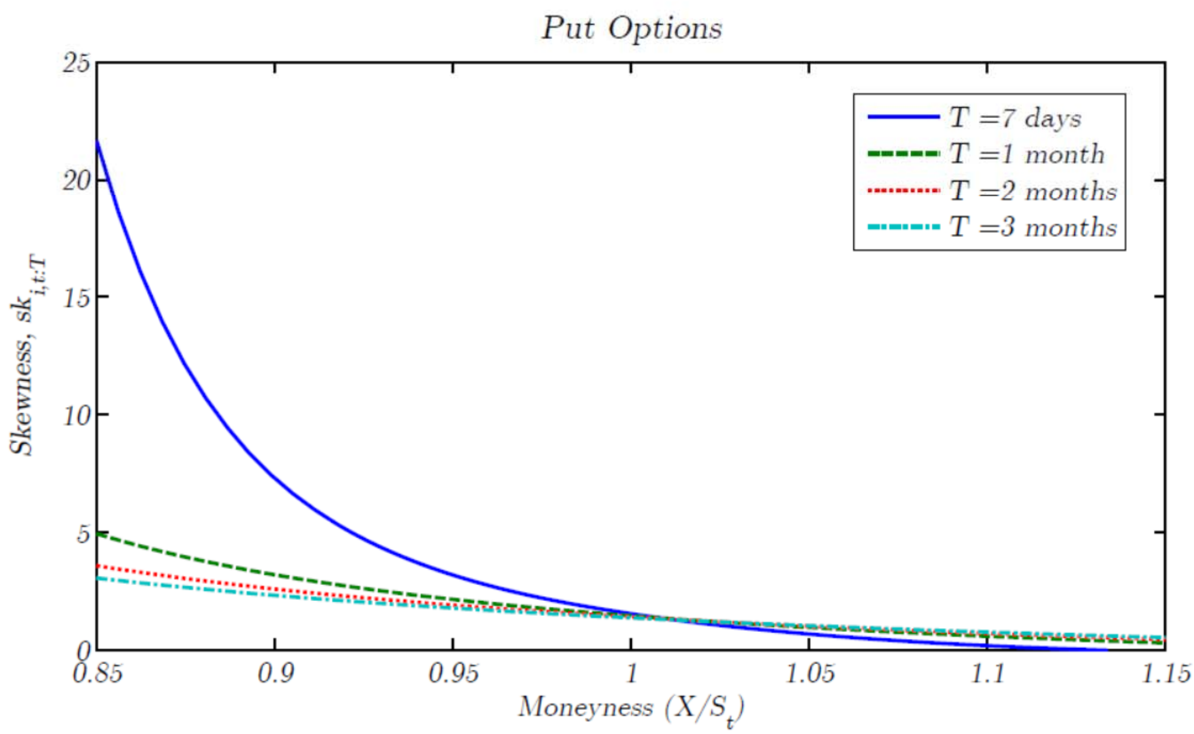
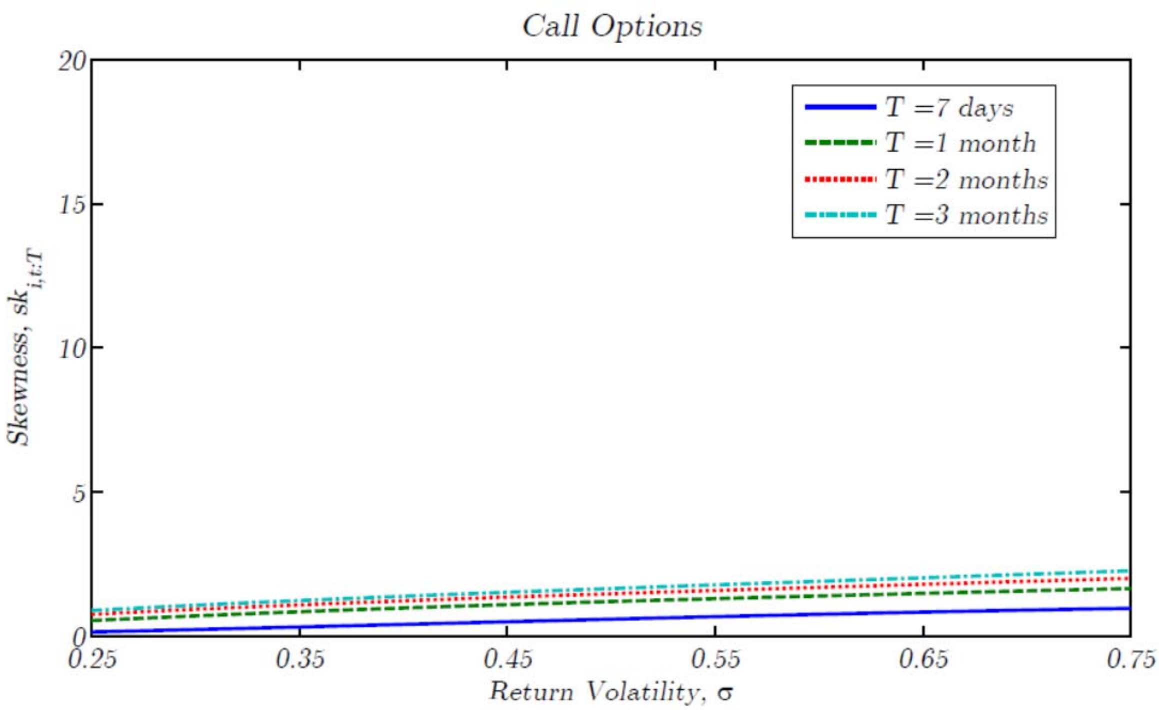


Figure 1: Option Return Skewness Against Moneyness (stock return volatility = 0.4, annualized expected return on the stock = 8%, risk-free rate = 5%).



