Internet Appendix for
"Stock Options as Lotteries"

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This Internet Appendix (hereafter IA) accompanies Boyer and Vorkink (2014) and reports additional results related to that paper. In Section I below we provide summary statistics on open interest for the ex-ante skewness portfolios analyzed in Tables II to VII of the paper. In Section II we investigate the sources of variation in our ex-ante skewness measure. In Section III we examine the importance of stock skewness for explaining variation in option skewness. In Section IV we examine CAPM alphas for option portfolios in the following five settings: 1) after sorting options unconditionally on moneyness and ex-ante coskewness, 2) using instantaneous betas, 3) after adjusting the window to estimate stock moments that are inputs to our ex-ante skewness measure, 4) after accounting for the possibility of early exercise, and 5) after unconditionally sorting on the raw third moment. In Section V we report the CAPM alphas of the stocks underlying the options after controlling for momentum effects. In Section VI we use a double sort procedure to individually control for a variety of option characteristics. And in Section VII we report the results of a simulation study to further investigate whether peso problems or estimation bias can explain our results.

I. Open Interest

In this section we report summary statistics on open interest for the options within each of the skewness/maturity portfolios analyzed in Tables II to VII of the paper. In Panel A of Table IA.I we report average open interest, the average number of outstanding contracts per option across portfolio formation dates.[1] Panel B of Table IA.I reports total dollar open interest across portfolio formation dates. Total dollar open interest on a given day is the sum of closing price times open interest across

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[1]We use closing open interest for the day before each portfolio formation date.

all contracts in a skewness/maturity portfolio. 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 options with 48 days to maturity.

In Panel A of Table IA.I we see that average open interest is monotonically increasing in skewness and significantly higher for options in the high skewness bins at all maturities. For example, among call options that expire in seven days, we observe an average of 2,400 (3,937) contracts outstanding per option for contracts in the low (high) ex-ante skewness bin. Average dollar open interest reported in Panel B of Table IA.I, however, is decreasing in ex-ante skewness because options with high skewness are relatively cheap. For example, among call options that expire in seven days, the average total open interest is $441 million ($19 million) across all contracts in the low (high) ex-ante skewness bin.

II. Variation in Ex-Ante Skewness

In this section we examine the influence of each input to our ex-ante skewness measure on the measure itself. On each portfolio formation date for options that expire in seven days, we independently rank options into 100 bins based on each input to our ex-ante skewness measure and on the measure itself. We then estimate Fama-Macbeth (1973) regressions using these ranks with the ex-ante skewness rank as the dependent variable and report results in Table IA.II. In the first column of Panels A and B of this table we see that moneyness alone explains on average about 92% of the cross-sectional variation in ex-ante skewness for calls (Panel A) and about 93% for puts (Panel B), measured by the average adjusted-R^2. Price alone also exhibits a high average adjusted-R^2 (column 2), but this is due to its correlation with moneyness. In column 6 we add price to moneyness and see that the incremental improvement to the adjusted-R^2 relative to column 1 is very small. The input with the greatest explanatory power after controlling for moneyness is volatility. In column 7 we see that adding volatility to moneyness improves the adjusted-R to 97% for both calls and puts.[2] Finally, in column 10 we include all our inputs and see that the adjusted-R^2 improves to 98%.

[2]We include the interaction term whenever we control for volatility and moneyness because the effect of volatility on skewness depends on moneyness (see Figure 2).

III. Underlying Skewness

Cross-sectional variation in the skewness of option returns is likely to be driven in part by variation in the skewness of the underlying assets. Although the lognormal assumption allows for variation in skewness across stocks, it cannot perfectly characterize such skewness. We choose to rely on the assumption of lognormality because of its simplicity and familiarity to the finance profession. Since the finance profession is familiar with the lognormal PDF, our option moments should be easier for readers to understand and less prone to accusations of cherry picking. We chose our methodology due to its clarity and trasparency and to avoid methodologies succeptible to black-box criticisms with little intuition and an abundance of degrees of freedom.

That being said, in this section we investigate the importance of variation in stock skewness for explaining the skewness of option returns. To do so, we forecast the skewness of stock returns using an approach that does not rely on the lognormal assumption and first sort stocks into *stock skewness terciles*. Then within each stock skewness tercile, we sort options into *option skewness terciles* as described in the paper under the assumption of lognormality. We then empirically investigate the skewness of option returns within each bin, measured as the average cross-sectional skewness among options within each bin, as in Table II Panel B of the paper.[3] This empirical measure of skewness also does not rely on the lognormal assumption. This double sort allows us to investigate how much variation in option skewness is driven by variation in stock return skewness versus other characteristics as captured by our ex-ante skewness measure by comparing the spread in empirical option skewness *across* stock skewness terciles to that *within* stock skewness terciles.

Our method to forecast stock return skewness closely follows Boyer, Mitton, and Vorkink (2010), who demonstrate the method's ability to forecast stock return skewness. Let m denote the current month, let $S(m)$ denote the set of trading days within month m, and let $N(m)$ denote the number of days in this set. In addition, let $v_{i,m}$ and $s_{i,m}$ denote historical estimates of volatility and skewness

[3]As discussed in the paper, 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.

(respectively) for stock i using daily data for all days in $S(m)$. We can then define $v_{i,m}$ and $s_{i,m}$ in the usual manner as

$$v_{i,m} = \left(\frac{1}{N(m)-1} \sum_{d \in S(m)} (\tilde{r}_{i,d} - \tilde{\mu}_{i,d})^2 \right)^{1/2}, \tag{IA.1}$$

$$s_{i,m} = \frac{1}{N(m)-2} \frac{\sum_{d \in S(m)} (\tilde{r}_{i,d} - \tilde{\mu}_{i,d})^3}{v_{i,m}^{3/2}}, \tag{IA.2}$$

where $\tilde{r}_{i,d}$ is the return for stock i over day d, and $\tilde{\mu}_{i,d}$ denotes an estimate of the expected stock return. We need measures of *expected* skewness for stock i at the end of month m, $E_m[s_{i,m+1}]$, rather than measures of historical skewness as defined in equation (IA.2). These estimates of expected skewness should be feasible in that they use information available to investors at the end of month m. To model investor perceptions of expected skewness in a feasible manner, we first estimate cross-sectional regressions separately at the end of each month m in our sample,

$$s_{i,m} = \beta_0^m + \beta_1^m s_{i,m-1} + \beta_2^m v_{i,m-1} + \boldsymbol{\gamma}^{\mathbf{m}} \mathbf{X}_{i,m-1} + \varepsilon_{i,m}, \tag{IA.3}$$

where $\mathbf{X}_{i,m-1}$ is a vector of additional firm-specific variables observable at the end of month $m-1$. Superscripts on regression parameters are included to emphasize that we estimate these parameters using information observable at the end of month m. Equation (IA.3) is similar to the panel estimations conducted in Chen, Hong, and Stein (2001) with the exception that we estimate the model each month. We then use the regression parameters from equation (IA.3), along with information observable at the end of each month m, to estimate expected skewness for each firm,

$$E_m[s_{i,m+1}] = \beta_0^m + \beta_1^m s_{i,m} + \beta_2^m v_{i,m} + \boldsymbol{\gamma}^{\mathbf{m}} \mathbf{X}_{i,m}. \tag{IA.4}$$

This approach not only allows the relation between firm-specific variables and skewness to vary over time, but also provides feasible estimates of expected skewness each month.

The firm-specific variables used to define $\mathbf{X}_{i,m-1}$ are

Momentum $(mom_{i,t-T})$: the cumulative return for firm i from the end of month $t-T-12$ through the end of month $t-T-1$.

Turnover $(turn_{i,t-T})$: the sum of daily turnover for firm i over month $t-T$. Daily turnover for day d is defined as volume for day d divided by shares outstanding reported on day d.

Nasdaq $(Nasd_{i,t-T})$: dummy variable indicating firms listed on NASDAQ (CRSP exchange code = 3 for month $t-T$).

Small $(Small_{i,t-T})$: dummy variable indicating firms in the bottom tercile ranked by size at the end of month $t-T$.

