

Understanding Index Option Returns

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Previous research concludes that options are mispriced based on the high average returns, CAPM alphas, and Sharpe ratios of various put selling strategies. One criticism of these conclusions is that these benchmarks are ill suited to handle the extreme statistical nature of option returns generated by nonlinear payoffs. We propose an alternative way to evaluate the statistical significance of option returns by comparing historical statistics to those generated by option pricing models. The most puzzling finding in the existing literature, the large returns to writing out-of-the-money puts, is not inconsistent (i.e., is statistically insignificant) relative to the Black-Scholes model or the Heston stochastic volatility model due to the extreme sampling uncertainty associated with put returns. This sampling problem can largely be alleviated by analyzing market-neutral portfolios such as straddles or delta-hedged returns. The returns on these portfolios can be explained by jump risk premiums and estimation risk. (*JEL C12, G13*)

It is a common perception that index options are mispriced, in the sense that certain option returns are excessive relative to their risks.¹ The primary evidence supporting mispricing is the large magnitude of historical S&P 500 put option

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¹ At this stage, a natural question is why to focus on returns and not option prices. Returns, as opposed to price levels, are typically analyzed because of their natural economic interpretation. Returns represent actual gains or losses on purchased securities. In contrast, common option pricing exercises use pricing errors to summarize fit, which are neither easily interpreted nor can be realized. In addition, we have stronger intuition about return-based measures such as excess returns, CAPM alphas, or Sharpe ratios as compared to pricing errors. Coval and Shumway (2001) provide additional motivation.

returns. For example, Bondarenko (2003) reports that average at-the-money (ATM) put returns are -40% , not per annum, but per month, and deep out-of-the-money (OTM) put returns are -95% per month. Average option returns and CAPM alphas are statistically significant, with p -values close to zero, and Sharpe ratios are larger than those of the underlying index.²

There are three obvious factors to consider when interpreting these results. Option returns are highly nonnormal and metrics assuming normality, such as CAPM alphas or Sharpe ratios, are inappropriate.³ Additionally, average put returns should be negative due to the leverage inherent in options and the presence of priced risks. Finally, options have only traded for a short period of time, and it is difficult to assess the statistical significance of option returns due to the short time spans and nonnormality of option returns. Together, these factors raise questions about the usual procedures of applying standard asset pricing metrics to analyze option returns.

In this paper, we use option pricing models as a benchmark to assess the evidence for index option mispricing and address the issues raised above. Option returns computed from formal option pricing models automatically reflect the leverage and kinked payoffs of options, anchor hypothesis tests at appropriate null values, provide a framework for assessing the impact of risk premiums, and provide a mechanism for assessing statistical uncertainty via finite-sample simulations. Ideally, an equilibrium model over economic fundamentals, such as consumption or dividends, would be used to assess the evidence for mispricing. However, as argued by Bates (2008) and Bondarenko (2003), such an explanation is extremely challenging inside the representative agent framework. This is not a surprise, since these models have difficulties explaining not only the low-frequency features of stock returns (e.g., the equity premium or excess volatility puzzles) but also high-frequency movements such as price jumps, high-frequency volatility fluctuations, or the leverage effect.

We address a more modest, but still important, goal of understanding the pricing of options relative to the underlying index, as opposed to pricing options relative to the underlying fundamental variables. To do this, we use affine-jump diffusion models of stock index returns. These models account for the key drivers of equity returns and option prices such as diffusive price shocks, stochastic volatility, and price jumps. The key step is one of calibration: we calibrate each model to fit the observed behavior of equity index returns over the sample for which option returns are available. In particular, this approach implies that our models replicate the historically observed equity premium and volatility.

² The returns are economically significant, as investors endowed with a wide array of utility functions find large certainty equivalent gains from selling put options (e.g., Driessen and Maenhout 2004b; Santa-Clara and Saretto 2007).

³ The shortcomings of these metrics have been understood for a long time (see Glosten and Jagannathan 1994; Goetzmann et al. 2007; Grinblatt and Titman 1989; and Leland 1999, among others). However, their use is still pervasive both in the industry and in academia.

Methodologically, we proceed using two main tools. First, we show that expected option returns (EORs) can be computed analytically, allowing us to examine the quantitative impact of different factors and parameter values on option returns. In particular, EORs anchor null hypothesis values when testing whether average option returns are significantly different from those generated by a given null model. Second, we simulate index sample paths to construct exact finite-sample distributions for the statistics analyzed. This procedure accounts for both the small sample sizes (on the order of 200 months) and the highly skewed and nonnormal nature of option return distributions. It also allows us to assess the statistical uncertainty of commonly used asset pricing benchmarks and statistics, such as average returns, CAPM alphas, or Sharpe ratios.⁴

Empirically, we present a number of interesting findings. We first analyze put returns, given their importance in the recent literature, and begin with the standard Black and Scholes (1973) and Heston (1993) stochastic volatility models. Although these models are too simple to accurately describe option *prices*, they provide key insights for understanding and evaluating option *returns*. Our first result is that average returns, CAPM alphas, and Sharpe ratios for deep OTM put returns are statistically *insignificant* when compared to the Black-Scholes model. Thus, one of the most puzzling statistics in the literature, the large average OTM put returns, is not inconsistent with the Black-Scholes model. Moreover, there is little evidence that put returns of any strike are inconsistent with Heston's (1993) stochastic volatility (SV) model, assuming no diffusive stochastic volatility risk premiums (i.e., the evolution of volatility under the objective, \mathbb{P} , and the risk-neutral, \mathbb{Q} , measures are the same).

We interpret these findings not as evidence that the Black-Scholes or Heston models are correct—we know they can be rejected on other grounds—but rather as highlighting the statistical difficulties present when analyzing option returns. Short samples and complicated option return distributions imply that standard statistics are so noisy that little can be concluded by analyzing option returns. It is well known that it is difficult to estimate the equity premium, and this uncertainty is only magnified when estimating average put returns.

This implies that tests using put option returns are not very informative about option mispricing, and we next turn to returns of alternative option portfolio strategies such as ATM straddles, crash-neutral straddles, covered puts, put spreads, and delta-hedged puts. These portfolios are more informative because they either reduce the exposure to the underlying index (straddles and delta-hedged puts) or dampen the effect of rare events (crash-neutral straddles and put spreads).

Of all of these portfolios, straddles are quite useful since straddles do not require a model to determine the initial portfolio position (unlike delta-hedged

⁴ The results are similar using alternative measures, such as Leland's alpha (Leland 1999) or the manipulation proof performance measure (Goetzmann et al. 2007).

puts) and the returns are approximately market neutral. Straddles are also more informative than individual puts, since average straddle returns are highly significant when compared to returns generated from the Black-Scholes model or a baseline stochastic volatility model without a diffusive volatility risk premium. The source of this significance is the well-known wedge between the ATM-implied volatility and the subsequent realized volatility.⁵ As argued by Pan (2002) and Broadie, Chernov, and Johannes (2007), it is unlikely that a diffusive stochastic volatility risk premium could generate this wedge because the options are short-dated, and a stochastic volatility risk premium would mainly impact longer-dated options.

We consider two mechanisms to generate wedges between realized and implied volatility in jump-diffusion models: jump risk premiums and estimation risk. The jump risk explanation uses the jump risk corrections implied by an equilibrium model as a simple device for generating \mathbb{Q} -measure jump parameters, given \mathbb{P} -measure parameters. Consistent with our original intent, such an adjustment does not provide an equilibrium explanation, as we calibrate the underlying index model to match the overall equity premium and volatility of returns. In the case of estimation risk, we assume that investors account for the uncertainty in spot volatility and parameters when pricing options.

Both of these explanations generate option returns that are broadly consistent with those observed historically. For example, average put returns are matched pointwise and the average returns of straddles, put spreads, crash-neutral straddles, and delta-hedged portfolios are all statistically insignificant.

These results indicate that, at least for our parameterizations, option returns are not puzzling relative to the benchmark models. Option and stock returns may remain puzzling relative to consumption and dividends, but there is little evidence for mispricing relative to the underlying stock index.