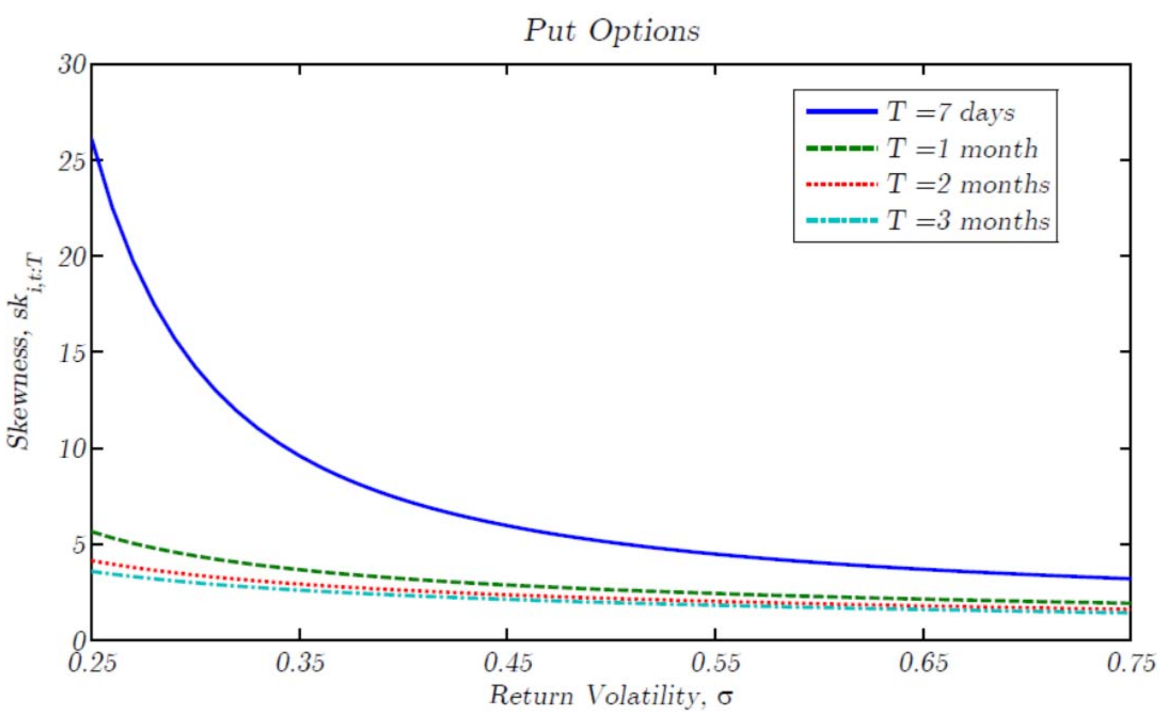
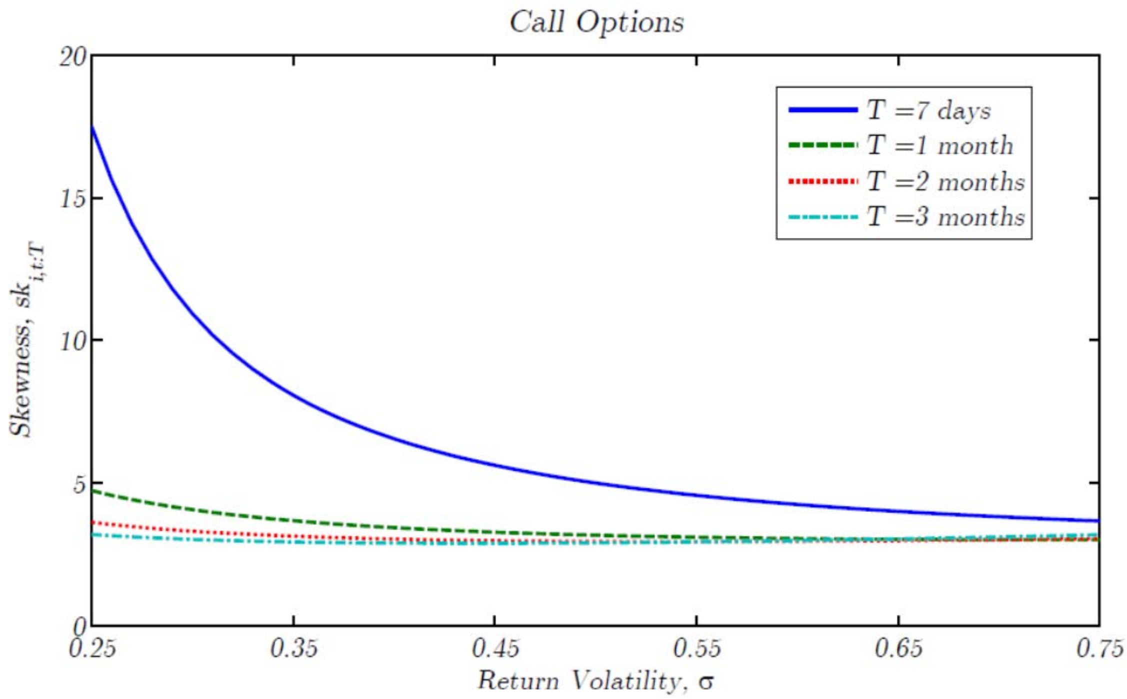


Figure 2: Option Return Skewness Against Return Volatility (Moneyness, (X/S_t) = 0.9, annualized expected return on the stock = 8%, risk-free rate = 5%).



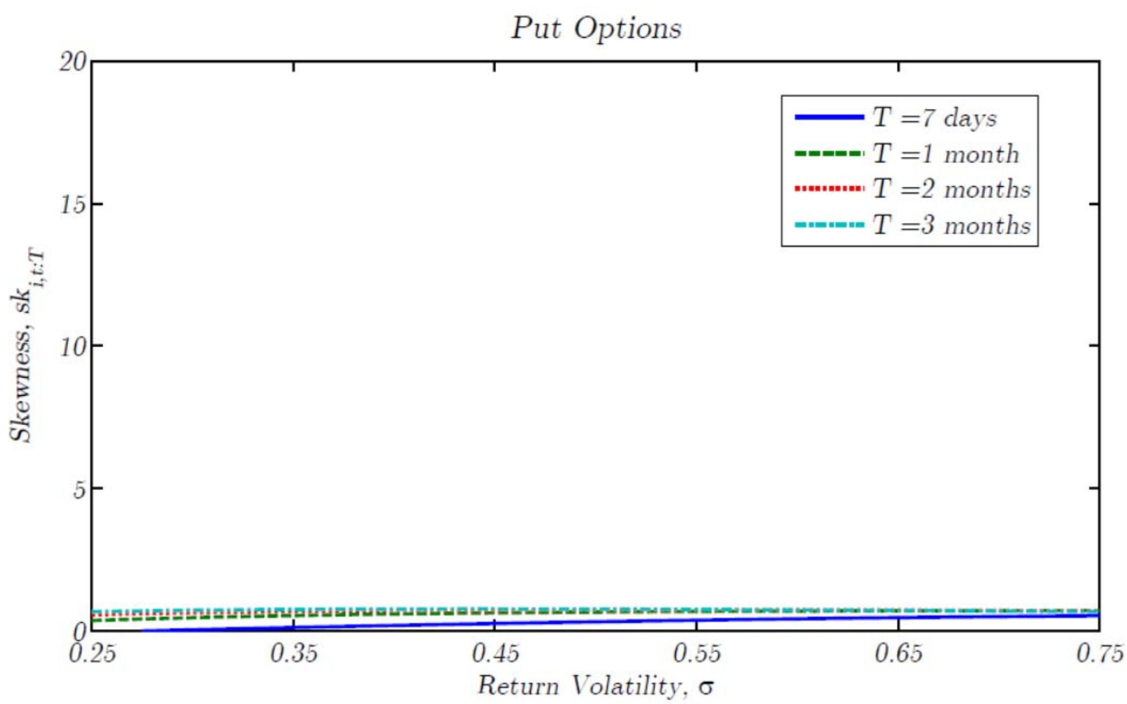


Figure 3: Option Return Skewness Against Return Volatility (Moneyness, (X/S_t) = 1.1, annualized expected return on the stock = 8%, risk-free rate = 5%).