Medium $(Med_{i,t-T}$:) dummy variable indicating firms in the middle tercile ranked by size at the end of month $t-T$.

Industry Dummies: dummies for 16 of the 17 industries defined by Ken French to create the "17 Industry Portfolios" on his website.

On each option portfolio formation date we first separate options by maturity as in the paper. Here we focus on seven- and 18-day options for brevity. As in the paper, the portfolio formation dates for the seven-day options fall on the second Friday of each month and for the 18-day options are the first trading day of each month. We then sort underlying assets with a given maturity into terciles based on $E_{m-1}[s_{i,m}]$, where m denotes the month in which the option portfolios are created and expire. On each portfolio formation date we then sort options with the same expiration date and stock skewness tercile into option skewness terciles, based on the lognormal assumption as described in the paper. In Table IA.III we report the average cross-sectional skewness of options within each bin.

Table IA.III indicates that call option skewness increases with the skewness of the underlying. This can be seen in Panel A, by noting that nearly all of the numbers in columns marked "Low-High" are negative. Put option skewness decreases with the skewness of the underlying. This can be seen in Panel B, by noting that all of the numbers in columns marked "Low-High" are positive. While these results are intuitive, only a few of them are statistically significant. Further, differences in option skewness *across* stock skewness bins (across the columns of Table IA.III) are quite small relative to differences in option skewness *within* stock skewness bins (down the rows of Table IA.III). The results of this table therefore suggest that other option characteristics as captured by our ex-ante skewness measure under the lognormal assumption are much more important than stock skewness for explaining variation in option skewness.

In Table IA.IV we report the CAPM alphas of the option portfolios defined for Table IA.III. Call alphas generally decrease with stock skewness: in Panel A of Table IA.IV nearly all of the numbers in columns marked "Low-High" are positive. Put alphas generally increase with stock skewness: in Panel B of this same table nearly all of the numbers in columns labeled "Low-High" are negative. These results suggest that option skewness arising from greater skewness of the underlying is also priced. However, similar to Table IA.III, differences across stock skewness bins (across the columns of Table IA.IV) are small relative to differences within stock skewness bins (down the rows of Table IA.IV).

Given the evidence of Tables IA.III and IA.IV, it appears that stock skewness is not of first-order importance for explaining variation in option skewness and that accounting for stock return skewness would, if anything, further strengthen our results. In light of these findings, the lognormal assumption appears to be conservative.

IV. Single Factor Regressions

In this section we begin by reporting the regression slopes (betas) associated with the regression intercepts (CAPM alphas) reported in Table V of the paper. We then report alternative estimates of regression intercepts (CAPM alpha) for the ex-ante skewness quintile portfolios analyzed in Tables II to VII of the paper.

A. Betas

Table IA.V reports the betas associated with the CAPM alphas reported in Table V of the paper. Here we see that betas for call portfolios are all positive and for put portfolios are all negative. Coval and Shumway (2001) show that option betas increase with the strike price holding all else fixed, including the underlying asset, for both calls and puts. Figure 1 and Section (II) above indicate that calls with high ex-ante skewness generally have high strike prices and puts with high ex-ante skew generally have low strike prices. In Table IA.V we see that betas increase with the strike price for puts, but not for calls. The reason is that the underlying asset is not held constant in Table IA.V across ex-ante skewness quintiles, but rather, is determined by the trading choices of market participants over the data sample and by our data screens discussed in the paper.

B. Unconditional Sorts

In this section we report CAPM alphas for portfolios of options unconditionally sorted by moneyness and then by ex-ante coskewness as defined in the Appendix in the published paper. The procedure we follow is identical to that of Table II of the paper with the exception that in Table II we unconditionally sort by ex-ante skewness. In Table IA.VI we report results after unconditionally sorting by moneyness. Here we see that the spread in alpha across portfolios with a given maturity are similar to those reported in Table V. For example, among call options that expire in seven days, the alpha spread across the high and low ex-ante skewness quintiles reported in Table V is 38.95% per week while the corresponding alpha spread for call options sorted by moneyness in Table IA.VI is 38.06% per week. In Table IA.VII we report results after unconditionally sorting by ex-ante coskewness, where we see that alpha spreads are insignificantly different from zero. For example, among call options that expire in seven days, the alpha spread across the high and low ex-ante skewness portfolios is -2.28 with a $t-$statistic of -0.44.

We argue in this paper that the large alpha spreads documented in Table IA.VI arise because moneyness is strongly related to total option skewness. In fact, after controlling for moneyness, we still find a significant relationship between ex-ante skewness and CAPM alphas (see Table IX of the paper). After controlling for ex-ante skewness, however, we find that the relation between moneyness and CAPM alpha documented in Table IA.VI largely disappears. On the other hand, Table IA.VII provides little evidence that systematic coskewness is priced in options on individual stocks.

C. Instantaneous Betas

In Table IA.VIII we present CAPM 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,

$$\beta_t^i = \Delta_t \frac{S_t}{C_t} \beta_{S,t}^{mkt}, \tag{IA.5}$$

where Δ_t is the option's delta, S_t is the underlying stock price, C_t is the underlying call (or put) price, 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 estimate the portfolio instantaneous beta, $\beta^i_{p,t}$, 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 CAPM alpha for each portfolio as

$$\alpha^i_p = \frac{1}{N}\sum_t \left[r_{p,t:T} - r_{f,t:T} - \beta^i_{p,t}(r_{m,t:T} - r_{f,t:T}) \right], \tag{IA.6}$$

where N corresponds to the number of portfolio formation dates in the data. Standard errors for the average CAPM alpha estimates are constructed using the method of Newey-West (1987). We report alphas as given in equation (IA.6) in Table IA.VIII and find them to be similar to the regression CAPM alphas given in Table V of the paper. For example, among options that expire in seven days, the CAPM alpha spread for call (put) options is 45.43% (47.54%) in Table IA.VIII and 38.95% (53.27%) in Table V of the paper.

D. Estimation Window for Stock Moments

Our measure of ex-ante expected skewness depends on estimates of the first two moments for the underlying stock. In the paper we use a six-month window of daily data to estimate these moments. Here we estimate these moments using a five-year window and use them to measure ex-ante skewness. CAPM alphas for portfolios sorted according to this alternate measure of ex-ante skewness are given in Table IA.IX. The only difference between Tables V and IA.IX is that for Table V, we use a six-month window to estimate stock moments while for Table IA.IX we use a five-year window. The results reported in these two tables are very similar, implying that the window length we use to estimate stock moments does not have a meaningful impact on our results.

While volatility is persistent and may be reasonably estimated using historical data, estimates of the expected return using historical data can be noisy (Merton (1980)). Figure IA.1 shows how our expected skewness measure varies with the expected stock return. This figure is a plot of expected skewness for theoretical options that expire in 21 days on an asset with annualized volatility of 0.4 and varying levels of moneyness and expected return. Consistent with Figure 1 of the paper, Figure IA.1 shows that option skewness is higher for out-of-the-money options. However, skewness does not seem to vary much with the expected stock return. Hence, even though our measure of the expected stock return is undoubtedly noisy, this noise does not seem to have much impact on our estimate of ex-ante expected skewness.

E. Early Exercise

Results of the paper use hold-to-expiration returns that ignore the possibility of early exercise. Here we report CAPM alphas for option portfolios sorted on ex-ante skewness, where we use a simple rule to account for the possibility of early exercise. We identify the first day, τ, after the portfolio formation date for each call (put) option contract on which $bid_\tau < S_\tau - X$ ($bid_\tau < X - S_\tau$), where bid_τ is the closing bid price for the option, S_τ is the closing price for the underlying stock, and X is the strike price. Such boundary conditions represent the first possible opportunity for which it may be optimal to exercise early.[4] If we find a day for which these boundary conditions are satisfied, we "exercise" the option and put the proceeds in an account that earns the risk-free rate through the maturity date of the contract. We then calculate call and put net returns, r^c and r^p, as

$$\begin{aligned} r^c &= \frac{S_\tau - X}{C_t} \exp\left[\frac{r_f(T-\tau)}{250}\right] - 1 \\ r^p &= \frac{X - S_\tau}{P_t} \exp\left[\frac{r_f(T-\tau)}{250}\right] - 1, \end{aligned} \tag{IA.7}$$

where C_t and P_t represent option prices on portfolio formation date t, and r_f represents the annualized risk-free rate. If no such date τ is found, then returns are calculated assuming the option is held to expiration.