The rest of the paper is outlined as follows. Section 1 outlines our methodological approach. Section 2 discusses our dataset and summarizes the evidence for put mispricing. Section 3 illustrates the methodology based on the Black-Scholes and Heston models. Section 4 investigates strategies based on option portfolios. Section 5 illustrates how a model with stochastic volatility and jumps in prices generate realistic put and straddle returns. Conclusions are given in Section 6.

1. Our Approach

We analyze returns to a number of option strategies. In this section, we discuss some of the concerns that arise in analyzing option returns, and then discuss our approach. To frame the issues, we focus on put option returns, but the results and discussion apply more generally to portfolio strategies such as put spreads, straddles, or delta-hedged returns.

⁵ Over our sample, ATM-implied volatility averaged 17% and the realized volatility was 15%.

Hold-to-expiration put returns are defined as

$$r_{t,T}^p = \frac{(K - S_{t+T})^+}{P_{t,T}(K, S_t)} - 1, \quad (1)$$

where $x^+ \equiv \max(x, 0)$ and $P_{t,T}(K, S_t)$ is the time- t price of a put option written on S_t , struck at K , and expiring at time $t + T$. Hold-to-expiration returns are typically analyzed both in academic studies and in practice for two reasons. First, option trading involves significant costs, and strategies that hold until expiration incur these costs only at initiation. For example, ATM (deep OTM) index option bid-ask spreads are currently on the order of 3–5% (10%) of the option price. The second reason, discussed fully in Section 2, is that high-frequency option returns generate a number of theoretical and statistical issues that are avoided using monthly returns.

The goal of this literature is to assess whether or not option returns are excessive, either in absolute terms or relative to their risks. Existing approaches rely on statistical models, as discussed in Appendix A. For example, it is common to compute average returns, CAPM alphas, or Sharpe ratios. Strategies that involve writing options generally deliver higher average returns than the underlying asset, have economically and statistically large CAPM alphas, and have higher Sharpe ratios than the market.

How should these results be interpreted? Options are effectively leveraged positions in the underlying asset (which typically has a positive expected return), so call (put) options have higher (lower) expected returns than the underlying. For example, expected put option returns are negative, which implies that standard t -tests of average option returns that test the null hypothesis that average returns are zero are improperly anchored. The precise magnitude of expected returns depends on a number of factors that include the specific model, the parameters, and factor risk premiums. In particular, EORs are very sensitive to both the equity premium and volatility.

It is important to control for the option's exposure to the underlying, which is commonly done by computing betas using a CAPM-style specification. This approach is motivated by the hedging arguments used to derive the Black-Scholes model. According to this model, the link between instantaneous derivative returns and excess index returns is

$$\frac{df(S_t)}{f(S_t)} = rdt + \frac{S_t}{f(S_t)} \frac{\partial f(S_t)}{\partial S_t} \left[\frac{dS_t}{S_t} - (r - \delta) dt \right], \quad (2)$$

where r is the risk-free rate, $f(S_t)$ the derivative price, and δ the dividend rate on the underlying asset. This implies that instantaneous changes in the derivative's price are *linear* in the index returns, dS_t/S_t , and *instantaneous* option returns are conditionally normally distributed. This instantaneous

CAPM is often used to motivate an *approximate* linear factor model for option returns

$$\frac{f(S_{t+T}) - f(S_t)}{f(S_t)} = \alpha_{t,T} + \beta_{t,T} \left(\frac{S_{t+T} - S_t}{S_t} - rT \right) + \varepsilon_{t,T}.$$

These linear factor models are used to adjust for leverage, via $\beta_{t,T}$, and as a pricing metric, via $\alpha_{t,T}$. In the latter case, $\alpha_{t,T} \neq 0$ is often interpreted as evidence of either mispricing or risk premiums.

As shown empirically and theoretically in Appendix B, standard option pricing models (including the Black-Scholes model) generate population values of $\alpha_{t,T}$ that are different from zero.⁶ In the Black-Scholes model, this is due to time discretization, but in more general jump-diffusion models, $\alpha_{t,T}$ can be nonzero for infinitesimal intervals due to the presence of jumps. This implies that it is inappropriate to interpret a nonzero $\alpha_{t,T}$ as evidence of mispricing. Similarly, Sharpe ratios account for leverage by scaling average excess returns by volatility, which provides an appropriate metric when returns are normally distributed or if investors have mean-variance preferences. Sharpe ratios are problematic in our setting because option returns are highly nonnormal, even over short time intervals.

Our approach is different. We view these intuitive metrics (average returns, CAPM alphas, and Sharpe ratios) through the lens of formal option pricing models. The experiment we perform is straightforward: we compare the observed values of these statistics in the data to those generated by option pricing models such as Black-Scholes and extensions incorporating jumps or stochastic volatility. The use of formal models plays two roles: it provides an appropriate null value for anchoring hypothesis tests, and it provides a mechanism for dealing with the severe statistical problems associated with option returns.

1.1 Models

We consider nested versions of a general model with mean-reverting stochastic volatility and lognormally distributed Poisson-driven jumps in prices. This model, proposed by Bates (1996) and Scott (1997) and referred to as the SVJ model, is a common benchmark (see, e.g., Andersen, Benzoni, and Lund 2002; Bates 1996; Broadie, Chernov, and Johannes 2007; Chernov et al. 2003; Eraker 2004; Eraker, Johannes, and Polson 2003; Pan 2002). As special cases of the model, we consider the Black and Scholes (1973) model, the Merton (1976) jump-diffusion model, and the Heston (1993) stochastic volatility model.

⁶ Leland (1999) makes this point in the context of the Black-Scholes model.

The model assumes that the ex-dividend index level S_t and its spot variance V_t evolve under the physical (or real-world) \mathbb{P} -measure according to

$$dS_t = (r + \mu - \delta)S_t dt + S_t \sqrt{V_t} dW_t^s(\mathbb{P}) + d \left(\sum_{j=1}^{N_t(\mathbb{P})} S_{\tau_{j-}} [e^{Z_j^s(\mathbb{P})} - 1] \right) - \lambda^{\mathbb{P}} \bar{\mu}^{\mathbb{P}} S_t dt, \quad (3)$$

$$dV_t = \kappa_v^{\mathbb{P}} (\theta_v^{\mathbb{P}} - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v(\mathbb{P}), \quad (4)$$

where r is the risk-free rate, μ is the cum-dividend equity premium, δ is the dividend yield, W_t^s and W_t^v are two correlated Brownian motions ($E[W_t^s W_t^v] = \rho t$), $N_t(\mathbb{P}) \sim \text{Poisson}(\lambda^{\mathbb{P}} t)$, $Z_j^s(\mathbb{P}) \sim \mathcal{N}(\mu_z^{\mathbb{P}}, (\sigma_z^{\mathbb{P}})^2)$, and $\bar{\mu}^{\mathbb{P}} = \exp(\mu_z^{\mathbb{P}} + (\sigma_z^{\mathbb{P}})^2/2) - 1$. Black-Scholes is a special case with no jumps ($\lambda^{\mathbb{P}} = 0$) and constant volatility ($V_0 = \theta_v^{\mathbb{P}}$, $\sigma_v = 0$), Heston's model is a special case with no jumps, and Merton's model is a special case with constant volatility. When volatility is constant, we use the notation $\sqrt{V_t} = \sigma$.

Options are priced using the dynamics under the risk-neutral measure \mathbb{Q} :

$$dS_t = (r - \delta)S_t dt + S_t \sqrt{V_t} dW_t^s(\mathbb{Q}) + d \left(\sum_{j=1}^{N_t(\mathbb{Q})} S_{\tau_{j-}} [e^{Z_j^s(\mathbb{Q})} - 1] \right) - \lambda^{\mathbb{Q}} \bar{\mu}^{\mathbb{Q}} S_t dt, \quad (5)$$

$$dV_t = \kappa_v^{\mathbb{Q}} (\theta_v^{\mathbb{Q}} - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v(\mathbb{Q}), \quad (6)$$

where $N_t(\mathbb{Q}) \sim \text{Poisson}(\lambda^{\mathbb{Q}} t)$, $Z_j^s(\mathbb{Q}) \sim \mathcal{N}(\mu_z^{\mathbb{Q}}, (\sigma_z^{\mathbb{Q}})^2)$, $W_t^s(\mathbb{Q})$ are Brownian motions, and $\bar{\mu}^{\mathbb{Q}}$ is defined analogously to $\bar{\mu}^{\mathbb{P}}$. The diffusive equity premium is μ^c , and the total equity premium is $\mu = \mu^c + \lambda^{\mathbb{P}} \bar{\mu}^{\mathbb{P}} - \lambda^{\mathbb{Q}} \bar{\mu}^{\mathbb{Q}}$. We generally refer to a nonzero μ as a diffusive risk premium. Differences between the risk-neutral and real-world jump and stochastic volatility parameters are referred to as jump or stochastic volatility risk premiums, respectively.