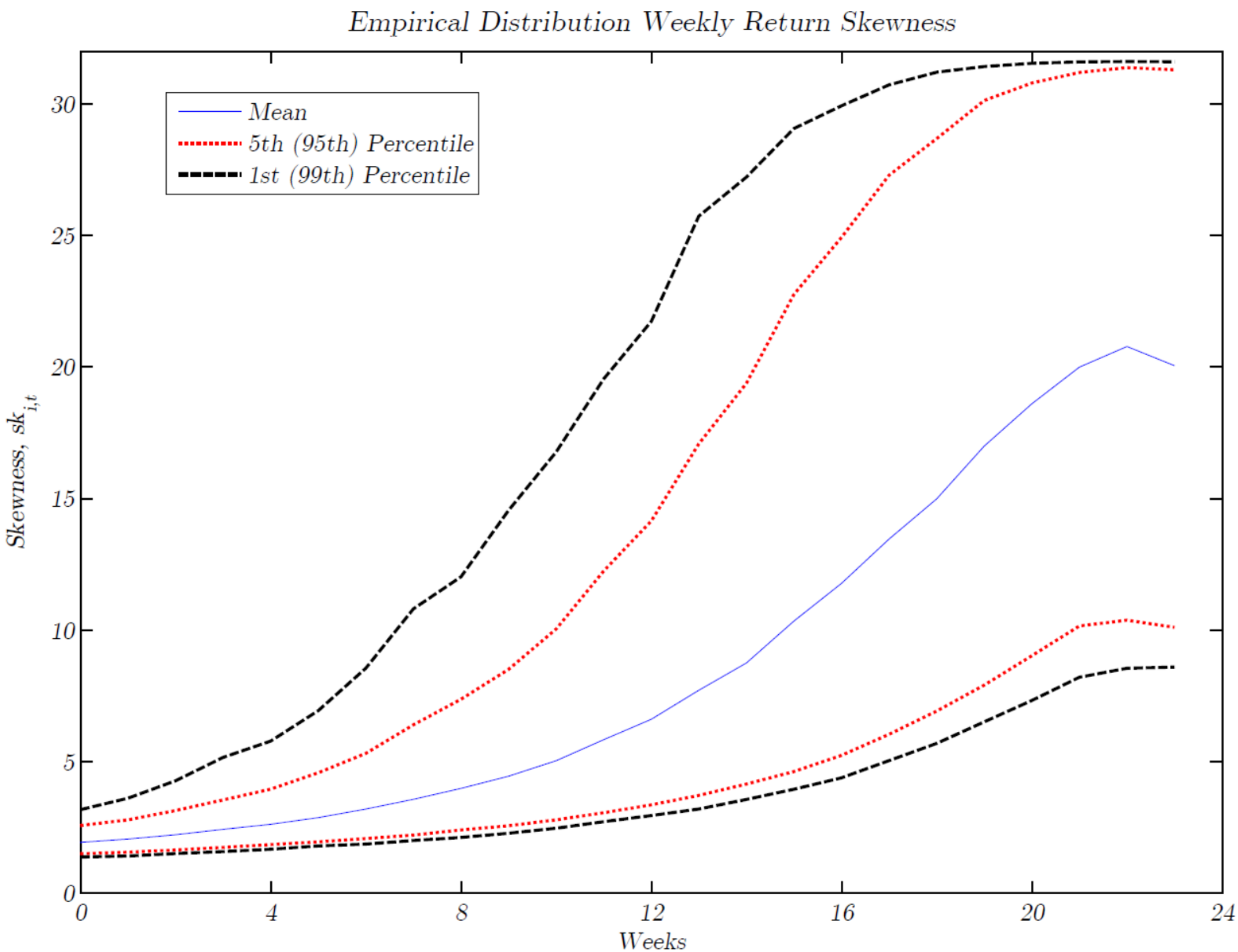


Figure 4: Empirical Distribution of Weekly Return Skewness for a 6-Month Maturity Call Option (Moneyness, (X/S_t) = 1.4, stock return volatility = 0.2, annualized expected return on the stock = 15%, risk-free rate = 5%)

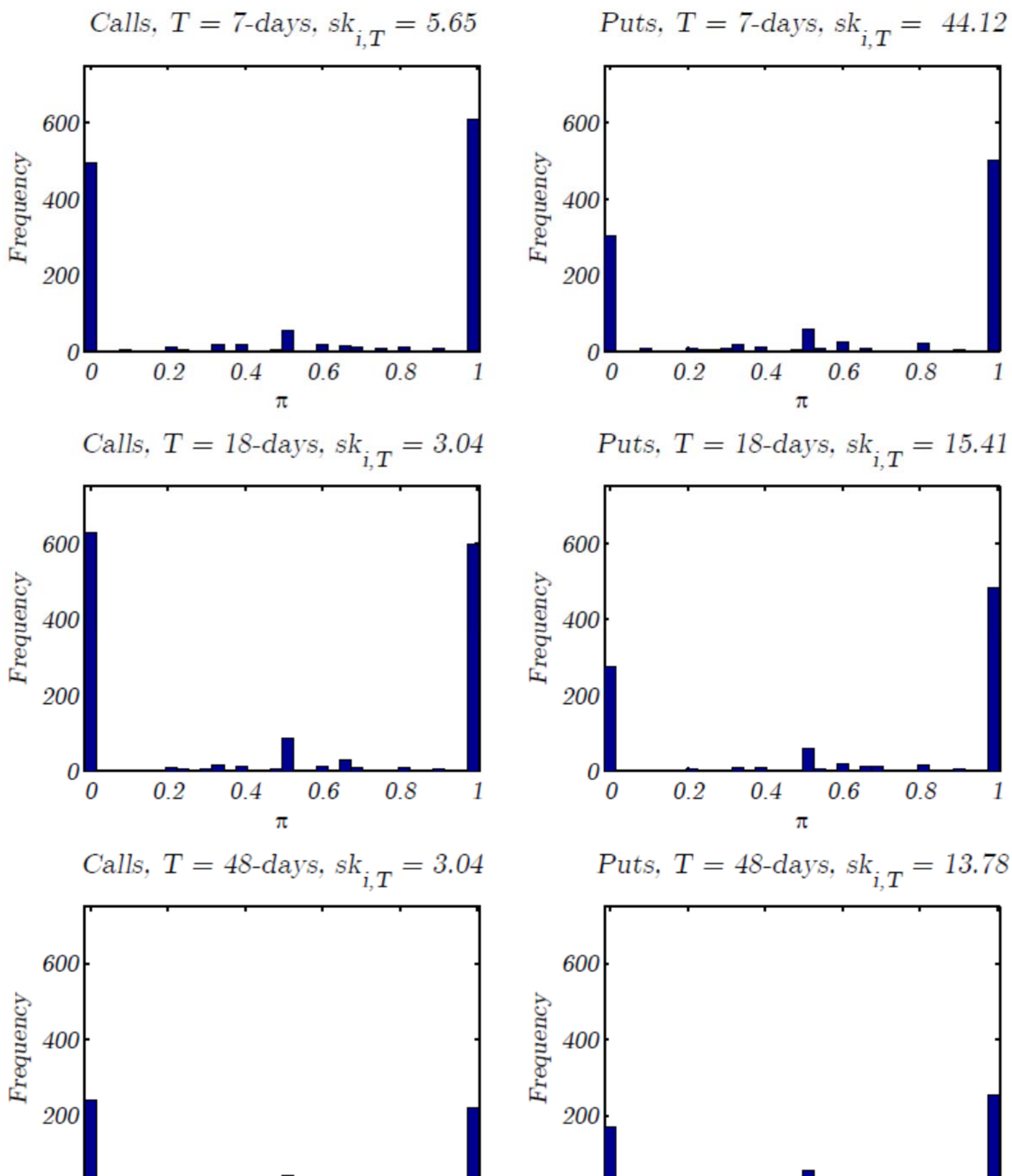


Figure 5: Histograms of π measures ($\pi = (Trade - Bid)/(Ask - Bid)$) for end of day option prices on options taken from Bloomberg during months of April, May, and June 2011. We limit our data on each transaction date to the top ex-ante skewness ($sk_{i,t:T}$) quintile for calls similarly for puts.