We report results that account for early exercise in this manner in Table IA.X. Here we see that the results are quite similar to those that do not account for the possibility of early exercise reported in Table V of the paper. For example, among calls (puts) that will expire in seven days, the CAPM alpha spread across the low and high ex-ante skewness quintiles is 39.04% (53.19%) in Table IA.X and 38.95% (53.27%) in Table V of the paper. The results suggest that accounting for early exercise has little impact on our results.

[4] Pool, Stoll, and Whaley (2007) use a similar "market-based approach" to determine optimal timing of early exercise.

F. *Alternate Skewness Measure*

We sort options by the third raw moment and in Table IA.XI report CAPM alphas for these portfolios. Again we see that little has changed relative to our previous results. The results of Table IA.XI suggest that variation in the numerator of our expected skewness measure (the option's third moment) is much more important for variation in expected skewness than variation in the denominator (the option's volatility).

V. Stock Alphas Controlling for Momentum

While we report significant CAPM alpha spreads for our ex-ante skewness portfolios in Table V, we also find that for options at longer maturities, CAPM alpha spreads for the underlying stocks are also significantly different from zero in Panel B of Table V of the paper. This raises the possibility that the reason we find significant spreads in CAPM alpha for options across the low and high ex-ante skewness quintiles is because the stocks underlying these options are somehow different in terms of some risk exposure or characteristic. We resolve this question in the paper by creating portfolios of options in the low and high ex-ante skewness bins on the same underlying assets, thus eliminating any differences in the characteristics of the underlying across these two ex-ante skewness quintiles. We still find significant CAPM alpha spreads across the low and high ex-ante skewness quintiles after holding the underlying assets fixed as reported in Table VI.

In this section we further investigate the reason behind the nonzero CAPM alpha spreads for stocks reported in Panel B of Table V of the paper. In particular, in Table IA.XII we report CAPM alphas of the underlying stocks for the option portfolios analyzed in Tables II to VII after controlling for the lagged six-month return. On each portfolio formation date we first sort the underlying stocks for options of a given maturity into deciles based on the six-month return just prior to the portfolio formation date. Then within each decile, we rank stocks into two bins based on the ex-ante skewness of the options written on them. We then equal-weight the returns for stocks with the same ex-ante skewness rank across all deciles. After creating two such portfolios for each formation date in our sample, we then estimate and compare the stock alphas.

In Table IA.XII we see that virtually all CAPM alphas are insignificant from zero, indicating that the reason many of the stock CAPM alphas in Table V of the paper are nonzero for options with 48 days to maturity is because of a momentum effect. In Table V of the paper we observe that at these longer maturities, it is primarily stocks for *out-of-the money calls* (high exercise relative to underlying) that have negative alphas, or stocks that have recently fallen in value. Similarly, it is primarily stocks for *in-the-money puts* (again, high exercise relative to underlying) that have negative alphas as well. Stocks whose prices have gone down recently will end up with out-of-the-money call options (high ex-ante skewness) and in-the-money put options. Given the momentum effect, these will likely experience continued negative performance in the future. Once we control for this effect as in Table IA.XII, the signficance of the stock alphas goes away.

We conduct a similar analysis where we examine the alphas of option portfolios after controlling for the lagged six-month return of the underlying asset in Panel E of Table IA.XIII. Here we see that CAPM alpha spreads across the low and high skewness option portfolios are still significantly different from zero. Hence, while momentum effects explain the nonzero alphas for underlying assets reported in Panel B of Table V of the paper, they do not seem capable of explaining the nonzero CAPM alphas of the option portfolios documented in Panel A of Table V of the paper.

VI. Double Sorts

In this section we conduct additional robustness checks to individually control for the potential influence of various stock and option characteristics on option returns, including each input to our measure of expected skewness, and show that our main results still hold. Our measure of expected skewness is a function of six variates: stock price, time to maturity, moneyness, expected stock return, stock return volatility, and option price. Motivated by the fact that others have investigated the relationship between moneyness and option returns (Coval and Shumway (2001) and Ni (2009)), we report tests that control for moneyness in the paper. (See Table IX.) In addition, because all quantitative comparisons in our paper are made across options with exactly the same maturity, we already perfectly control for maturity effects. We therefore conduct tests to control for variation in the stock price, expected stock return, stock return volatility, and option price. We also conduct this exercise for each of the characteristics considered in our Fama-McBeth (1973) regressions, namely, volume, bid-ask spread, and volatility smirk, as well as the past six-month underlying stock return and option vega.

On each portfolio formation date we first sort options of a given maturity into deciles based on some characteristic. Then within each characteristic-sorted decile, we rank options into two ex-ante skewness bins. We then equal-weight the returns for options with the same ex-ante skewness rank across all characteristic deciles, thereby creating two portfolios similar in terms of the given characteristic but different in terms of their ex-ante skewness. After creating two such portfolios for each formation date in our sample, we then estimate and compare their CAPM alphas.

Table IA.XIII reports the results. Here we see that the negative relation between option skewness and CAPM alpha still exists even after controlling for variation in these other variables. The smallest alpha spread between the conditionally sorted low and high skewness portfolios is 12.50 with a t-statistic of 5.39, found for puts in Panel I where we control for variation in the option price. Since option price and moneyness are highly correlated, controlling for price gives similar results to controlling for moneyness.

VII. Simulation Study

In this section we investigate whether more robust models of stock return dynamics can generate the patterns in individual stock options we observe in the data. Broadie, Chernov, and Johannes (2009) discuss some of the concerns regarding the empirical analysis of option returns and allege that standard methods to compute pricing errors for options can be misleading. Some of these problems arise because option returns are nonnormal, nonlinear, non-additive and may suffer from peso problems in finite samples. First, option returns deviate substantially from normality and the small-sample distributions of standard CAPM alpha estimates may not conform with asymptotic inference. Second, the nonlinear relation between option and stock returns is likely to cause e_t in the regression given by equation (5) in the paper to be correlated with $r_{m,t:T}$, thereby causing OLS estimates of alpha to be biased and inconsistent. Third, because returns are non-additive, expectations and betas do not scale linearly with time.[5] This implies, for example, that if stock prices

[5]While log-returns are additive and are a satisfactory approximation for simple stock returns, they may not be a satisfactory approximation for the returns of options held to maturity as noted by Coval and Shumway (2001). The

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. Finally, finite samples of option returns 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 nonnormality of option returns, we estimate bootstrapped p-values for our CAPM alpha estimates. To do this, we create non-overlapping samples for options that expire in seven, 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 CAPM alphas using this new sample. We then repeat this procedure 10,000 times. In Panel A of Table IA.IV we report the estimated CAPM alphas using the non-overlapping data sample, asymptotic t-statistics, and boot-strapped p-values for spreads in alpha for both the high and low skewness portfolios along with their difference. 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 nonnormality of option returns.

To deal with other empirical difficulties associated with option returns we compare estimated pricing errors to those generated by a formal option pricing model, as in Broadie, Chernov, and Johannes (2009). In so doing, we anchor hypothesis tests at more appropriate null values, deal with the statistical problems associated with option returns, and also develop a framework to address the issue of peso problems. We simulate a Black-Scholes (1973) 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 (1973) model and estimate CAPM alphas for option returns over discrete horizons exactly as we do for our results in Table V. We repeat the exercise 1,000 times.

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.

The objective of our simulation is to determine how often, in a world in which preference for skewness has no impact on prices, we can generate results as extreme as those reported in Panel A. Although true instantaneous alphas are zero by construction, the estimated alphas will be nonzero for two reasons. First, the estimated alphas are somewhat biased given the nonlinear 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 V.

The results of this simulation are given in Panel B of Table IA.IV where for brevity we only report the high and low skewness portfolios along with their difference. 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, nonlinearity, non-additivity, and peso problems do not appear adequate to explain our results.