Both the parameters θ_v and κ_v can potentially change under the risk-neutral measure (Cheredito, Filipovic, and Kimmel 2007). We explore changes in $\theta_v^{\mathbb{P}}$ and constrain $\kappa_v^{\mathbb{Q}} = \kappa_v^{\mathbb{P}}$, because, as discussed below, average returns are not sensitive to empirically plausible changes in $\kappa_v^{\mathbb{P}}$. Changes of measure for jump processes are more flexible than those for diffusion processes. We assume that the jump size distribution is lognormal under \mathbb{Q} with potentially different means and variances. Below we discuss in detail two mechanisms, risk premiums and estimation risk, to calibrate the risk-neutral parameters.

1.2 Methodological framework

Methodologically, we rely on two main tools: analytical formulas for expected returns and Monte Carlo simulation to assess statistical significance.

1.2.1 Analytical expected option returns. Expected put option returns are given by

$$E_t^{\mathbb{P}}(r_{i,T}^p) = \frac{E_t^{\mathbb{P}}[(K - S_{t+T})^+]}{P_{i,T}(S_t, K)} - 1 = \frac{E_t^{\mathbb{P}}[(K - S_{t+T})^+]}{E_t^{\mathbb{Q}}[e^{-rT}(K - S_{t+T})^+]} - 1. \quad (7)$$

From this expression, it is clear that any model that admits “analytical” option prices, such as affine models, will allow EORs to be computed explicitly since both the numerator and denominator are known analytically. Higher moments can also be computed. Surprisingly, despite a large literature analyzing option returns, the fact that EORs can be easily computed has neither been noted nor applied.⁷

EORs do not depend on S_t . To see this, define the initial moneyness of the option as $\kappa = K/S_t$. Option homogeneity implies that

$$E_t^{\mathbb{P}}(r_{i,T}^p) = \frac{E_t^{\mathbb{P}}[(\kappa - R_{i,T})^+]}{E_t^{\mathbb{Q}}[e^{-rT}(\kappa - R_{i,T})^+]} - 1, \quad (8)$$

where $R_{i,T} = S_{t+T}/S_t$ is the gross index return.⁸ EORs depend only on the moneyness, maturity, interest rate, and distribution of index returns.⁹

This formula provides exact EORs for finite holding periods regardless of the risk factors of the underlying index dynamics and without using CAPM-style approximations. These analytical results are primarily useful as they allow us to assess the exact *quantitative* impact of risk premiums or parameter configurations. Equation (7) implies that the gap between the \mathbb{P} and \mathbb{Q} probability measures determines EORs, and the magnitude of the returns is determined by the relative shape and location of the two probability measures.¹⁰ In models without jump or stochastic volatility risk premiums, the gap is determined by the fact that the \mathbb{P} and \mathbb{Q} drifts differ by the equity risk premium. In models with priced stochastic volatility or jump risk, both the shape and location of the distribution can change, leading to more interesting patterns of expected returns across different moneyness categories.

⁷ This result is closely related to that of Rubinstein (1984), who derived it specifically for the Black-Scholes case and analyzed the relationship between hold-to-expiration and shorter holding period expected returns.

⁸ Glosten and Jagannathan (1994) use option homogeneity to benchmark payoff from one dollar invested in a mutual fund with unknown asset composition against a portfolio consisting of the index with a payoff of $R_{i,T}$ and an option with a payoff $(R_{i,T} - \kappa)^+$. Subsequently, Glosten and Jagannathan use the Black-Scholes model to value the benchmark portfolio.

⁹ When stochastic volatility is present in a model, the expected option returns can be computed analytically conditional on the current variance value: $E^{\mathbb{P}}(r_{i,T}^p|V_t)$. The unconditional expected returns can be computed using iterated expectations and the fact that

$$E^{\mathbb{P}}(r_{i,T}^p) = \int E^{\mathbb{P}}(r_{i,T}^p|V_t) p(V_t) dV_t.$$

The integral can be estimated via Monte Carlo simulation or by standard deterministic integration routines.

¹⁰ For monthly holding periods, $1 \leq \exp(rT) \leq 1.008$ for $0\% \leq r \leq 10\%$ and $T = 1/12$ years, so the discount factor has a negligible impact on EORs.

1.2.2 Finite-sample distribution via Monte Carlo simulation. To assess statistical significance, we use Monte Carlo simulation to compute the distribution of various returns statistics, including average returns, CAPM alphas, and Sharpe ratios. We are motivated by concerns that the use of limiting distributions to approximate the finite-sample distribution is inaccurate in this setting. Our concerns arise due to the relatively short sample and extreme skewness and nonnormality of option returns.

To compute the finite-sample distribution of various option return statistics, we simulate $N = 215$ months (the sample length in the data) of index levels $G = 25,000$ times using standard simulation techniques. For each month and index simulation trial, put returns for a fixed moneyness are

$$r_{t,T}^{p,(g)} = \frac{(\kappa - R_{t,T}^{(g)})^+}{P_T(\kappa)} - 1, \quad (9)$$

where

$$P_T(\kappa) \triangleq \frac{P_{t,T}(S_t, K)}{S_t} = e^{-rT} E_t^{\mathbb{Q}}[(\kappa - R_{t,T})^+],$$

$t = 1, \dots, N$ and $g = 1, \dots, G$. Average option returns for simulation g using N months of data are

$$\bar{r}_T^{p,(g)} = \frac{1}{N} \sum_{t=1}^N r_{t,T}^{p,(g)}.$$

The set of G average returns forms the finite-sample distribution. Similarly, we can construct finite-sample distributions for Sharpe ratios, CAPM alphas, and other statistics of interest for any option portfolio.

This parametric bootstrapping approach provides exact finite-sample inference under the null hypothesis that a given model holds. It can be contrasted with the nonparametric bootstrap, which creates artificial datasets by sampling with replacement from the observed data. The nonparametric bootstrap, which essentially reshuffles existing observations, has difficulties dealing with rare events. In fact, if an event has not occurred in the observed sample, it will never appear in the simulated finite-sample distribution. This is an important concern when dealing with put returns, which are sensitive to rare events.

1.3 Parameter estimation

We calibrate our models to fit the realized historical behavior of the underlying index returns over our observed sample. Thus, the \mathbb{P} -measure parameters are estimated directly from historical index return data, and not consumption or dividend behavior. For parameters in the Black-Scholes model, this calibration is straightforward, but in models with unobserved volatility or jumps, the estimation is more complicated, as it is not possible to estimate all of the parameters via simple sample statistics.

Table 1
 \mathbb{P} -measure parameters

r	μ	$\lambda^{\mathbb{P}}$	$\mu_z^{\mathbb{P}}$	$\sigma_z^{\mathbb{P}}$	$\sqrt{\theta_v^{\mathbb{P}}}$ (SV)	$\sqrt{\theta_v^{\mathbb{P}}}$ (SVJ)	$\kappa_v^{\mathbb{P}}$	σ_v	ρ
4.50%	5.41%	0.91 (0.34)	-3.25% (1.71)	6.00% (0.99)	15.00%	13.51% (1.28)	5.33 (0.84)	0.14 (0.01)	-0.52 (0.04)

This table reports values of \mathbb{P} -measure parameters that we use in our computational examples. Standard errors from the SVJ estimation are reported in parentheses. Parameters are given in annual terms.