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. Panel B reports for each maturity the average number of options in each 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	61,712	61,712	0	61,712	1,163
1997	88,339	88,305	18	88,323	1,486
1998	111,454	111,397	9	111,406	1,741
1999	143,355	143,232	0	143,232	1,911
2000	232,162	232,097	0	232,097	1,990
2001	174,691	174,512	0	174,512	1,961
2002	160,494	160,442	0	160,442	2,062
2003	167,649	167,392	0	167,392	2,003
2004	198,448	197,650	0	197,650	2,236
2005	231,626	229,889	87	229,976	2,355
2006	287,662	285,785	52	285,837	2,533
2007	354,402	351,516	125	351,641	2,730
2008	390,459	387,728	6	387,734	2,690
2009	262,478	230,679	31,147	261,826	2,504
Total	2,864,931	2,822,336	31,444	2,853,780	
% of Total		98.51%	1.10%	99.61%	

Panel B. Average # of Securities

Skew Quintile	7	18	48	78	108	138	168	198
	Days to Expiration							
Calls								
Low	276	438	449	201	197	188	173	137
2	277	439	450	202	198	188	174	138
3	277	439	450	202	198	188	174	138
4	277	439	450	202	198	188	174	138
High	276	439	450	201	197	188	173	137
Unique Underlying	729.59	962.87	934.42	371.19	365.27	355.29	345.31	290.86
Underlying Span	1.69	1.93	1.89	1.91	1.80	1.72	1.62	1.51
Puts								
Low	230	342	306	126	122	112	98	81
2	230	342	307	127	123	113	99	81
3	230	342	307	127	123	113	99	81
4	230	342	307	127	123	113	99	81
High	230	342	306	126	122	113	99	81
Unique Underlying	589.51	743.26	637.56	250.21	244.43	231.45	215.85	186.89
Underlying Span	1.72	1.94	1.92	1.87	1.79	1.71	1.61	1.52

Table II
Average Expected Skewness

Panel A reports the average expected skewness for individual equity option portfolios taken from the Ivy database over the period 1996 - 2009. The portfolios are constructed by sorting on ex-ante skewness calculated as in equation (4). Each period we take the median of the ex-ante skewness measure for each portfolio and then report the time series average of these medians. Panel B reports the average cross-sectional skewness for these same portfolios. The last two rows of Panel B report differences across the high and low skewness qunitiles along with Newey-West (1987) *t*-statistics testing whether the differences are equal to zero.

Panel A. Average Expected Skewness								
	Days to Expiration							
Skew Quintile	7	18	48	78	108	138	168	198
Calls								
Low	0.40	0.55	0.86	0.93	1.03	1.12	1.21	1.24
2	1.03	1.18	1.51	1.61	1.73	1.86	2.00	2.05
3	1.82	1.93	2.20	2.43	2.57	2.77	3.01	3.12
4	3.36	3.11	3.23	3.79	4.03	4.37	4.81	5.07
High	24.94	7.31	6.27	8.57	8.92	9.76	11.03	11.91
Puts								
Low	0.24	0.31	0.42	0.23	0.10	0.05	-0.07	-0.24
2	1.00	1.12	1.27	1.20	1.09	1.08	0.98	0.77
3	1.91	2.03	2.15	2.27	2.19	2.21	2.16	1.93
4	3.75	3.77	3.65	4.23	4.18	4.27	4.42	4.12
High	15.78	13.52	10.04	14.62	13.82	13.57	15.18	13.94

Panel B. Average Cross-Sectional Skewness								
	Days to Expiration							
Skew Quintile	7	18	48	78	108	138	168	198
Calls								
Low	0.86	0.99	1.56	1.55	1.89	2.26	2.57	2.36
2	1.52	2.03	2.84	2.71	2.92	3.11	3.27	3.11
3	2.95	3.47	3.96	3.62	3.69	3.77	3.64	3.66
4	5.04	5.46	5.50	4.89	4.69	4.65	4.60	4.09
High	9.11	9.58	8.23	7.14	6.62	6.37	5.72	5.20
Low-High	-8.29	-8.62	-6.73	-5.63	-4.76	-4.12	-3.19	-2.85
(t-stat)	-(25.66)	-(23.72)	-(21.44)	-(21.56)	-(17.88)	-(16.63)	-(14.77)	-(13.05)
Puts								
Low	0.95	1.07	1.61	1.26	1.30	1.39	1.59	1.35
2	1.89	2.35	2.54	2.26	2.31	2.29	2.29	2.07
3	3.61	3.88	3.65	3.11	3.19	2.94	2.76	2.48
4	6.00	6.13	5.20	4.29	3.98	3.70	3.36	3.03
High	10.08	10.24	8.37	6.11	5.62	5.02	4.48	3.96
Low-High	-9.13	-9.19	-6.75	-4.84	-4.35	-3.61	-2.89	-2.62
(t-stat)	-(29.75)	-(27.24)	-(20.75)	-(21.00)	-(18.75)	-(16.43)	-(15.11)	-(16.45)

Table III
Bid-Ask Spreads, Volume, and Open Interest

This table reports additional summary statistics for the options that survive the data filter outlined in Appendix B. Each period we first measure the average characteristic (either bid-ask spread, volume, or open interest) across options for each portfolio 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, and Panel C reports the average open interest for the day prior to the portfolio formation date. 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.

Panel A. Bid-Ask Spread

	Days to Expiration							
Skew Quintile	7	18	48	78	108	138	168	198
	Calls							
Low	0.07	0.06	0.06	0.06	0.06	0.07	0.07	0.07
2	0.13	0.11	0.10	0.09	0.09	0.09	0.09	0.08
3	0.23	0.19	0.14	0.13	0.11	0.11	0.11	0.10
4	0.46	0.34	0.20	0.19	0.16	0.14	0.13	0.12
High	1.01	0.84	0.48	0.49	0.36	0.29	0.24	0.20
Low-High	-0.94	-0.78	-0.42	-0.43	-0.30	-0.23	-0.17	-0.13
(st. error)	(0.011)	(0.013)	(0.012)	(0.017)	(0.014)	(0.012)	(0.011)	(0.011)
	Puts							
Low	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
2	0.14	0.12	0.10	0.10	0.09	0.09	0.09	0.08
3	0.25	0.20	0.13	0.13	0.11	0.10	0.10	0.09
4	0.47	0.35	0.19	0.17	0.14	0.12	0.11	0.10
High	0.93	0.77	0.41	0.39	0.28	0.22	0.17	0.14
Low-High	-0.86	-0.70	-0.34	-0.33	-0.21	-0.15	-0.10	-0.07
(st. error)	(0.015)	(0.018)	(0.014)	(0.016)	(0.012)	(0.011)	(0.009)	(0.008)

Panel B: Volume

	Days to Expiration							
Skew Quintile	7	18	48	78	108	138	168	198
	Calls							
Low	182.70	139.39	89.56	63.01	60.03	57.43	53.51	54.48
2	342.48	264.05	139.70	96.01	78.15	76.31	63.26	55.16
3	488.52	371.36	170.56	110.05	92.80	75.30	67.64	53.89
4	483.47	362.87	175.63	118.35	94.58	84.77	70.26	56.96
High	318.59	247.20	145.51	104.22	93.97	83.55	73.73	59.41
Low-High	-135.89	-107.81	-55.95	-41.21	-33.95	-26.12	-20.22	-4.93
(st. error)	(14.72)	(13.12)	(8.18)	(7.02)	(6.60)	(6.03)	(5.15)	(4.00)
	Puts							
Low	160.29	157.39	96.58	70.72	68.20	67.55	65.34	56.23
2	290.57	223.87	134.49	88.77	79.91	75.12	66.32	54.60
3	413.04	312.30	152.45	96.89	86.92	81.97	72.40	54.17
4	392.38	291.13	145.77	108.67	83.94	81.38	63.19	53.22
High	253.60	180.14	108.35	75.54	75.21	67.36	61.48	51.46
Low-High	-93.31	-22.75	-11.77	-4.82	-7.01	0.19	3.86	4.78
(st. error)	(8.72)	(12.77)	(5.16)	(4.08)	(4.18)	(6.75)	(4.06)	(3.94)