A. Jump-Diffusion Model

We next replicate the entire data set of option returns under a model that can generate more flexible distributions in returns than the lognormal assumption. In this case, we adopt the Merton (1976) jump diffusion model for a couple of reasons. First, we want to investigate a model where idiosyncratic unpriced jumps were present, not jumps in the market return that are then translated into stock returns through systematic pricing. Second, because we study the full cross section of options, we need a model that is relatively tractable and that can be applied to a variety of options across a large cross-section of underlyings at each point in time. This constraint proves to be nontrivial; at certain points in time in the option return data we have more than 1,000 underlying stocks on the options in a single maturity bin, but across all skewness bins and for both calls and puts. We acknowledge that more general models of stock returns are available and able to generate more general return distributions than the Merton (1976) model. That said, we believe that this model allows us to investigate the robustness of our results to the assumption that price changes follow a continuous lognormal distribution.

In his option pricing model, Merton (1976) generates an option pricing formula for the case in which stock returns are driven by both continuous and jump components as shown below,

$$dS/S = (\mu - \lambda k)dt + \sigma dZ + dq, \tag{IA.8}$$

where μ is the instantaneous stock return, σ is the standard deviation of stock returns conditional on no jump arrivals, λ is the jump intensity parameter specified as the mean arrival per unit of time, k is the expected value of the jump realization, dZ is a Weiner process, and $q(t)$ is a jump process assumed to be independent of dZ. Following Merton (1976), equation (IA.8) can be written as

$$\begin{aligned} dS/S &= (\mu - \lambda K)dt + \sigma dZ && \text{if the Poisson event does not occur} \\ dS/S &= (\mu - \lambda K)dt + \sigma dZ + (Y-1) && \text{if the Poisson event occurs,} \end{aligned}$$

where Y is a random variable denoting the jump. One particular case considered by Merton (1976) assumes that Y follows a lognormal distribution; in our simulation study we adopt this assumption as well. In particular, we assume $log(Y_i) \sim N(\gamma, \delta^2)$, where $\gamma = \log(1+k)$. Under these assumptions the stock return is shown as

$$S(t)/S = \exp\left[\left(\mu - \frac{\sigma^2}{2} - \lambda k\right)t + \sigma Z(t)\right] Y(n), \tag{IA.9}$$

where $Y(n) = \prod_{i=1}^{n} Y_i$, and n is a Poisson-distributed variable with parameter λt governing the arrival process of the jumps. In this case, the returns of the stock will be lognormally distributed given that both the continuous part of stock movements, $\sigma Z(t)$, as well as the jump process, $Y(n)$, are both lognormally distributed. This approach makes feasible the exercise of simulating a large cross-section of stock returns on each date. While the nature of the stock return distribution does not change relative to Black-Scholes (1973) (stock returns are still lognormal), we do allow the volatility to increase relative to the Black-Scholes (1973) case and for the mass of the distribution to move away from the center of the distribution. Under these assumptions the price of an option, $F(S,t)$ on stock S with maturity date, τ, is defined as

$$F(S,\tau) = \sum_{n=0}^{\infty} \frac{e^{-\hat{\lambda}\tau}\left(\hat{\lambda}\tau\right)^{n}}{n!} BS_n(S,\tau), \tag{IA.10}$$

where $\hat{\lambda} = \lambda(1+k)$, BS_n represents the Black-Scholes (1973) option formula, only in this case the risk-free rate, r, is replaced with $r - \lambda k + n\gamma/\tau$, and the stock return variance, σ^2, is replaced with $\sigma^2 + n\delta^2/\tau$. Consequently, option prices can be solved for analytically by approximation of the infinite sum in equation (IA.10).

B. Simulation exercise

To investigate the role that jumps may have in explaining option returns in our base results, we conduct a simulation exercise under the distribution assumptions described above. To simulate stock returns under the jump process, we require values for the parameters in the jump process, namely $\lambda, k,$and δ^2. To help select values for these parameters, we turn to Ball and Torous (1985) who investigate the fit of the Merton (1976) model using options trading on a set of 30 NYSE-listed stocks. They report estimated values for these parameters on the 30 stocks, which provides a set of values that we use in simulating the Merton model over our set of options. We adopt two main approaches in drawing parameter values from the Ball and Torous (1985) paper. Our first approach is to use the mean value of each of these three parameters over the estimated values. In Ball and Torous (1985) each parameter value is estimated twice, providing a sample of 60 estimates for each parameter. This approach is intended to represent the likely values of the jump process parameters for the stock in our sample. We apply the same jump process parameter values across all stocks in our data given our study analyzes the full cross section of options (and related underlyings). Our second approach is to take the maximum estimated values as a representation of extreme jump process parameters estimated in Ball and Torous (1985).[6]

[6]We have one exception to the maximal values approach. In one case, the value of the jump intensity parameter, λ, is estimated to be 1,138 with the next largest value 22 and a mean value of just under 2. In this case we take the maximal value to be the second largest value, 22, and ignore the true maximum. We ran the simulation with the true maximal value for λ and found these values did not resolve the low returns in high-skewed options. In fact, this paramterization

For the other parameters, we follow our Black-Scholes (1973) simulation discussed above and 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. In this case, on each day, we price options using the Merton (1976) model in equation (IA.10) using the existing option characteristics and the jump parameter values as discussed above. To construct holding period returns we need to simulate stock returns, which are constructed using equation (IA.9). We maintain a similar market return component across all options within a given maturity bin and also maintain a common stock return across all stocks within a given maturity bin. As before, we simulate stock returns that are then used to construct holding period option returns. We next construct portfolio returns of the options and estimate the CAPM alphas of the portfolios using a market model as in the Black-Scholes (1973) simulation case. We repeat the exercise 1,000 times and calculate the average CAPM alpha spreads across the low and high ex-ante skewness portfolios. The results of these simulations are reported in Panel C of Table IA.IV. We report the simulation results of the Merton (1976) simulation under various sets of jump parameters. In the first set of results of Panel C, titled "(1) - Mean Values," we report results using the mean values of jump parameters taken from Ball and Torous (1985). This simulation generates CAPM alpha spreads that are closer to those we observe in the data, relative to the results of Panel B, but are still statistically significantly different from those estimated in the data, with *p*-values for five of the six portfolios smaller than 0.01. In the next three sets of results, we report the results of the simulation where the maximum jump parameter values are used. In the second set of results, titled "(2) - Max Values, Zero Mean Jumps," we constrain the mean of the jump process to be zero, and in the third (fourth) set of results we allow the mean jump process to be at its maximal positive (negative) value from Ball and Torous (1985). In each of these sets of results where maximum jump values are used, the alpha spreads are still statistically significantly different than those estimated in the data, with *p*-values in all cases less than 0.01.

We again acknowledge that many other, even more general, models of stock price dynamics and associated option prices exist and may help to explain the patterns observed in stock option returns.

led to large positive returns on highly skewed call and put options, making the observed patterns in returns look even more anomalous.

The results reported in Table IA.IV, however, suggest that the accomodation of jumps, as in Merton (1976), cannot reconcile the large negative returns on high ex-ante options as observed in the data.