For all of the models that we consider, the interest rate and equity premium match those observed over our sample, $r = 4.5\%$ and $\mu = 5.4\%$. Since we analyze futures returns and futures options, $\delta = r$. In each model, we also constrain the total volatility to match the observed monthly volatility of futures returns, which was 15%. In the most general model we consider, we do this by imposing that

$$\sqrt{\theta_v^{\mathbb{P}} + \lambda^{\mathbb{P}}((\mu_z^{\mathbb{P}})^2 + (\sigma_z^{\mathbb{P}})^2)} = 15\%$$

and by modifying $\theta_v^{\mathbb{P}}$ appropriately. In the Black-Scholes model, we set the constant volatility to be 15%.

To obtain the values of the remaining parameters, we estimate the SVJ model using daily S&P 500 index returns spanning the same time period as our options data, from 1987 to 2005. We use MCMC methods to simulate the posterior distribution of the parameters and state variables following Eraker, Johannes, and Polson (2003) and others. The parameter estimates (posterior means) and posterior standard deviations are reported in Table 1. The parameter estimates are in line with the values reported in previous studies (see Brodie, Chernov, and Johannes 2007 for a review).

Of particular interest for our analysis are the jump parameters. The estimates imply that jumps are relatively infrequent, arriving at a rate of about $\lambda^{\mathbb{P}} = 0.91$ per year. The jumps are modestly sized with a mean of -3.25% and a standard deviation of 6%. Given these values, a “two sigma” downward jump size will be equal to -15.25% . Therefore, a crash-type move of -15% or less will occur with a probability of $\lambda^{\mathbb{P}} \cdot 5\%$, or approximately once in twenty years.

As we discuss in greater detail below, estimating jump intensities and jump size distributions is extremely difficult. The estimates are highly dependent on the observed data and on the specific model. For example, different estimates would likely be obtained if we assumed that the jump intensity was dependent on volatility (as in Bates 2000 or Pan 2002) or if there were jumps in volatility. Again, our goal is not to exhaustively analyze every potential specification but rather to understand option returns in common specifications and for plausible parameter values.

We discuss the calibration of \mathbb{Q} -measure parameters later. At this stage, we only emphasize that we do not use options data to estimate any of the

parameters. Estimating \mathbb{Q} -parameters from option prices for use in understanding observed option returns would introduce a circularity, as we would be explaining option returns with information extracted from option prices.

2. Initial Evidence for Put Mispricing

We collect historical data on S&P 500 futures options from August 1987 to June 2005, a total of 215 months. These options are American, but our statistics are computed using the European values estimated through the procedure from Broadie, Chernov, and Johannes (2007). This sample is considerably longer than those previously analyzed and starts in August of 1987, when one-month “serial” options were introduced. Contracts expire on the third Friday of each month, which implies there are 28 or 35 calendar days to maturity depending on whether it was a four- or five-week month. We construct representative daily option prices using the approach in Broadie, Chernov, and Johannes (2007); details of this procedure are given in Appendix C.

Using these prices, we compute option returns for fixed moneyness, measured by strike divided by the underlying, ranging from 0.94 to 1.02 (in 2% increments). This range covers the most actively traded options (85% of one-month option transactions occur in this range). We did not include deeper OTM or ITM strikes because of missing values. Payoffs are computed using settlement values for the S&P 500 futures contract. Figure 1 shows the time series for 6% OTM and ATM put returns, highlighting some of the issues present when evaluating the statistical significance of statistics generated by option returns. Put returns have infrequent but very large values and many repeated values, since OTM expirations generate returns of -100% . We also compute returns for a range of portfolio strategies, including covered puts, put spreads (crash-neutral put portfolios), ATM and crash-neutral straddles, and delta-hedged puts. We first consider raw put returns, as this has been the primary focus in the existing literature.

As mentioned earlier, we use hold-to-maturity returns. The alternative would be higher frequency returns, weekly or even daily. The intuition for considering high-frequency returns comes from Black-Scholes dynamic hedging arguments, indicating that option returns become approximately normal over high frequencies. Appendix D describes the difficulties associated with high-frequency option returns. In summary, we argue that high-frequency returns generate additional theoretical, data, and statistical problems. In particular, simulation evidence shows that moving from monthly to weekly returns exacerbates the statistical issues because the distribution of average returns becomes even more nonnormal and dispersed.

The first piece of evidence commonly cited supporting mispricing is the large magnitude of the returns. According to Table 2, average monthly returns are -57% for 6% OTM strikes (i.e., $K/S = 0.94$) and -30% for ATM strikes and are statistically different from zero since the p -values are close to zero. In particular, to check that our results are consistent with previous findings, we

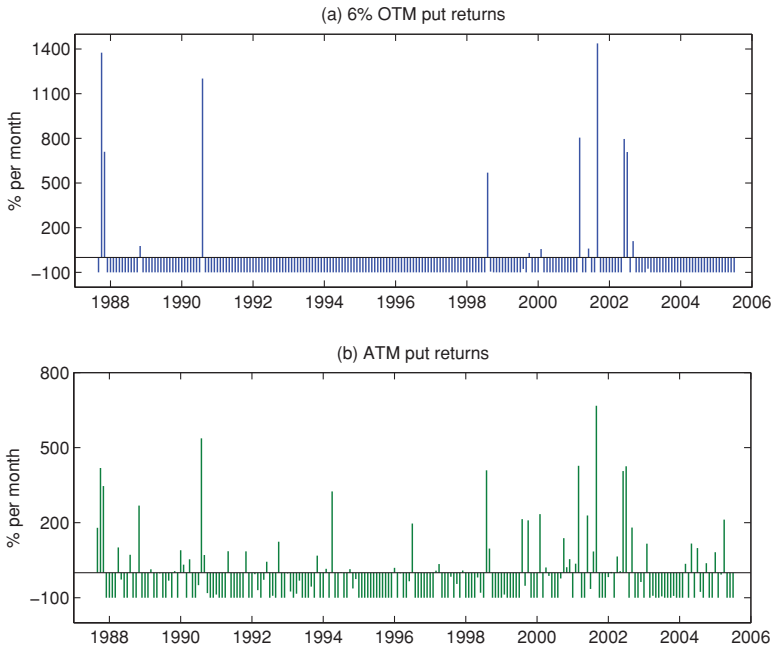


Figure 1
Time series of options returns.

Table 2
Average put option returns

Moneyness	0.94	0.96	0.98	1.00	1.02
08/1987 to 06/2005	-56.8	-52.3	-44.7	-29.9	-19.0
Standard error	14.2	12.3	10.6	8.8	7.1
<i>t</i> -stat	-3.9	-4.2	-4.2	-3.3	-2.6
<i>p</i> -value, %	0.0	0.0	0.0	0.0	0.4
Skew	5.5	4.5	3.6	2.5	1.8
Kurt	34.2	25.1	16.7	10.5	7.1
Subsamples					
01/1988 to 06/2005	-65.2	-60.6	-51.5	-34.1	-21.6
01/1995 to 09/2000	-85.5	-71.6	-63.5	-50.5	-37.5
10/2000 to 02/2003	+67.2	+54.3	+44.5	+48.2	+40.4
08/1987 to 01/2000	-83.9	-63.2	-55.7	-39.5	-25.5

The first panel contains the full sample (215 monthly returns) results, with standard errors, *t*-statistics, *p*-values, and skewness and kurtosis statistics. The second panel analyzes subsamples. All relevant statistics are in percentages per month.

compare our statistics to the one in the Bondarenko (2003) sample from 1987 to 2000. The average returns are very close, but ours are slightly more negative for every moneyness category except the deepest OTM category. Bondarenko (2003) uses closing prices and has some missing values. Our average returns are slightly more negative than those reported for similar time periods by Santa-Clara and Saretto (2007).

Table 3
Risk-corrected measures of average put option returns

Moneyness	0.94	0.96	0.98	1.00	1.02
CAPM α , %	-48.3	-44.1	-36.8	-22.5	-12.5
Std.err., %	11.6	9.3	7.1	4.8	2.9
<i>t</i> -stat	-4.1	-4.7	-5.1	-4.6	-4.2
<i>p</i> -value, %	0.0	0.0	0.0	0.0	0.0
Sharpe ratio	-0.27	-0.29	-0.29	-0.23	-0.18

The first panel provides CAPM α 's with standard errors and the second panel provides put option Sharpe ratios (as a reference, the monthly Sharpe ratio for the market over our time period was about 0.1). These quantities were computed based on the full sample of 215 monthly returns from August 1987 to June 2005. All relevant statistics except for the Sharpe ratios are in percentages per month. Sharpe ratios are monthly. The *p*-values are computed under the (incorrect) null hypothesis that average option returns are equal to zero.