Table III (*continued*)

Panel C: Open Interest								
	Days to Expiration							
Skew Quintile	7	18	48	78	108	138	168	198
	Calls							
Low	2400	2043	1436	1980	1653	1413	1106	805
2	2715	2351	1387	2141	1769	1452	1108	749
3	2885	2614	1492	2295	1868	1509	1146	814
4	3347	2898	1657	2630	2078	1625	1241	918
High	3937	3535	2264	3011	2498	1949	1437	1054
Low-High	-1537	-1492	-828	-1031	-844	-536	-331	-249
(st. error)	(84.4)	(105.3)	(94.0)	(146.7)	(134.9)	(118.7)	(98.7)	(95.2)
	Puts							
Low	2000	1838	1386	2119	1790	1482	1132	845
2	2248	1952	1321	2139	1837	1510	1187	892
3	2420	2211	1343	2178	1803	1481	1160	844
4	2870	2500	1471	2190	1751	1413	1059	758
High	3299	2809	1822	2284	1856	1419	1103	787
Low-High	-1299	-972	-436	-165	-65	64	29	59
(st. error)	(77.6)	(93.8)	(89.1)	(116.7)	(111.8)	(93.9)	(88.4)	(70.1)

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 - 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, using the mid-point of the bid and ask prices as the proxy for price. Panel A reports the results for call options while Panel B reports the results for put options. The final two rows of each panel report differences in average returns across the high and low skewness qunitiles along with Newey-West (1987) *t*-statistics that test whether these differences are equal to zero. Statistical significance at the 10%, 5% and 1% significance levels is indicated, respectively by *, **, and ***.

Panel A. Calls

Skew Quintile	Days to Expiration 7	18	48	78	108	138	168	198
Low	1.87	0.22	0.83	0.84	0.97	0.86	1.06	1.11
2	1.34	0.83	1.03	0.99	1.12	1.20	1.00	1.13
3	-0.78	0.97	1.01	0.64	0.66	0.51	0.62	0.73
4	-3.92	0.56	0.09	-0.23	0.41	0.21	0.14	0.36
High	-35.25 ***	-8.76 ***	-2.58 ***	-1.58 **	-1.13 **	-0.74 *	-0.20	0.11
Low-High	37.11 ***	8.98 ***	3.40 ***	2.42 ***	2.11 ***	1.60 ***	1.26 ***	1.00 ***
(t-stat)	(7.56)	(4.07)	(5.05)	(4.50)	(5.80)	(5.13)	(3.60)	(3.25)

Panel B. Puts

Skew Quintile	Days to Expiration 7	18	48	78	108	138	168	198
Low	-5.38 **	-0.90	0.02	0.01	-0.01	0.07	0.26	0.21
2	-8.51 **	-0.74	-0.33	-0.16	-0.16	-0.07	0.12	0.18
3	-15.52 ***	-2.24	-1.00	-0.70	-0.14	0.03	-0.02	0.15
4	-31.78 ***	-4.67	-1.77	-1.28	-0.79	-0.44	-0.14	-0.18
High	-59.98 ***	-13.73 ***	-3.16	-1.97	-1.41 *	-0.77	-0.51	-0.38
Low-High	54.60 ***	12.83 ***	3.18 *	1.98 **	1.40 **	0.84	0.77 *	0.59 *
(t-stat)	(14.13)	(3.92)	(1.94)	(1.98)	(2.00)	(1.51)	(1.88)	(1.79)

Table V
Alphas for Calls

Panel A and B report the estimated alphas for portfolios of individual equity call options taken from the Ivy database over the period 1996 - 2009. Portfolios are formed by sorting on skewness as in equation (4) and returns are holding period returns to expiration as in equation (3) for calls, using the mid-point of the bid and ask prices as the proxy for price. Each panel reports alphas corresponding to the method used to obtain market beta. In Panel A we obtain betas by regressing option portfolio returns on excess market returns as in equation (5); in Panel B, we report alphas constructed using the instantaneous beta at the time the option is purchased as described in equation (6) of the paper. Panel C reports the estimated alphas of the underlying stocks for the portfolios of options in Panels A and B. We obtain stock alphas by regressing stock portfolio returns on excess market returns. In the final rows of each panel we report differences in alphas 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 Alphas Based on Regression Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-1.20	-0.01	0.37	0.42	0.54	0.47	0.66	0.71
2	-3.44 *	0.53	0.43	0.43	0.54	0.69	0.52	0.66
3	-6.90 **	0.62	0.32	0.02	0.09	0.01	0.14	0.28
4	-10.71 **	0.17	-0.61	-0.86	-0.23	-0.30	-0.32	-0.11
High	-40.15 ***	-9.10 ***	-3.22 ***	-2.18 ***	-1.67 ***	-1.25 ***	-0.74 *	-0.40
Low-High	38.95 ***	9.09 ***	3.58 ***	2.60 ***	2.21 ***	1.72 ***	1.40 ***	1.10 **
(t-stat)	(9.00)	(4.27)	(5.36)	(4.95)	(4.99)	(3.81)	(3.02)	(2.57)

Panel B: Option Alphas Based on Instantaneous Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-2.27 ***	-0.37	0.06	0.15	0.25	0.18	0.38 **	0.42 **
2	-5.83 ***	0.07	0.03	0.10	0.33	0.51 *	0.32	0.49 **
3	-10.47 ***	-0.14	-0.05	-0.26	-0.12	-0.17	0.01	0.17
4	-15.90 ***	-0.61	-0.98	-1.13 **	-0.36	-0.44	-0.42 *	-0.13
High	-47.79 ***	-9.81 ***	-3.50 ***	-2.47 ***	-1.78 ***	-1.27 ***	-0.68 **	-0.33
Low-High	45.53 ***	9.44 ***	3.56 ***	2.62 ***	2.03 ***	1.45 ***	1.06 ***	0.75 **
(t-stat)	(7.89)	(3.70)	(4.35)	(4.39)	(4.84)	(4.46)	(3.13)	(2.51)

Panel C: Underlying Stock Alphas Based on Regression Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-0.02	0.00	0.05	0.08	0.09 *	0.07	0.08	0.09 *
2	-0.15	-0.03	0.00	0.00	0.03	0.04	0.02	0.05
3	-0.22 *	-0.06	-0.06	-0.08	-0.09 *	-0.10 *	-0.08	-0.07
4	-0.23 *	-0.06	-0.13 **	-0.19 ***	-0.16 ***	-0.18 ***	-0.19 ***	-0.16 **
High	-0.03	-0.04	-0.21 ***	-0.24 ***	-0.25 ***	-0.27 ***	-0.24 ***	-0.19 *
Low-High	0.01	0.05	0.26 ***	0.32 ***	0.34 ***	0.33 ***	0.32 ***	0.27 **
(t-stat)	(0.08)	(0.44)	(2.71)	(3.31)	(3.03)	(2.78)	(2.61)	(2.20)