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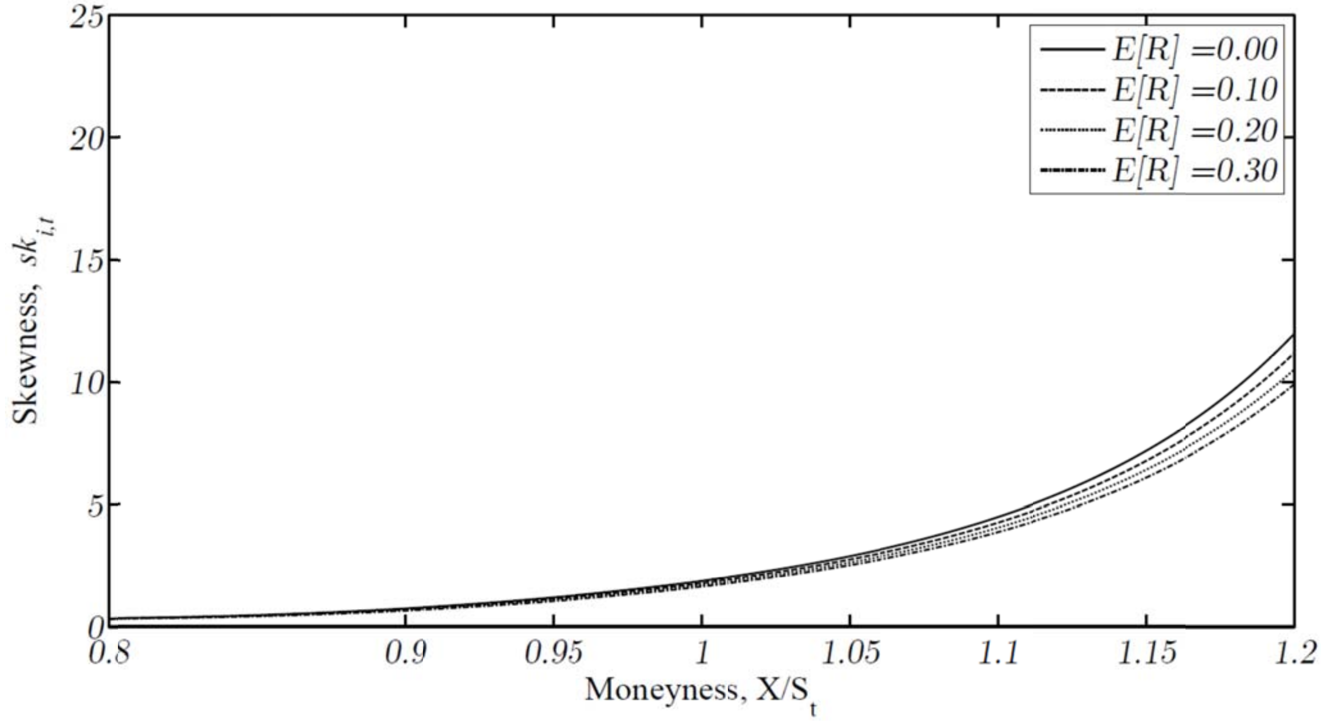
Panel A: Call Options



Panel B: Put Options

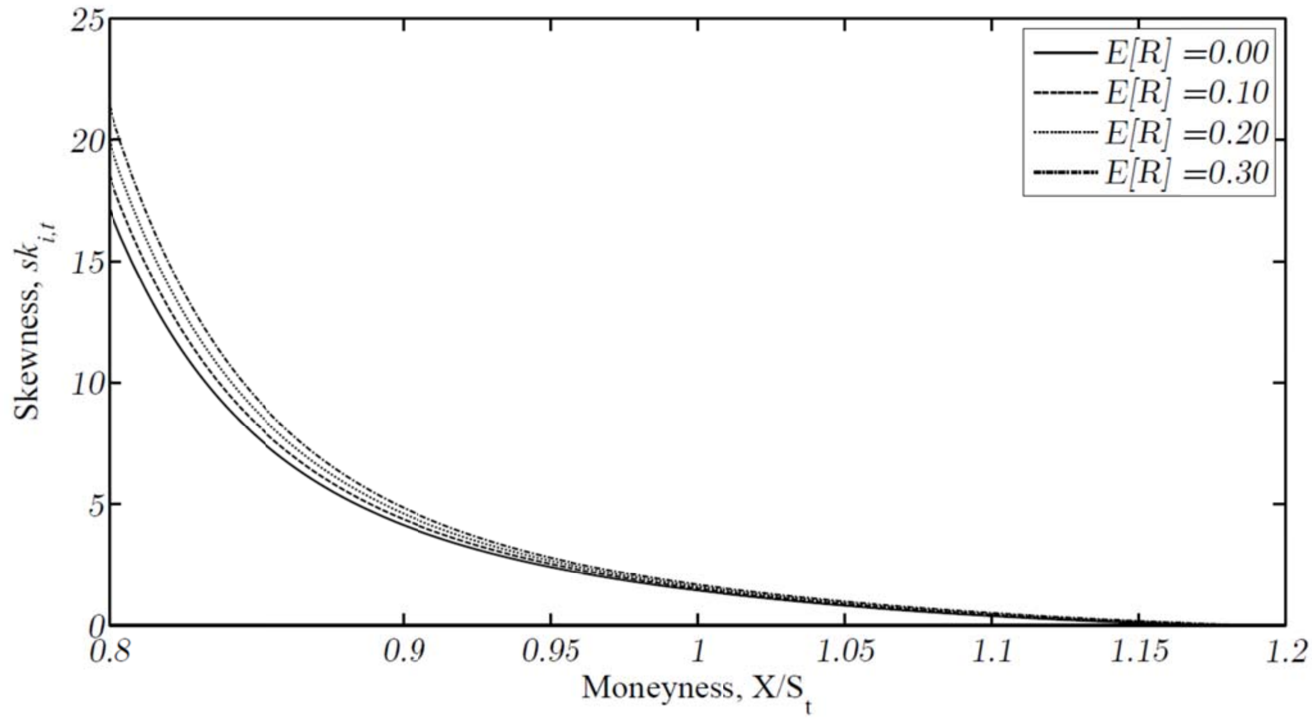


Figure IA.1: Expected Stock Returns and Option Return Skewness Option Return Skewness Against Moneyness (stock return volatility, σ, = 0.4, risk-free rate = 5%, and days-to-maturity = 21) for a range of stock expected return values (E[r]). Panel A plots return skewness for a call option, while Panel B plots skewness for a put option.

Table IA.I
Open Interest

This table reports additional summary statistics for the options that survive the data filter outlined in Section B of the Appendix in the published paper. For Panel A we first measure, for each portfolio formation date, the average open interest across options for each portfolio and then report the time-series average of this measure. We define open interest as the number of contracts outstanding on the day prior to the portfolio formation date. For Panel B we first measure the total dollar open interest across options within each ex-ante skewness quntile on each portfolio formation date, and then report the time-series average of this measure. Total dollar open interest is the sum of closing $price \times open\ interest$ on the portfolio formation date across all options within each ex-ante skewness quintile. Each panel reports results separately for call and put options, 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.

	Call Options			Put Options		
	Days to Expiration			Days to Expiration		
Skew Quintile	7	18	48	7	18	48
	Panel A. Average Open Interest per Contract					
Low	2400	2043	1436	2000	1838	1386
2	2715	2351	1387	2248	1952	1321
3	2885	2614	1492	2420	2211	1343
4	3347	2898	1657	2870	2500	1471
High	3937	3535	2264	3299	2809	1822
Low-High	-1537	-1492	-828	-1299	-972	-436
(st. error)	(84.44)	(105.32)	(94.01)	(77.6)	(93.8)	(89.1)
	Panel B. Average Total Dollar Open Interest (millions)					
Low	441.21	686.26	553.26	272.71	400.97	303.73
2	177.78	310.43	230.38	126.14	184.46	143.07
3	88.12	167.60	143.73	65.80	112.17	96.83
4	41.94	84.84	88.25	34.67	64.12	68.09
High	18.69	34.09	45.69	16.39	27.95	34.80
Low-High	422.52	652.16	507.56	256.32	373.02	268.93
(st. error)	(13.27)	(10.33)	(7.49)	10.39	9.98	5.92

Table IA.II
Fama-MacBeth Regressions on Ex-Ante Skewness

In this table we report the results of Fama MacBeth (1973) regressions on option portfolio ex-ante skewness using portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. On each portfolio formation date for options that expire in seven days we independently rank options into 100 bins based on each input to our ex-ante skewness measure, and on the measure itself. We then estimate Fama Macbeth (1973) regressions using these ranks with the ex-ante skewness rank as the dependent variable. Panel A reports the time-series average of estimated coefficents for call option portfolios while Panel B reports the analogous results for put option portfolios. Each column represents a cross-sectional regression using a set of explanatory variables that are indicated in the first column. These include moneyness (X/S), option price (price), stock volatility (σ^s), stock mean return (μ^s), stock price (S), and a moneyness-volatility interaction term (X/S x σ^s). We include the interaction term whenever we control for volatility and moneyness because the effect of volatility on skewness depends on moneyness. (See Figure 2 of the paper.) We report *t*-statistics based on Newey West (1987) standard errors directly below coefficient averages. In the final row of each table we report the average adjusted R^2 for each of the Fama MacBeth (1973) regressions.