The bottom panel of Table 2 reports average returns over subsamples. Average put returns are unstable over time. For example, put returns were extremely negative during the late 1990s during the dot-com “bubble” but were positive and large from late 2000 to early 2003. The subsample starting in January 1988 provides the same insight: if the extremely large positive returns realized around the crash of 1987 are excluded, returns are much lower. Doing so generates a sample selection bias and clearly demonstrates a problem with tests using short sample periods.¹¹

Table 3 reports CAPM alphas and Sharpe ratios, which delever and/or risk-correct option returns to account for the underlying exposure. CAPM alphas are highly statistically significant, with *p*-values near zero. The Sharpe ratios of put positions are larger than those on the underlying market. For example, the monthly Sharpe ratio for the market over our time period was about 0.1, and the put return Sharpe ratios are two to three times larger. Based largely on this evidence and additional robustness checks, the literature concludes that put returns are puzzling and options are likely mispriced. We briefly review the related literature in Appendix A.

3. The Role of Statistical Uncertainty

This section highlights the difficulties of establishing mispricing based on historical put returns. To do this, we use the simplest option pricing models, the Black-Scholes and SV models. We show that expected returns are highly sensitive to the underlying equity premium and volatility and also document the extreme finite-sample problems associated with tests using returns of individual options. In particular, the biggest puzzle in the literature—the large deep OTM put returns—is not inconsistent with the Black-Scholes model.

¹¹ In simulations of the Black-Scholes model, excluding the largest positive return lowers *average* put option returns by about 15% for the 6% OTM strike. This outcome illustrates the potential sample selection issues and how sensitive option returns are to the rare but extremely large positive returns generated by events such as the crash of 1987.

Table 4
Population expected returns in the Black-Scholes model

σ	μ	Moneyness						
		0.94	0.96	0.98	1.00	1.02	1.04	1.06
10%	4%	-27.6	-22.5	-17.6	-13.3	-9.7	-6.9	-5.0
	6%	-38.7	-32.2	-25.7	-19.7	-14.5	-10.5	-7.7
	8%	-48.3	-40.8	-33.1	-25.7	-19.2	-14.1	-10.4
15%	4%	-15.4	-13.0	-10.8	-8.8	-7.1	-5.6	-4.5
	6%	-22.5	-19.2	-16.1	-13.2	-10.7	-8.6	-6.9
	8%	-29.1	-25.0	-21.1	-17.5	-14.3	-11.5	-9.3
20%	4%	-10.3	-8.9	-7.7	-6.5	-5.5	-4.6	-3.9
	6%	-15.2	-13.3	-11.5	-9.9	-8.4	-7.1	-6.0
	8%	-20.0	-17.6	-15.3	-13.2	-11.2	-9.5	-8.1

The parameter μ is the cum-dividend equity premium and σ is the volatility. These parameters are reported on an annual basis; expected option returns are monthly percentages.

3.1 Black-Scholes

In this section, we analyze EORs in the Black-Scholes model and analyze the finite-sample distribution of average option returns, CAPM alphas, and Sharpe ratios. Table 4 displays EORs computed by Equation (8). The cum-dividend equity premium ranges from 4% to 8% and volatility ranges from 10% to 20%.

The impact of μ is approximately linear and quantitatively large, as the difference in EORs between high and low equity premiums is about 10% for ATM strikes and larger for deep OTM strikes. Because of this, any historical period that is “puzzling” because of high realized equity returns will generate even more striking option returns. For example, the realized equity premium from 1990 to 1999 was 9.4%, and the average volatility was only 13% over the same period. If fully anticipated, these values would, according to Equation (8), generate 6% OTM and ATM EORs of about -40% and -23%, respectively, which are much lower than the EORs using the full sample equity premium and volatility.

Option returns are sensitive to volatility. As volatility increases, expected put option returns increase (i.e., become less negative). For example, for 6% OTM puts with $\mu = 6\%$, EORs change from -39% for $\sigma = 10\%$ to -15% for $\sigma = 20\%$. Thus volatility has a quantitatively large impact that varies across strikes. Unlike the approximately linear relationship between EORs and μ , the relationship between put EORs and volatility is concave. This concavity implies that fully anticipated time-variation in volatility results in more negative EORs than that if volatility were constant at the average value.

EORs are extremely difficult to estimate. As a first illustration, the top panel in Figure 2 shows the finite-sample distribution for 6% OTM average put returns constructed from 25,000 sample paths, each of length 215. The solid vertical line is the observed sample value. The upper panel shows the large variability in average put return estimates: the (5%, 95%) confidence band is -65% to +28%. The figure also shows the marked skewness of the distribution of average monthly option returns, which is expected given the strong positive

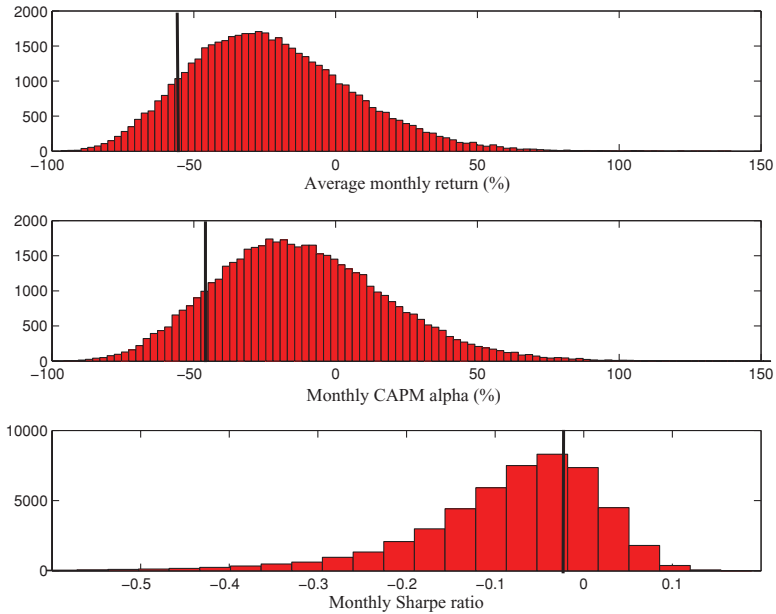


Figure 2
Finite-sample distribution

This figure shows histograms of the finite-sample distribution of various statistics. The top panel provides the distribution of average 6% OTM put returns, the middle panel 6% OTM put CAPM alphas, and the bottom panel 6% OTM put Sharpe ratios. The distributions are computed using 25,000 artificial histories, 215 months each, simulated from the Black-Scholes model. The solid vertical line is the observed value from the data.

skewness of purchased put options. This also indicates that the distribution of average put returns is not well approximated by a normal distribution, at least in samples of this size.

Table 5 summarizes EORs and p -values corresponding to observed average returns for various strikes. Note first that put average returns increase with moneyness, are negative, and therefore are less than the risk-free rate. These patterns are consistent with the prediction derived in Coval and Shumway (2001) under general assumptions. However, because of the extreme noise associated with these statistics, it would be hard to use this monotonicity to discern alternative explanations of options returns.

The p -values have increased dramatically relative to Table 2. For example, the p -values using standard t -statistics for the ATM options increase by roughly a factor of ten and by more than 10,000 for deep OTM put options. This dramatic increase occurs for two reasons: our procedure (1) anchors the null hypothesis at values generated by the option pricing model and (2) accounts for the large sampling uncertainty in the distribution of average option returns.