Table VI
Alphas for Puts

Panel A and B report the estimated alphas for portfolios of individual equity put options taken from the Ivy database over the period 1996 - 2009. Portfolios are formed by sorting on skewness as in equation (4) and returns are holding period returns to expiration, using the mid-point of the bid and ask prices as the proxy for price. Each panel reports alphas corresponding to the method used to obtain market beta. In Panel A we obtain betas by regressing option portfolio returns on excess market returns as in equation (5); in Panel B, we report alphas constructed using the instantaneous beta at the time the option is purchased as described in equation (6) of the paper. Panel C reports the estimated alphas of the underlying stocks for the portfolios of options in Panels A and B. We obtain stock alphas by regressing stock portfolio returns on excess market returns. In the final rows of each panel we report differences in alphas 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: Alphas Based on Regression Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-2.42 **	-0.79	0.41	0.33	0.28	0.32	0.53 **	0.44 **
2	-3.56 **	-0.52	0.26	0.35	0.27	0.29	0.48	0.50 *
3	-9.30 ***	-1.93	-0.27	-0.07	0.39	0.49	0.39	0.51
4	-25.59 ***	-4.27 **	-0.93	-0.55	-0.21	0.10	0.34	0.24
High	-55.68 ***	-13.37 ***	-2.12	-1.01	-0.62	-0.06	0.12	0.14
Low-High	53.27 ***	12.58 ***	2.53	1.35	0.90	0.38	0.41	0.29
(t-stat)	(12.73)	(4.43)	(1.42)	(1.09)	(0.86)	(0.40)	(0.53)	(0.46)

Panel B: Alphas Based on Instantaneous Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-1.56 **	-0.27	0.39	0.37 *	0.27 *	0.30 **	0.48 ***	0.39 ***
2	-1.99	0.30	0.35	0.37	0.33	0.34 **	0.48 ***	0.48 ***
3	-6.29 **	-0.71	-0.10	0.08	0.46	0.55 **	0.41 **	0.53 ***
4	-20.73 ***	-2.84	-0.67	-0.36	-0.03	0.21	0.42 *	0.27
High	-49.10 ***	-11.75 ***	-1.89	-0.90	-0.50	-0.02	0.13	0.18
Low-High	47.54 ***	11.47 ***	2.28	1.26	0.77	0.32	0.35	0.21
(t-stat)	(10.30)	(3.90)	(1.54)	(1.41)	(1.19)	(0.64)	(0.94)	(0.70)

Panel C: Underlying Stock Alphas Based on Regression Betas

Skew	Days to Expiration							
Quintile	7	18	48	78	108	138	168	198
Low	-0.13	-0.10	-0.21 ***	-0.27 ***	-0.24 ***	-0.24 ***	-0.25 ***	-0.22 **
2	-0.20 *	-0.06	-0.12 **	-0.15 ***	-0.14 ***	-0.17 ***	-0.15 ***	-0.15 ***
3	-0.25 *	-0.02	-0.05	-0.06	-0.09 **	-0.11 ***	-0.11 ***	-0.09 **
4	-0.23 *	-0.01	0.02	-0.01	0.02	0.00	-0.04	-0.04
High	-0.13	0.01	0.08	0.07	0.12	0.15	0.12	0.13
Low-High	-0.01	-0.11	-0.29 **	-0.34 ***	-0.35 ***	-0.39 ***	-0.37 ***	-0.36 **
(t-stat)	-(0.04)	-(0.89)	-(2.53)	-(3.08)	-(3.07)	-(2.99)	-(2.61)	-(2.57)

Table VII
Fama-McBeth Regressions – 18 Days to Maturity

This table reports the time-series average of cross-sectional regression parameters following Fama and McBeth (1973) using individual equity options taken from the Ivy database over the period 1996 - 2009. Each month we construct 100 portfolios by sorting options on ex-ante skewness, $sk_{t:T}$, 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 beta as defined by equation (5) in the paper, β^{MOM}, which corresponds to a regression momentum beta on the momentum factor provided by Ken French, and β^{VOL}, the volatility risk beta of the option portfolio obtained by regressing portfolio returns on returns of a zero-delta index straddle. 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 on a value from 0 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% significance levels is indicated, respectively by *, **, and ***.

Panel A. Call Options

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$sk_{t:T}$	-0.097								-0.426 ***
	-(3.23) ***								-(4.43)
β^{mkt}		0.804 ***							2.137 ***
		(3.03)							(7.64)
β^{mom}			-0.059						0.205
			-(0.11)						(0.36)
β^{vol}				-17.668 ***					2.371
				-(6.69)					(1.00)
X/S					-0.098 ***				0.245 ***
					-(3.06)				(2.57)
Volume						0.209 ***			0.023
						(3.41)			(0.62)
Spread							-0.134 ***		-0.041
							-(3.62)		-(0.74)
Smirk								0.005	-0.026
								(0.14)	-(1.05)

Panel B. Put Options

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$sk_{t:T}$	-0.142 ***								-0.571 ***
	-(2.81)								-(4.19)
β^{mkt}		0.194							-0.495
		(0.66)							-(1.43)
β^{mom}			3.538 ***						0.366
			(5.46)						(0.64)
β^{vol}				-2.052					3.634 *
				-(1.19)					(1.79)
X/S					0.144 ***				-0.301 **
					(2.71)				-(2.27)
Volume						0.139			0.130 ***
						(1.45)			(2.95)
Spread							-0.189 ***		-0.042
							-(2.87)		-(0.73)
Smirk								-0.184 ***	-0.027
								-(4.92)	-(1.06)

Table VIII
Double Sorts

This table reports the estimated alphas for portfolios of individual equity options taken from the Ivy database over the period 1996 - 2009. We adopt a double sort procedure to net out the influence of a particular characteristic. For a given portfolio formation date, we first sort options according to a given characteristic into 10 portfolios and then within each decile, sort options into two portfolios by ex-ante skewness. We then average the one-period returns across all characteristic sorted portfolios to create returns of two portfolios with similar levels of the characteristic, but different in terms of skewness. We conduct this double sorting exercise separately for volume (Panel A), vega (Panel B), volatility smirk (Panel C), the bid-ask spread (Panel D), and prior six-month stock return (Panel E). We obtain alphas by regressing option portfolio returns on excess market returns as in equation (5). In the final rows of each panel we report differences in alphas across the low and high skewness portfolios along with Newey-West (1987) *t*-statistics. Statistical significance at the 10%, 5% and 1% significance levels is indicated, respectively by *, **, and ***.