Panel A. Call Options										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
X/S_0	0.957					0.712	1.377	0.951	0.953	1.183
	(1324.76)					(143.06)	(375.01)	(732.08)	(925.41)	(235.43)
price		-0.910				-0.273				-0.157
		-(433.15)				-(53.91)				-(40.01)
σ^s			0.094				0.413			0.406
			(15.52)				(58.05)			(57.38)
μ^s				-0.166				-0.117		-0.121
				-(26.33)				-(49.86)		-(79.26)
S_0					-0.103				-0.045	0.052
					-(13.80)				-(18.68)	(32.91)
$(X/S_0) \times \sigma^s$							-(0.01)			-0.007
							-(115.04)			-(115.99)
Adj R^2	91.6%	82.8%	1.4%	3.3%	1.9%	93.1%	96.7%	93.0%	91.9%	98.3%

Panel B. Put Options										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
X/S_0	-0.965					-0.847	-1.306	-0.953	-0.954	-1.195
	-(1191.01)					-(132.95)	-(312.60)	-(696.69)	-(708.13)	-(274.00)
price		-0.884				-0.133				-0.081
		-(388.88)				-(20.60)				-(26.26)
σ^s			-0.066				-0.389			-0.353
			-(9.88)				-(53.59)			-(55.71)
μ^s				0.213				0.115		0.122
				(26.86)				(41.07)		(78.48)
S_0					0.205				0.069	0.030
					(25.84)				(26.08)	(23.04)
$(X/S_0) \times \sigma^s$							(0.01)			0.006
							(74.90)			(77.64)
Adj R^2	93.1%	78.1%	1.0%	5.4%	5.1%	93.6%	97.0%	94.5%	93.6%	98.4%

Table IA.III

Stock Skewness and Option Skewness

This table reports the average cross-sectional skewness of portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. On each option portfolio formation date we first filter out all options other than those with seven-day or 18-day maturities. We then sort underlying assets with a given maturity into terciles based on ex-ante stock skewness as seen in equation (IA.4). We next sort options with the same expiration date and stock skewness tercile into option skewness terciles, based on our ex-ante skewness measure. We report the time-series average of the cross-sectional skewness estimate for each maturity, stock skewness, and option skewness bin. We report results for both call options (Panel A) and put options (Panel B). The final two rows of each panel report differences in average skewness across the high and low skewness qunitiles along with Newey-West (1987) *t*-statistics that test whether these differences are equal to zero. The final two columns of each call or put option group report differences in average option skewness across the high and low stock skewness terciles along with Newey-West (1987) *t*-statistics that test whether these differences are equal to zero. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A. Call Options

Skew Quintile	7 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High	18 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High
Low	1.00 ***	1.05 ***	1.12 ***	-0.13	1.14 ***	1.30 ***	1.57 ***	-0.44 ***
				-(1.55)				-(4.81)
Medium	2.78 ***	2.84 ***	3.15 ***	-0.37 **	3.01 ***	3.28 ***	3.62 ***	-0.61 ***
				-(2.46)				-(3.95)
High	6.43 ***	6.27 ***	6.25 ***	0.18	6.86 ***	6.53 ***	6.76 ***	0.03
				(0.79)				(0.10)
Low-High	-5.45 ***	-5.23 ***	-5.14 ***		-5.74 ***	-5.27 ***	-5.23 ***	
(t-stat)	-(22.84)	-(23.91)	-(23.88)		-(22.33)	-(23.35)	-(20.27)	

Panel B. Put Options

Skew Quintile	7 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High	18 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High
Low	1.25 ***	1.17 ***	1.12 ***	0.13	1.50 ***	1.54 ***	1.38 ***	0.12
				(1.02)				(1.35)
Medium	3.45 ***	3.27 ***	3.20 ***	0.26	3.69 ***	3.78 ***	3.31 ***	0.39 **
				(1.36)				(2.24)
High	6.94 ***	6.89 ***	6.64 ***	0.34	7.15 ***	7.14 ***	6.73 ***	0.45 *
				(1.44)				(1.69)
Low-High	-5.72 ***	-5.75 ***	-5.56 ***		-5.63 ***	-5.59 ***	-5.33 ***	
(t-stat)	-(25.76)	-(28.05)	-(26.14)		-(22.75)	-(20.47)	-(20.79)	

Table IA.IV
Stock Skewness and CAPM Pricing Errors

This table reports regression CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. On each option portfolio formation date we first filter out all options other than those with seven-day or 18-day maturities. We then sort underlying assets with a given maturity into terciles based on ex-ante stock skewness as seen in equation (IA.4). We next sort options with the same expiration date and stock skewness tercile into option skewness terciles, based on our ex-ante skewness measure. We report results for both call options (Panel A) and put options (Panel B). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). The final two rows of each panel report differences in CAPM pricing errors across the high and low skewness qunitiles along with Newey-West (1987) *t*-statistics that test whether these differences are equal to zero. The final two columns of each call or put option group report differences in CAPM pricing errors across the high and low stock skewness terciles along with Newey-West (1987) *t*-statistics that test whether these differences are equal to zero. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A. Call Options

Skew Quintile	7 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High	18 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High
Low	0.77	-2.26 *	-4.42 ***	5.19 ***	0.35	-0.08	-0.36	0.71
Medium	-0.03	-7.74 **	-13.39 ***	13.35 ***	0.86	0.84	-0.10	0.96
High	-23.06 ***	-30.40 ***	-35.59 ***	12.53 **	-5.89 **	-5.29 **	-6.63 **	0.74
Low-High	23.83 ***	28.15 ***	31.17 ***		6.25 ***	5.21 **	6.27 ***	
(t-stat)	(4.66)	(5.92)	(9.24)		(2.88)	(2.25)	(3.08)	

Panel B. Put Options

Skew Quintile	7 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High	18 Days to Expiration, Expected Stock Skewness: Low	Medium	High	Low-High
Low	-4.91 ***	-3.15 **	-0.61	-4.30 **	-2.06 ***	-0.91	0.48	-2.54 ***
Medium	-12.69 ***	-8.63 ***	-9.59 ***	-3.10	-2.67	-2.40 *	-0.40	-2.27
High	-39.93 ***	-49.73 ***	-49.33 ***	9.40	-10.22 ***	-11.05 ***	-9.37 ***	-0.85
Low-High	35.01 ***	46.58 ***	48.72 ***		8.16 ***	10.14 ***	9.85 ***	
(t-stat)	(5.57)	(11.14)	(11.03)		(2.61)	(4.06)	(3.93)	

Table IA.V
Option Betas

This table reports regression betas for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on ex-ante skewness as in equations (1) to (4) and returns are holding period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. We report regression betas for both call options (first set of columns) and put options (last set of columns). In the final two rows we report differences in betas across the high and low skewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Skew Quintile	Call Options Days to Expiration 7	18	48	Put Options Days to Expiration 7	18	48
Low	15.96 ***	11.45 ***	8.10 ***	-9.99 ***	-7.56 ***	-6.39 ***
2	22.17 ***	13.65 ***	9.01 ***	-16.54 ***	-12.42 ***	-9.32 ***
3	19.98 ***	12.17 ***	8.77 ***	-20.73 ***	-16.07 ***	-11.17 ***
4	15.55 ***	9.95 ***	7.56 ***	-20.62 ***	-19.76 ***	-12.85 ***
High	9.89 ***	6.78 ***	5.56 ***	-14.40 ***	-18.35 ***	-15.59 ***
Low-High	6.07 **	4.67 ***	2.54 ***	4.41 **	10.79 ***	9.20 **
(t-stat)	(2.18)	(2.84)	(2.60)	(2.03)	(2.86)	(1.96)

Table IA.VI
Unconditional Sort on Moneyness

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on moneyness and returns are holding-period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low moneyness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated, by *, **, and ***, respectively.