Next, average 6% OTM option returns are not statistically different from those generated by the Black-Scholes model, with a p -value of just over 8%. Based only on the Black-Scholes model, we have our first striking conclusion:

Table 5
Option returns, CAPM α 's, and Sharpe ratios

		Moneyneess	0.94	0.96	0.98	1.00
Average returns	Data, %		-56.8	-52.3	-44.7	-29.9
	BS	$E^{\mathbb{P}}, \%$	-20.6	-17.6	-14.6	-12.0
		p -value, %	8.1	1.7	0.4	2.2
	SV	$E^{\mathbb{P}}, \%$	-25.8	-21.5	-17.5	-13.7
		p -value, %	24.1	9.3	3.0	7.3
	CAPM α s	Data, %		-48.3	-44.1	-36.8
BS		$E^{\mathbb{P}}, \%$	-17.9	-15.3	-12.7	-10.4
		p -value, %	12.6	2.7	0.3	1.2
SV		$E^{\mathbb{P}}, \%$	-23.6	-19.5	-15.8	-12.4
		p -value, %	39.1	14.1	3.4	8.7
Sharpe ratios		Data		-0.27	-0.29	-0.29
	BS	$E^{\mathbb{P}}$	-0.05	-0.07	-0.08	-0.09
		p -value, %	4.9	1.9	1.2	4.0
	SV	$E^{\mathbb{P}}$	-0.04	-0.07	-0.09	-0.10
		p -value, %	21.5	12.0	7.7	14.3

This table reports population expected option returns, CAPM α 's, and Sharpe ratios and finite-sample distribution p -values for the Black-Scholes (BS) and stochastic volatility (SV) models. We assume that all risk premiums (except for the equity premium) are equal to zero. The p -values are computed using the finite-sample distributions of the respective statistics. The distributions were constructed from 25,000 simulated paths, each with 215 monthly observations.

deep OTM put returns are insignificant when compared to the Black-Scholes model. This is particularly interesting since the existing literature concludes that deep OTM put options are the most anomalous or mispriced. We arrive at the exact opposite conclusion: there is no evidence that OTM put returns are excessive. It is important to note that other strikes are still significant, with p -values below 5%.

Next, consider CAPM alphas, which are reported in the second panel of Table 5. For every strike, the alphas are quite negative and their magnitudes are economically large, ranging from -18% for 6% OTM puts to -10% for ATM puts. Although Black-Scholes is a single-factor model, the alphas are quite negative in population, which is expected, as discussed in Section 2. This shows the fundamental problem that arises when applying linear factor models to nonlinear option returns.

To see the issue more clearly, Figure 3 displays two simulated time series of monthly index and OTM option returns. The regression estimates in the top (bottom) panel correspond to $\alpha = 64\%$ ($\alpha = -51\%$) per month and $\beta = -58$ ($\beta = -19$). The main difference between the two simulations is a *single* large observation in the upper panel, which substantially shifts the constant and intercept estimates obtained by least squares. More formally, the middle panel of Figure 2 depicts the finite-sample distribution of CAPM alphas for 6% OTM puts, and the middle panel of Table 5 provides finite-sample p -values for the observed alphas. For the deep OTM puts, observed CAPM alphas are not statistically different from those generated by Black-Scholes. For the other strikes, the observed alphas are generally too low to be consistent with the

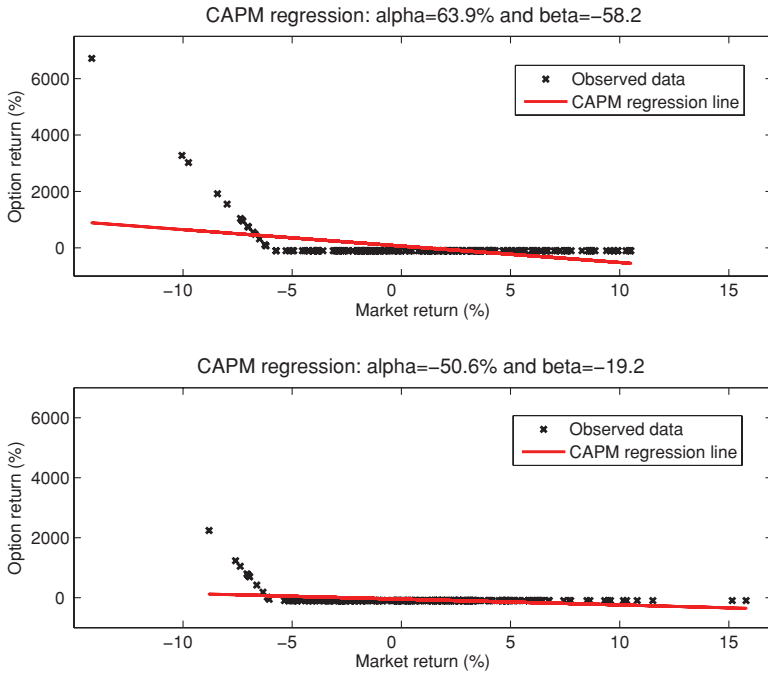


Figure 3
CAPM regressions

Results of CAPM regressions for 6% OTM put option returns. The CAPM regression coefficients are computed from two artificial histories, 215 months each, simulated from the Black-Scholes model.

Black-Scholes model, although again the p -values are much larger than those based on asymptotic theory.

Finally, consider Sharpe ratios. The bottom panel of Figure 2 illustrates the extremely skewed finite-sample distribution of Sharpe ratios for 6% OTM puts. The third panel of Table 5 reports population Sharpe ratios for put options of various strikes and finite-sample p -values. As a comparison, the monthly Sharpe ratio of the underlying index over our sample period is 0.1. The Sharpe ratios are modestly statistically significant for every strike, with p -values between 1% and 5%.

At this stage it is natural to wonder whether alternative metrics, such as the ones proposed by Goetzmann et al. (2007) and Leland (1999), would help in detecting option mispricing. Although not reported, the conclusions are essentially identical using alternative measures such as Leland’s alpha or the Manipulation Proof Performance Metric of Goetzmann et al. (2007). These measures were intended for the different problem of detecting managerial skill, when managers can rebalance positions over time or trade options, assuming the underlying assets, in particular options, are correctly priced. In our setting, these metrics generate similar conclusions, because they also have extremely high

finite-sample uncertainty. For example, Leland's measure requires estimates of average option returns and moments of nonlinear functions of the underlying return, both of which are difficult to estimate. The fact that Leland's alpha is very close to the CAPM alpha has been previously noted in Goetzmann et al. (2007).

3.2 Stochastic volatility

Next, consider the SV model. We assume the overall equity premium is the same as in the previous section, 5.4%, but that $\theta_v^Q = \theta_v^P$, which implies that there is not a diffusive volatility premium. Table 5 provides population average returns, CAPM alphas, and Sharpe ratios for the SV model, as well as p -values.

First, expected put returns are lower in the SV model than in the Black-Scholes model. This is due to the fact that EORs are a concave function of volatility, which implies that fluctuations in volatility, even if fully anticipated, decrease expected put returns. Compared to the Black-Scholes model, expected put returns are about 2% lower for ATM strikes and about 5% lower for the deep OTM strikes. While not extremely large, the lower EORs, combined with an increased sampling uncertainty generated by changing volatility, significantly increase p -values. For deep OTM puts, the p -value is now almost 25%, indicating that roughly one in four simulated sample paths generates *more negative* 6% OTM average put returns than those observed. For the other strikes, none of the average returns are significant at the 1% level, and most are not significant at the 5% level.

CAPM alphas for put returns are more negative in population for the SV model than the Black-Scholes model, consistent with the results for expected returns. The observed alphas are all insignificant, with the exception of the 0.98 strike, which has a p -value of about 3%. The results for the Sharpe ratios are even more striking, with none of the strikes statistically significantly different from those generated by the SV model.

3.3 Discussion

The results in the previous section generate a number of new findings and insights regarding relative pricing tests using option returns. In terms of population properties, EORs are quite negative in the Black-Scholes model, and even more so in the stochastic volatility model. The leverage embedded in options magnifies the equity premium, and the concavity of EORs as a function of volatility implies that randomly changing volatility decreases expected put option returns. Single-factor CAPM-style regressions generate negative CAPM alphas in population, with the SV model generating more negative returns than Black-Scholes. This result is a direct outcome of computing returns of assets with nonlinear payoffs over noninfinitesimal horizons and regressing these returns on index returns. Therefore, extreme care should be taken when interpreting negative alphas from factor model regressions using put returns.