Panel A: Controlling for Volume

Skew Rank	Days to Expiration: 7	18	48	78	108	138	168	198
				Call Options				
Low	-2.94 *	0.38	0.40	0.36	0.48	0.47	0.50	0.61 *
High	-21.93 ***	-3.48 *	-1.48 **	-1.21 **	-0.76 *	-0.61 *	-0.39	-0.14
	18.99 ***	3.85 ***	1.88 ***	1.57 ***	1.24 ***	1.08 ***	0.89 ***	0.75 ***
(t-stat)	(6.81)	(2.97)	(4.52)	(5.23)	(4.05)	(3.83)	(3.07)	(2.83)
				Put Options				
Low	-3.78 **	-0.91	0.24	0.23	0.23	0.30	0.50 *	0.48 *
High	-34.65 ***	-7.41 ***	-1.29	-0.60	-0.16	0.18	0.26	0.27
Low-High	30.87 ***	6.50 ***	1.52	0.83	0.39	0.13	0.23	0.22
(t-stat)	(10.56)	(3.63)	(1.54)	(1.27)	(0.73)	(0.25)	(0.56)	(0.60)

Panel B: Controlling for Vega

Skew Rank	Days to Expiration: 7	18	48	78	108	138	168	198
				Call Options				
Low	-3.70 **	0.29	0.20	0.18	0.29	0.25	0.33	0.41
High	-21.17 ***	-3.39 *	-1.28 *	-1.04 **	-0.57	-0.39	-0.23	0.05
Low-High	17.46 ***	3.67 ***	1.48 ***	1.22 ***	0.86 ***	0.64 ***	0.56 **	0.36 **
(t-stat)	(6.30)	(2.87)	(4.01)	(4.20)	(3.49)	(2.73)	(2.51)	(2.03)
				Put Options				
Low	-4.22 ***	-0.87	0.15	0.24	0.22	0.24	0.43 *	0.27
High	-34.22 ***	-7.45 ***	-1.20	-0.60	-0.15	0.24	0.32	-0.40
Low-High	30.00 ***	6.58 ***	1.35	0.83	0.37	0.00	0.11	0.61 ***
(t-stat)	(9.99)	(3.79)	(1.37)	(1.26)	(0.71)	(0.01)	(0.27)	(4.85)

Panel C: Controlling for Volatility Smirk

Skew Rank	Days to Expiration: 7	18	48	78	108	138	168	198
				Call Options				
Low	-3.16 *	0.57	0.55	0.27	0.37	0.32	0.41	0.16
High	-20.22 ***	-2.64	-0.73	-0.41	-0.11	0.00	0.16	0.08
Low-High	17.05 ***	3.21 *	1.28 **	0.68	0.48	0.33	0.25	0.00
(t-stat)	(4.79)	(1.74)	(2.53)	(1.39)	(1.41)	(1.30)	(1.02)	(0.00)
				Put Options				
Low	-4.16	-1.42	-0.01	0.02	-0.01	0.21	0.30	0.13
High	-42.79 **	-9.06 ***	-1.74	-0.90	-0.25	0.02	0.24	0.31
Low-High	38.63 ***	7.64 ***	1.74	0.92	0.24	0.19	0.08	-0.17
(t-stat)	(11.71)	(3.46)	(1.50)	(1.26)	(0.40)	(0.29)	(0.18)	-(0.46)

Table XIII (*continued*)

Panel D: Controlling for Bid-Ask Spread

Skew Rank	Days to Expiration 7	18	48	78	108	138	168	198
	Call Options							
Low	-4.85 **	0.28	0.11	0.12	0.39	0.39	0.42	0.52 **
High	-20.04 ***	-3.39 *	-1.19 *	-0.98 *	-0.67 *	-0.53	-0.31	-0.06
Low-High	15.19 ***	3.67 ***	1.30 ***	1.11 ***	1.06 ***	0.91 ***	0.73 **	0.58 **
(t-stat)	(8.55)	(3.28)	(3.32)	(3.46)	(3.64)	(3.26)	(2.45)	(2.03)
	Put Options							
Low	-10.45 ***	-1.26	0.22	0.26	0.40	0.46	0.50 *	0.50 *
High	-28.05 ***	-7.06 ***	-1.27	-0.61	-0.32	0.02	0.26	0.25
Low-High	17.60 ***	5.79 ***	1.49 *	0.87	0.71	0.43	0.25	0.25
(t-stat)	(7.83)	(5.41)	(1.84)	(1.41)	(1.26)	(0.92)	(0.61)	(0.75)

Panel E: Controlling for Prior Six-Month Stock Return

Skew Rank	Days to Expiration 7	18	48	78	108	138	168	198
	Call Options							
Low	-3.32 **	0.29	0.08	-0.05	0.08	0.11	0.18	0.30
High	-21.58 ***	-3.02	-0.98	-0.73	-0.27	-0.09	0.03	0.20
Low-High	18.25 ***	3.32 **	1.06 **	0.68	0.35	0.20	0.14	0.10
(t-stat)	(6.17)	(2.28)	(2.32)	(1.55)	(1.01)	(0.76)	(0.66)	(0.47)
	Put Options							
Low	-4.18 **	-1.45 **	-0.33	0.03	0.04	0.15	0.23	0.24
High	-33.81 ***	-7.28 ***	-0.87	-0.56	0.03	0.33	0.53	0.53
Low-High	29.63 ***	5.83 ***	0.54	0.59	0.01	-0.18	-0.31	-0.29
(t-stat)	(10.64)	(3.36)	(0.53)	(0.86)	(0.03)	-(0.39)	-(0.70)	-(0.81)

Table IX
Double Sorts on Moneyness

This table reports the estimated alphas for portfolios of individual equity options taken from the Ivy database over the period 1996 - 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 in terms of skewness. In Panel B we reverse this procedure, and first sort options by ex-ante skewness into10 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 in terms of moneyness. We obtain alphas by regressing option portfolio returns on excess market returns as in equation (5). In the final rows of each panel we report differences in alphas across the two conditionally sorted portfolios along with Newey-West (1987) *t*-statistics. Statistical significance at the 10%, 5% and 1% significance levels is indicated, respectively by *, **, and ***.

Panel A: Controlling for Moneyness								
Skew	Days to Expiration							
Rank	7	18	48	78	108	138	168	198
Call Options								
Low	-8.05 ***	0.54	0.25	0.17	0.50	0.46	0.45	0.67 **
High	-16.86 ***	-3.64 ***	-1.32 **	-1.03 ***	-0.78 **	-0.60 **	-0.35	-0.21
Low-High	8.81 ***	4.17 ***	1.57 ***	1.20 **	1.27 ***	1.06 ***	0.80 ***	0.88 ***
(t-stat)	(4.93)	(3.73)	(2.58)	(2.55)	(3.26)	(3.25)	(2.72)	(2.93)
Put Options								
Low	-14.43 ***	-1.63	0.35	0.40	0.45	0.61 *	0.69 **	0.65 **
High	-24.13 ***	-6.70 ***	-1.40 *	-0.75	-0.38	-0.12	0.07	0.09
Low-High	9.70 ***	5.07 ***	1.76 ***	1.15 **	0.83 *	0.72 *	0.62 *	0.56 **
(t-stat)	(4.05)	(4.66)	(2.68)	(2.48)	(1.89)	(1.94)	(1.90)	(1.99)

Panel B: Controlling for Ex-Ante Skewness								
Moneyness	Days to Expiration							
Rank	7	18	48	78	108	138	168	198
Call Options								
Low	-10.73 ***	-1.61	-0.58	-0.56 *	-0.44 *	-0.19	-0.06	0.03
High	-14.20 ***	-1.50	-0.51	-0.30	0.14	0.04	0.15	0.42
Low-High	3.48 *	-0.11	-0.07	-0.26	-0.58 *	-0.23	-0.21	-0.39
(t-stat)	(1.91)	-(0.09)	-(0.12)	-(0.55)	-(1.67)	-(0.92)	-(1.15)	-(1.85)
Put Options								
Low	-20.32 ***	-3.60 **	0.07	0.28	0.46	0.65	0.76	0.70 *
High	-18.29 ***	-4.74 ***	-1.13 **	-0.64	-0.40	-0.18	0.00	0.04
Low-High	-2.04	1.14	1.20 **	0.92 ***	0.86 ***	0.83 ***	0.76 ***	0.66 ***
(t-stat)	-(0.91)	(1.01)	(2.41)	(2.60)	(3.26)	(3.63)	(3.00)	(3.08)