	Call Options			Put Options		
k/S_0	Days to Expiration			Days to Expiration		
Quintile	7	18	48	7	18	48
Low	-2.42 **	-0.37	-0.03	-52.42 ***	-11.32 ***	-0.79
2	-3.40 **	0.03	0.09	-26.33 ***	-4.51 **	-0.56
3	-5.03 *	0.70	0.01	-11.82 ***	-2.50 **	-0.70
4	-11.11 **	-0.36	-0.14	-4.12 **	-1.90 ***	-0.59 *
High	-40.48 ***	-7.82 ***	-2.64 ***	-1.81	-0.69	-0.01
Low-High	38.06 ***	7.44 ***	2.61 ***	-50.61 ***	-10.63 ***	-0.78
(t-stat)	(9.00)	(2.94)	(3.78)	-(12.70)	-(3.95)	-(0.49)

Table IA.VII
Unconditional Sort on Ex-Ante Coskewness

This table reports regression CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on ex-ante coskewness as described in Section A.2 of the paper's Appendix and returns are holding-period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low coskewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Coskew	Call Options Days to Expiration			Put Options Days to Expiration		
Quintile	7	18	48	7	18	48
Low	-10.81 ***	-3.39 ***	-1.16 ***	-18.54 ***	-6.23 ***	-0.69
2	-13.14 ***	-1.93 *	-0.60	-19.02 ***	-3.67 ***	-0.31
3	-15.38 ***	-2.09	-0.38	-19.33 ***	-3.61 ***	-0.04
4	-14.51 ***	-0.61	-0.19	-18.91 ***	-2.41	-0.44
High	-8.52	0.24	-0.37	-20.69 ***	-4.98 **	-1.18
Low-High	-2.28	-3.63	-0.79	2.15	-1.25	0.49
(t-stat)	-(0.44)	-(1.50)	-(0.98)	(0.47)	-(0.62)	(0.50)

Table IA.VIII
CAPM Pricing Errors using Instantaneous Betas

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on skewness as in equations (1) to (4) and returns are holding-period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. In this table, we report CAPM pricing errors constructed using the instantaneous beta at the time the option is purchased as described in equation (IA.6) of the Internet Appendix. In the final two rows we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Skew	Call Options Days to Expiration			Put Options Days to Expiration		
Quintile	7	18	48	7	18	48
Low	-2.27 ***	-0.37	0.06	-1.56 **	-0.27	0.39
2	-5.83 ***	0.07	0.03	-1.99	0.30	0.35
3	-10.47 ***	-0.14	-0.05	-6.29 **	-0.71	-0.10
4	-15.90 ***	-0.61	-0.98	-20.73 ***	-2.84	-0.67
High	-47.79 ***	-9.81 ***	-3.50 ***	-49.10 ***	-11.75 ***	-1.89
Low-High	45.53 ***	9.44 ***	3.56 ***	47.54 ***	11.47 ***	2.28
(t-stat)	(7.89)	(3.70)	(4.35)	(10.30)	(3.90)	(1.54)

Table IA.IX
CAPM Pricing Errors
Using Five-yearear Window to Estimate Stock Moments

This table reports regression CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 – 2009. Option portfolios are formed by sorting on skewness as in equations (1) to (4) and returns are holding-period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. In this table we report results where we use five-year windows of data to estimate inputs into the ex-ante skewness measure. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Skew	Call Options Days to Expiration			Call Options Days to Expiration		
Quintile	7	18	48	7	18	48
Low	-1.33	-0.27	0.15	-2.73 ***	-0.80 *	0.07
2	-3.45 *	0.28	0.31	-3.52 **	-1.39 *	-0.23
3	-6.75 **	0.94	0.24	-11.27 ***	-1.99	-0.41
4	-10.94 **	1.22	0.11	-22.86 ***	-3.56 *	-0.34
High	-39.89 ***	-9.96 ***	-3.52 ***	-56.07 ***	-13.10 ***	-1.74
Low-High	38.56 ***	9.69 ***	3.68 ***	53.34 ***	12.30 ***	1.81
(t-stat)	(8.89)	(4.36)	(6.05)	(13.56)	(4.39)	(1.06)

Table IA.X
CAPM Pricing Errors assuming Optimal Early Exercise

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on skewness as in equations (1) to (4) and returns are holding period returns that account for early exercise as noted in equation (IA.7). We use the midpoint of the bid and ask prices as the proxy for price. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Call Options			Put Options		
Skew	Days to Expiration			Days to Expiration		
Quintile	7	18	48	7	18	48
Low	-1.64 ***	-0.37	-0.03	-2.07 ***	-0.83 **	0.14
2	-4.10 ***	0.02	0.02	-4.11 ***	-0.53	-0.01
3	-7.73 ***	0.22	0.04	-9.66 ***	-1.80	-0.46
4	-11.53 ***	0.43	-0.63	-24.47 ***	-4.31 **	-1.18 *
High	-40.68 ***	-8.99 ***	-3.20 ***	-55.25 ***	-12.82 ***	-2.09
Low-High	39.04 ***	8.62 ***	3.17 ***	53.19 ***	11.99 ***	2.23
(t-stat)	(9.25)	(3.92)	(4.85)	(12.28)	(4.25)	(1.39)

Table IA.XI
Unconditional Sorts on Raw Third Moment

This table reports CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 2009. Option portfolios are formed by sorting on the raw third moment of the option return (numerator of our ex-ante skewness measure) and returns are holding-period returns to expiration as in equation (3), using the midpoint of the bid and ask prices as the proxy for price. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the option portfolios obtained by regressing option portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low coskewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Skew Quintile	Call Options Days to Expiration 7	18	48	Put Options Days to Expiration 7	18	48
Low	-1.05	-0.08	0.06	-2.73 ***	-1.12 **	-0.04
2	-3.91 **	0.19	-0.10	-3.64 **	-1.35	-0.28
3	-6.76 **	0.90	-0.23	-9.14 ***	-1.31	-0.42
4	-9.97 **	0.57	-0.20	-22.41 ***	-3.09	-0.64
High	-40.70 ***	-9.37 ***	-2.24 **	-58.59 ***	-14.00 ***	-1.28
Low-High	39.65 ***	9.29 ***	2.30 ***	55.86 ***	12.88 ***	1.24
(t-stat)	(8.94)	(3.73)	(2.62)	(15.09)	(4.58)	(0.70)

Table IA.XII
Stock CAPM Pricing Errors Controlling for lagged six-month return

This table reports CAPM pricing errors for portfolios stocks underlying the individual equity options taken from the Ivy database over the period 1996 to 2009. On each portfolio formation date we first sort the underlying stocks for options of a given maturity into deciles based on the six-month return just prior to the portfolio formation date. Then, within each decile, we rank stocks into two bins based on the ex-ante skewness of the options written on them. Next we equal-weight the returns for stocks with the same ex-ante skewness rank across all deciles. After creating two such portfolios for each formation date in our sample, we estimate and compare the stock CAPM pricing errors. We report results for both call options (first set of columns) and put options (last set of columns). We report CAPM pricing errors for the stock portfolios obtained by regressing stock portfolio returns on excess market returns as in equation (5). In the final two rows we report differences in CAPM pricing errors across the high and low skewness quintiles along with GMM *t*-statistics calculated using the approach of Newey and West (1987). Statistical significance at the 10%, 5%, and 1% significance levels is indicated by *, **, and ***, respectively.