In terms of sampling uncertainty, three results stand out. First, sampling uncertainty is substantial for put returns, so much so that the returns for many of

the strikes are statistically insignificant. This is especially true for the stochastic volatility model where stochastic volatility increases the sampling uncertainty. Second, in terms of statistical efficiency, average returns are generally less noisy than CAPM alphas or Sharpe ratios. For example, comparing the p -values for the average returns to those for CAPM alphas in the stochastic volatility model, the p -values for CAPM alphas are always larger. This is also generally true when comparing average returns to Sharpe ratios, with the exception of deep OTM strikes. This occurs because the sampling distribution of CAPM alphas is more dispersed, with OLS regressions being very sensitive to outliers. Third, across models and metrics, the most difficult statistics to explain are the 2% OTM put returns. This result is somewhat surprising, since slightly OTM strikes have not been previously identified as particularly difficult to explain.

How do we interpret these results? The BS and SV models are clearly *not* perfect specifications, since they can be rejected in empirical tests using option prices. However, these models do incorporate the major factors driving option returns and demonstrate that average raw put returns are so noisy that little can be said about put option mispricing. If option returns are to be useful, more informative test portfolios must be used.

4. Portfolio-Based Evidence for Option Mispricing

This section explores whether returns on option portfolios are more informative about a potential option mispricing than individual option returns. We consider a variety of portfolios including covered puts, which consist of a long put position combined with a long position in the underlying index; ATM straddles, which consist of a long position in an ATM put and an ATM call; crash-neutral straddles, which consist of a long position in an ATM straddle combined with a short position in one unit of 6% OTM put; put spreads (also known as crash-neutral puts), which consist of a long position in an ATM put and a short position in a 6% OTM put; and delta-hedged puts, which consist of a long put position combined with a position in delta units of the underlying index.¹² As observed earlier, a large part of the variation in average put returns is driven by the underlying index. All of the above-mentioned portfolios mitigate the impact of the level of the index or the tail behavior of the index (e.g., crash-neutral straddles or put spreads).

In each case, we analyze the returns to the long side to be consistent with earlier results. In analyzing these positions, we ignore the impact of margin for the short option positions that appear in the crash-neutral straddles and puts. As shown by Santa-Clara and Saretto (2007), margin requirements are substantial for short option positions. Table 6 evaluates expected returns for each of these strategies using the Black-Scholes and SV models. CAPM alphas and Sharpe

¹² The discussion of some shortcomings of analyzing delta-hedged returns and the results for delta-hedged portfolios are provided in Appendix E.

Table 6
Sample average returns for put-based portfolios

Strategy data, %		ATMS -15.7	CNS -9.9	PSP -21.2
BS	$E^{\mathbb{P}}$, %	1.1	2.2	-11.1
	p -val, %	0.0	0.8	12.5
SV	$E^{\mathbb{P}}$, %	1.4	2.2	-13.1
	p -val, %	0.0	0.9	17.1

The table reports sample average returns for various put-based portfolios based on 215 monthly returns. Population expected returns and finite-sample p -values are computed from the Black-Scholes (BS) and stochastic volatility (SV) models using 25,000 artificial histories, 215 observations each, simulated from the respective models. We assume that volatility risk premiums are equal to zero. ATMS, CNS, and PSP refer to the statistics associated with at-the-money straddles, crash-neutral straddles, and put spreads, respectively.

ratios are not reported because they do not add new information, as discussed in the previous section. The table does not include average returns on the covered put positions, since the t -statistics are not significant.

Table 6 shows that the magnitude of the ATM straddle returns is quite large, more than 15% per month. The corresponding p -values, computed from the finite-sample distribution as described in Section 1.2.2, are approximately zero. As expected, the returns on the portfolios are less noisy than for individual option positions. Interestingly, put spreads have p -values between 10% and 20% and are less significant than individual put returns, at least for near-the-money strikes.

ATM straddle returns are related to the wedge between expected volatility under the \mathbb{Q} measure and realized volatility under the \mathbb{P} measure. In our sample, realized monthly volatility is approximately 15% (annualized) and ATM-implied volatility 17%.¹³ What is interesting about this gap is that it has not vanished during the latter part of the sample. For example, during the last two one-year periods, from July 2003 to July 2004 and from July 2004 to July 2005, the gap was 5.3% and 1.9%, respectively. This property suggests that the returns cannot be explained solely by factors that have dramatically increased over time, such as overall liquidity. The next section investigates two explanations for this gap: estimation risk and jump risk premiums.

5. The Role of Risk Premiums

In this section, we focus our discussion on straddles and analyzing mechanisms that can generate the gap between \mathbb{P} and \mathbb{Q} measures. The two mechanisms that we consider are estimation risk and jump risk premiums, although we generically refer to the gap as risk premiums. Both mechanisms also include an equity premium discussed earlier. We also discuss one other potential explanation, diffusive stochastic volatility risk premiums (differences in the drifts of the volatility process under \mathbb{P} and \mathbb{Q}), but find this explanation implausible.

¹³ Bakshi and Madan (2006) link this gap to the skewness and kurtosis of the underlying returns via the representative investor's preferences. Chernov (2007) relates this gap to volatility and jump risk premiums.

5.1 Differences between \mathbb{P} and \mathbb{Q}

In a purely diffusive stochastic volatility model (i.e., without jumps in volatility), a wedge between expected volatility under \mathbb{P} and \mathbb{Q} can arise from a diffusive volatility risk premium. The simplest version of this assumes that $\theta_v^{\mathbb{Q}} > \theta_v^{\mathbb{P}}$ and has been informally suggested as an explanation for the large straddle returns by, e.g., Coval and Shumway (2001). We argue that this is unlikely to be the main, or even a significant, driver of the observed straddle returns.

The difference between expected variance under \mathbb{Q} - and \mathbb{P} -measures in the SV model is given by

$$E^{\mathbb{Q}}[V_{t,T}] - E^{\mathbb{P}}[V_{t,T}] = (\theta_v^{\mathbb{Q}} - \theta_v^{\mathbb{P}}) \left(1 + \frac{\exp(-\kappa_v^{\mathbb{P}}T) - 1}{\kappa_v^{\mathbb{P}}T} \right),$$

where $E^{\mathbb{M}}[V_{t,T}]$ denotes the expected average total variance under the measure \mathbb{M} (\mathbb{Q} or \mathbb{P}) between time t and $t + T$, assuming continuous observations (see, e.g., Chernov 2007). Because volatility is highly persistent (i.e., $\kappa_v^{\mathbb{P}}$ is small) and T is small for one-month options, $\theta_v^{\mathbb{Q}}$ needs to be much larger than $\theta_v^{\mathbb{P}}$ to generate a large gap between \mathbb{Q} and \mathbb{P} that is required to obtain the straddle returns consistent with observed data.¹⁴

Our computations show that $\sqrt{\theta_v^{\mathbb{Q}}} = 22\%$ would generate statistically insignificant straddle returns. However, such a large value of $\theta_v^{\mathbb{Q}}$ implies that the term structure of implied volatilities would be steeply upward sloping on average, which can be rejected based on observed implied volatility term structures—a point discussed by Pan (2002) and Broadie, Chernov, and Johannes (2007). This implies that a large diffusive stochastic volatility risk premium can be rejected as the sole explanation for the short-dated straddle returns. Combined with the previous results, this observation implies that the SV model is incapable of explaining short-dated straddle returns.

A more promising explanation relies on price jumps, and to explore this we consider the Bates (1996) and Scott (1997) SVJ model in Equations (3) and (4). From a theoretical perspective, gaps in the \mathbb{P} - and \mathbb{Q} -measure jump parameters are promising because

$$E^{\mathbb{Q}}[V_{t,T}] - E^{\mathbb{P}}[V_{t,T}] = (\theta_v^{\mathbb{Q}} - \theta_v^{\mathbb{P}}) \left(1 + \frac{e^{-\kappa_v^{\mathbb{P}}T} - 1}{\kappa_v^{\mathbb{P}}T} \right) + \lambda^{\mathbb{Q}}((\mu_z^{\mathbb{Q}})^2 + (\sigma_z^{\mathbb{Q}})^2) - \lambda^{\mathbb{P}}((\mu_z^{\mathbb{P}})^2 + (\sigma_z^{\mathbb{P}})^2). \quad (10)$$

In contrast to the SV model, differences between the \mathbb{P} - and \mathbb{Q} -measure jump parameters have an impact on expected variance for all maturities and do

¹⁴ We constrain $\kappa_v^{\mathbb{P}} = \kappa_v^{\mathbb{Q}}$. Some authors have found that $\kappa_v^{\mathbb{Q}} < \kappa_v^{\mathbb{P}}$, which implies that $\theta_v^{\mathbb{Q}}$ would need to be even larger to generate a noticeable impact on expected option returns.

not depend on slow rates of mean-reversion. The main issue is determining reasonable parameter values for $\lambda^{\mathbb{Q}}$, $\mu_z^{\mathbb{Q}}$, and $\sigma_z^{\mathbb{Q}}$.