Table X
Stock Alphas Controlling for Lagged Six-Month Stock Return

This table reports the estimated alphas for portfolios of underlying stocks on options found in the Ivy database over the period 1996 - 2009. We adopt a double sort procedure to net out the influence of the lagged six month stock return. For a given portfolio formation date, we first sort options by the lagged six-month return of their underlying stocks into 10 portfolios and then within each lagged return decile sort options into two portfolios by their ex-ante skewness. We then take the underlying stocks for these options and average the one-period stock returns across all lagged return sorted portfolios to create returns of two stock portfolios with similar levels of lagged returns, but different in terms of the skewness of the options written on them. We obtain stock alphas by regressing stock portfolio returns on excess market returns as in equation (5). In the final rows of each panel we report differences in alphas across the two conditionally sorted portfolios along with Newey-West (1987) *t*-statistics. Statistical significance at the 10%, 5% and 1% significance levels is indicated, respectively by *.

Skew				Days to Expiration				
Rank	7	18	48	78	108	138	168	198
				Call Options				
Low	-0.11	-0.02	-0.02	-0.04	-0.01	-0.02	-0.01	0.02
High	-0.12	0.01	-0.05	-0.08	-0.08	-0.08	-0.08	-0.06
Low-High	0.00	-0.03	0.03	0.04	0.06 *	0.07	0.07	0.08 *
(t-stat)	(0.09)	-(0.98)	(1.11)	(1.21)	(1.68)	(1.47)	(1.40)	(1.67)
				Put Options				
Low	-0.13	0.02	-0.03	-0.07	-0.05	-0.07	-0.06	-0.05
High	-0.20	-0.01	-0.01	-0.04	-0.01	-0.01	-0.04	-0.03
Low-High	0.07	0.04	-0.02	-0.03	-0.04	-0.06 *	-0.01	-0.02
(t-stat)	(1.43)	(1.28)	-(1.23)	-(0.97)	-(1.30)	-(1.89)	-(0.51)	-(0.71)

Table XI
Weekly Alphas Non-Overlapping Data
Bootstrapped p-values and Simulation p-values

Panel A reports the estimated alphas for individual equity option portfolios taken from the Ivy database over the period 1996 - 2009. The portfolios are formed every-other month so that returns are non-overlapping. The portfolios are constructed by sorting on expected skewness as in equation (4) and the returns are holding period returns as in equations (3) for calls using the mid-point of the bid and ask prices as the proxy for price. We estimate a one-factor model as in equation (5) on the portfolio returns and report the alpha from those estimations. The bottom rows of Panel A report differences in alphas across the high and low skewness portfolios along with *t*-statistics and boot-strapped p-values that test whether these differences are equal to zero. Panel B reports the results of a Black-Scholes simulation exercise, in which the CAPM holds instantaneously, skewness has no effect on pricing, and the simulation is calibrated to match the moments of the actual non-overlapping data. The simulation is repeated 1000 times, and we report the average alpha for each skewness/maturity portfolio across simulations. The bottom rows of Panel B report differences in alphas across the high and low skewness portfolios along with the fraction of simulations which generated alpha spreads as extreme as those in Panel A.

Panel A. Actual Data

	Calls				Puts		
Skew	Days to Expiration			Skew	Days to Expiration		
Rank	7	18	48	Rank	7	18	48
1 (Low)	-1.00	-0.13	0.48	1 (Low)	-1.11	0.04	0.47
2	-5.61	-0.70	0.64	2	-2.06	-0.25	0.52
3	-13.80	-2.64	0.85	3	-9.25	-2.88	0.25
4	-18.00	-3.96	-0.12	4	-24.09	-7.09	-0.65
5 (High)	-52.74	-14.13	-2.93	5 (High)	-57.68	-16.91	-2.49
Diff	51.73	14.01	3.40	Diff	56.57	16.95	2.95
t-stat	(11.37)	(5.93)	(3.91)	t-stat	(9.37)	(5.77)	(2.41)
p-value	(0.00)	(0.00)	(0.00)	p-value	(0.00)	(0.00)	(0.00)

Panel B: Black-Scholes Simluation

	Calls				Puts		
Skew	Days to Expiration			Skew	Days to Expiration		
Rank	7	18	48	Rank	7	18	48
1 (Low)	-10.13	1.84	2.99	1 (Low)	-10.81	-7.42	-5.91
2	-9.13	-6.52	-5.35	2	-10.30	-7.40	-6.21
3	-8.19	-5.68	-3.25	3	-9.84	-7.20	-6.69
4	-5.18	-4.13	-1.70	4	-8.78	-6.69	-7.22
5 (High)	-2.53	-0.24	1.77	5 (High)	-7.03	-5.95	-8.57
Diff	-7.60	2.08	1.22	Diff	-3.77	-1.48	2.66
p-values	(0.00)	(0.00)	(0.01)	p-values	(0.00)	(0.00)	(0.46)

Table XII
Alphas from Writing Options at the Bid

This table reports the estimated alphas for portfolios of individual equity call options taken from the Ivy database over the period 1996 - 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 betas 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 alphas across the high and low skewness quintiles along with GMM t-statistics calculated using the approach of Newey and West (1987) that test whether these differences are equal to zero.

Panel A: Calls

Skew Qunitile	Days to Expiration: 7	18	48	78	108	138	168	198
Low	-2.44 ***	-1.42 ***	-0.88 **	-0.74 **	-0.78 ***	-0.67 **	-0.85 ***	-0.87 ***
2	-3.88 **	-2.99 ***	-1.29 **	-0.91 **	-0.87 *	-0.98 **	-0.76 **	-0.85 **
3	-6.42 **	-5.20 ***	-1.52 **	-0.71	-0.53	-0.33	-0.40	-0.48 *
4	-15.45 ***	-9.61 ***	-1.20	-0.18	-0.39	-0.15	0.01	-0.14
High	-4.80	-10.26 ***	-0.78	-0.21	0.44	0.47	0.17	-0.07
Low-High	2.35	8.84 ***	-0.10	-0.53	-1.23 **	-1.13 **	-1.02 *	-0.81
(t-stat)	(0.32)	(2.76)	-(0.11)	-(0.75)	-(2.22)	-(2.15)	-(1.91)	-(1.63)

Panel B: Puts

Skew Qunitile	Days to Expiration: 7	18	48	78	108	138	168	198
Low	-1.29	-0.77	-1.00 **	-0.70 **	-0.53 *	-0.53 **	-0.72 ***	-0.59 ***
2	-4.00 **	-2.49 ***	-1.15 **	-0.88 **	-0.62 *	-0.55 **	-0.72 **	-0.69 **
3	-5.85 *	-3.32 **	-0.91	-0.63	-0.82 *	-0.88 **	-0.63 *	-0.73 **
4	-0.69	-4.26 *	-0.69	-0.23	-0.33	-0.56	-0.64	-0.45
High	24.46 ***	-1.29	-0.73	-0.32	-0.28	-0.67	-0.65	-0.44
Low-High	-25.75 ***	0.52	-0.27	-0.38	-0.25	0.14	-0.07	-0.15
(t-stat)	-(3.84)	(0.14)	-(0.13)	-(0.27)	-(0.22)	(0.13)	-(0.07)	-(0.21)