	Call Options			Put Options		
Skew	Days to Expiration			Days to Expiration		
Rank	7	18	48	7	18	48
Low	-0.11	-0.02	-0.02	-0.13	0.02	-0.03
High	-0.12	0.01	-0.05	-0.20	-0.01	-0.01
Low-High	0.00	-0.03	0.03	0.07	0.04	-0.02
(t-stat)	(0.09)	-(0.98)	(1.11)	(1.43)	(1.28)	-(1.23)

Table IA.XIII
Double Sorts

This table reports the estimated CAPM pricing errors for portfolios of individual equity options taken from the Ivy database over the period 1996 to 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 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), prior six-month stock return (Panel E), underlying stock volatility (Panel F), underlying stock price (Panel G), underlying stock expected return (Panel H), and option price (Panel I). We obtain CAPM pricing errors by regressing option portfolio returns on excess market returns as in equation (5). We report results for both call options (first set of columns) and put options (last set of columns). In the final rows of each panel we report differences in CAPM pricing errors across the low and high skewness portfolios along with Newey-West (1987) *t*-statistics. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Skew	Call Options			Put Options		
	Days to Expiration			Days to Expiration		
Rank	7	18	48			
Panel A: Controlling for Volume						
Low	-2.94 *	0.38	0.40	-3.78 **	-0.91	0.24
High	-21.93 ***	-3.48 *	-1.48 **	-34.65 ***	-7.41 ***	-1.29
Low-High	18.99 ***	3.85 ***	1.88 ***	30.87 ***	6.50 ***	1.52
(t-stat)	(6.81)	(2.97)	(4.52)	(10.56)	(3.63)	(1.54)
Panel B: Controlling for Vega						
Low	-3.70 **	0.29	0.20	-4.22 ***	-0.87	0.15
High	-21.17 ***	-3.39 *	-1.28 *	-34.22 ***	-7.45 ***	-1.20
Low-High	17.46 ***	3.67 ***	1.48 ***	30.00 ***	6.58 ***	1.35
(t-stat)	(6.30)	(2.87)	(4.01)	(9.99)	(3.79)	(1.37)
Panel C: Controlling for Volatility Smirk						
Low	-3.16 *	0.57	0.55	-4.16	-1.42	-0.01
High	-20.22 ***	-2.64	-0.73	-42.79 **	-9.06 ***	-1.74
Low-High	17.05 ***	3.21 *	1.28 **	38.63 ***	7.64 ***	1.74
(t-stat)	(4.79)	(1.74)	(2.53)	(11.71)	(3.46)	(1.50)
Panel D: Controlling for Bid-Ask Spread						
Low	-4.85 **	0.28	0.11	-10.45 ***	-1.26	0.22
High	-20.04 ***	-3.39 *	-1.19 *	-28.05 ***	-7.06 ***	-1.27
Low-High	15.19 ***	3.67 ***	1.30 ***	17.60 ***	5.79 ***	1.49 *
(t-stat)	(8.55)	(3.28)	(3.32)	(7.83)	(5.41)	(1.84)

Table IA.XIII *(continued)*

Panel E: Controlling for Prior Six-Month Stock Return												
Low	-3.32	**	0.29		0.08		-4.18	**	-1.45	**	-0.33	
High	-21.58	***	-3.02		-0.98		-33.81	***	-7.28	***	-0.87	
Low-High	18.25	***	3.32	**	1.06	**	29.63	***	5.83	***	0.54	
(t-stat)	(6.17)		(2.28)		(2.32)		(10.64)		(3.36)		(0.53)	
Panel F: Controlling for Stock Volatility												
Low	-3.33	**	0.30		0.28		-4.31	***	-1.06		0.06	
High	-21.55	***	-3.40	*	-1.36	**	-34.12	***	-7.26	***	-1.11	
Low-High	18.21	***	3.71	***	1.64	***	29.81	***	6.20	***	1.17	
(t-stat)	(6.48)		(2.95)		(4.62)		(10.26)		(3.47)		(1.23)	
Panel G: Controlling for Stock Price												
Low	-3.36	**	0.14		0.09		-4.01	**	-1.34	*	-0.05	
High	-21.52	***	-3.24	*	-1.17	*	-34.42	***	-6.99	***	-1.01	
Low-High	18.15	***	3.39	**	1.26	***	30.41	***	5.65	***	0.96	
(t-stat)	(6.27)		(2.46)		(3.29)		(11.14)		(3.37)		(1.02)	
Panel H: Controlling for Stock Expected Return												
Low	-3.33	**	0.21		-0.03		-4.41	***	-1.37	*	-0.24	
High	-21.54	***	-3.31	*	-1.05		-34.03	***	-6.95	***	-0.82	
Low-High	18.21	***	3.51	**	1.02	**	29.62	***	5.58	***	0.58	
(t-stat)	(6.34)		(2.49)		(2.35)		(11.06)		(3.24)		(0.60)	
Panel I: Controlling for Option Price												
Low	-5.81	**	0.12		0.07		-13.02	***	-1.28		0.35	
High	-19.07	***	-3.23	*	-1.14	*	-25.52	***	-7.04	***	-1.40	
Low-High	13.26	***	3.35	***	1.21	***	12.50	***	5.76	***	1.75	***
(t-stat)	(6.57)		(2.98)		(3.27)		(5.39)		(5.35)		(2.46)	

Table IA.XIV
Bootstrapped *p*-values and Simulation *p*-values

Panel A reports the estimated CAPM pricing errors for individual equity option portfolios taken from the Ivy database over the period 1996 to 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) using the midpoint 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 intercept from those estimations. The bottom rows of Panel A report differences in CAPM pricing errors across the high and low skewness portfolios along with *t*-statistics and bootstrapped *p*-values that test whether these differences are equal to zero. Panel B reports the results of a Black-Scholes (1973) 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 1,000 times, and we report the average CAPM pricing error (alpha) for each skewness/maturity portfolio across simulations. The bottom rows of Panel B report differences in CAPM alphas across the high and low skewness portfolios along with the fraction of simulations which generated CAPM alpha spreads as extreme as those in Panel A. Panel C reports the results of a Merton (1976) jump-diffusion simulation exercise in which the CAPM holds instantaneously. In addition to lognormal continuous movements in stock prices, idiosyncratic jumps in the stock price moves are allowed as well. Skewness again has no effect on pricing, and the simulation is calibrated to match the moments of the actual non-overlapping data. The simulation is repeated 1,000 times, and we report the average CAPM alpha for each skewness/maturity portfolio across simulations. The bottom rows of Panel C reports differences in CAPM alphas across the high and low skewness portfolios along with the fraction of simulations that generated CAPM alpha spreads as extreme as those in Panel A.

Panel A. Bootstrap Results						
	Call Options			Put Options		
Skew	Days to Expiration			Days to Expiration		
Rank	7	18	48	7	18	48
Low	-1.00	-0.13	0.48	-1.11	0.04	0.47
High	-52.74	-14.13	-2.93	-57.68	-16.91	-2.49
Low-High	51.73	14.01	3.40	56.57	16.95	2.95
t-stat	(11.37)	(5.93)	(3.91)	(9.37)	(5.77)	(2.41)
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Black-Scholes Simluation (percent alphas)						
Low	0.23	0.17	0.12	-0.30	-0.24	-0.17
High	1.70	0.37	0.32	-6.10	-1.08	-0.98
Low-High	-1.47	-0.20	-0.19	5.80	0.84	0.82
p-values	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)

Table IA.XIV *(continued)*

Panel C: Merton (1976) Jump Simluation (percent alphas)

(1) - Mean Values: λ = 2, α=0.00, δ=.0224, σREL = 1.0059						
Low	0.18	0.15	0.12	-0.28	-0.20	-0.17
High	-2.91	0.34	0.23	-10.25	-2.59	-1.01
Low-High	3.09	-0.18	-0.11	9.96	2.38	0.85
p-values	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)
(2) - Max Values, Zero Mean Jump: λ = 22, α = 0.00, δ = 0.0837, σREL = 1.602						
Low	0.57	0.47	3.33	0.31	0.21	3.02
High	-9.45	-0.91	4.89	-20.91	-4.55	4.93
Low-High	10.03	1.38	-1.56	21.23	4.76	-1.91
p-values	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(3) - Max Values, Max Positive Mean Jump: λ = 22, α = 0.002, δ = 0.0837, σREL = 1.602						
Low	0.66	0.49	3.44	0.24	0.19	2.94
High	-11.15	-1.43	4.98	-19.26	-3.95	4.84
Low-High	11.81	1.92	-1.54	19.50	4.14	-1.90
p-values	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(4) - Max Values, Max Negative Mean Jump: λ = 22, α = -0.002, δ = 0.0837, σREL = 1.602						
Low	0.49	0.43	3.23	0.41	0.26	3.12
High	-7.83	-0.36	4.84	-21.86	-4.80	5.11
Low-High	8.32	0.78	-1.61	22.27	5.06	-2.00
p-values	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)