One way to obtain the risk-neutral parameter values is to estimate these parameters from option data, as in Broadie, Chernov, and Johannes (2007). However, this approach is not useful for understanding whether options are mispriced. If option prices are used to calibrate $\lambda^{\mathbb{Q}}$, $\mu_z^{\mathbb{Q}}$, and $\sigma_z^{\mathbb{Q}}$, then the exercise is circular, since one implicitly assumes that options are correctly priced. We take a different approach and consider jump risk premiums and estimation risk as plausible explanations for differences between \mathbb{P} - and \mathbb{Q} -measure parameters.

5.2 Factor risk premiums

Bates (1988) and Naik and Lee (1990) introduce extensions of the standard log-normal diffusion general equilibrium model incorporating jumps in dividends. These models provide a natural starting point for our analysis. In this application, a particular concern with these models is that, when calibrated to dividends, they lead to well-known equity premium and excess volatility puzzles.¹⁵

Because our empirical exercise seeks to understand the pricing of options given the observed historical behavior of returns, we use the functional forms of the risk correction for the jump parameters, ignoring the general equilibrium implications for equity premium and volatility by fixing these quantities to be consistent with our observed historical data on index returns, 5.4% and 15%, respectively. The risk corrections are given by

$$\lambda^{\mathbb{Q}} = \lambda^{\mathbb{P}} \exp\left(\mu_z^{\mathbb{P}}\gamma + \frac{1}{2}\gamma^2(\sigma_z^{\mathbb{P}})^2\right), \quad (11)$$

$$\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}} - \gamma(\sigma_z^{\mathbb{P}})^2, \quad (12)$$

where γ is risk aversion, and the \mathbb{P} -measure parameters are those estimated from stock index returns (and not dividend or consumption data) and were discussed earlier. The volatility of jump sizes, $\sigma_z^{\mathbb{P}}$, is the same across both probability measures.

We consider the benchmark case of $\gamma = 10$. This is certainly in the range of values considered to be reasonable in applications. From Equations (11) and (12), this value generates $\lambda^{\mathbb{Q}}/\lambda^{\mathbb{P}} = 1.65$ and $\mu_z^{\mathbb{P}} - \mu_z^{\mathbb{Q}} = 3.6\%$. The corresponding \mathbb{Q} -parameter values are given in Table 7. We do not consider a stochastic volatility risk premium, $\theta_v^{\mathbb{P}} < \theta_v^{\mathbb{Q}}$, since most standard equilibrium models do not incorporate randomly changing volatility.

There are other theories that generate similar gaps between \mathbb{P} and \mathbb{Q} jump parameters. Given the difficulties in estimating the jump parameters, Liu, Pan,

¹⁵ Benzoni, Collin-Dufresne, and Goldstein (2005) extend the Bansal and Yaron (2004) model to incorporate rare jumps in the latent dividend growth rates. They show that this model can generate a reasonable volatility smile, but they do not analyze the issues of straddle returns, or equivalently, the difference between implied and realized volatility. Their model does not incorporate stochastic volatility.

Table 7
Q-measure parameters

	$\lambda^{\mathbb{Q}}$	$\mu_z^{\mathbb{Q}}$	$\sigma_z^{\mathbb{Q}}$	$\sqrt{\theta_v^{\mathbb{Q}}}$
Jump risk premiums	1.51	-6.85%	$\sigma_z^{\mathbb{P}}$	$\sqrt{\theta_v^{\mathbb{P}}}$
Estimation risk	1.25	-4.96%	6.99%	14.79%

The table displays Q-measure parameters for the two scenarios that we explore. In addition, in the estimation risk scenario, we value options with the spot volatility \sqrt{V}_t incremented by 1%.

and Wang (2005) consider a representative agent who is averse to the uncertainty over jump parameters. Although their base parameters differ, the \mathbb{P} - and \mathbb{Q} -measure gaps they generate for their base parameterization and the “high-uncertainty aversion” case are $\lambda^{\mathbb{Q}}/\lambda^{\mathbb{P}} = 1.96$ and $\mu_z^{\mathbb{P}} - \mu_z^{\mathbb{Q}} = 3.9\%$, which are similar in magnitude to those that we consider.¹⁶ We do not have a particular vested interest in the standard risk-aversion explanation *vis-à-vis* an uncertainty aversion explanation. Our only goal is to use a reasonable characterization for the difference between \mathbb{P} - and \mathbb{Q} -measure jump parameters.¹⁷

5.3 Estimation risk

Another explanation for observed option returns is estimation risk, capturing the idea that parameters and state variables are unobserved and cannot be perfectly estimated from short historical datasets. One argument for why the estimation risk appears in options is provided by Garleanu, Pedersen, and Poteshman (2005). They argue that jumps and discrete trading imply that market makers cannot perfectly hedge, and therefore estimation risk could play an important role and be priced.

In our context, estimation risk arises because it is difficult to estimate the parameters and spot volatility in our models. In particular, jump intensities, parameters of jump size distributions, long-run mean levels of volatility, and volatility mean reversion parameters are all notoriously difficult to estimate. The uncertainty about drift parameters in the stochastic volatility process will have a minor impact on short-dated option returns due to the high persistence of volatility.¹⁸ The uncertainty in jump parameters can have a significant impact.¹⁹

It is also important to consider difficulties in estimating the unobserved spot volatility. Even with high-frequency data, there are dozens of different

¹⁶ Specifically, Liu, Pan, and Wang (2005) assume that $\gamma = 3$, the coefficient of uncertainty aversion $\phi = 20$, and the penalty coefficient $\beta = 0.01$. The \mathbb{P} -measure parameters they use are $\lambda^{\mathbb{P}} = 1/3$, $\mu_z^{\mathbb{P}} = -1\%$, and $\sigma_z^{\mathbb{P}} = 4\%$. We thank Jun Pan for helpful discussions regarding the details of their calibrations.

¹⁷ An additional explanation for gaps between \mathbb{P} and \mathbb{Q} jump parameters is the argument in Garleanu, Pedersen, and Poteshman (2005). Although they do not provide a formal parametric model, they argue that market incompleteness generated by jumps or the inability to trade continuously, combined with exogenous demand pressure, qualitatively implies gaps between realized volatility and implied volatility.

¹⁸ The argument is similar to the diffusive volatility premium argument in the previous section.

¹⁹ Eraker, Johannes, and Polson (2003) provide examples of the estimation uncertainty impact on the implied volatility smiles. Appendix F discusses the impact of uncertainty in a Bayesian context.

methods for estimating volatility, depending on the frequency of data assumed and whether or not jumps are present. One could argue that it is possible to estimate V_t from options, but this requires an accurate model and parameter estimates. Estimates of V_t differ dramatically across models. In practice, any estimate of V_t is a noisy measure because of all these factors.

To capture the impact of estimation risk, without introducing a formal model for how investors calculate and price estimation risk, we consider the following intuitive approach. We assume that the parameters that we report in Table 1 represent the true data-generating process. However, investors priced options taking into account estimation risk by increasing/decreasing the \mathbb{Q} -measure parameters by one standard deviation from the \mathbb{P} -parameters reported in Table 1. Similarly, to reflect the difficulties in estimating the spot variance V_t , we increase the spot volatility that investors use to value options by 1%. This adjustment is realistic since it implies bid-ask spreads of about 5% for ATM options and 10% for OTM options.²⁰ The full set of assumed parameter values is reported in the second line of Table 7.

5.4 Results

Table 8 reports the results for the jump risk premiums and estimation risk explanations, with the parameters given in Table 7.²¹ For both explanations, the p -values are insignificant. Therefore, option returns computed from a model with stochastic volatility and jumps that incorporates an equity premium and jump risk premiums and/or estimation risk appear to be consistent with the observed data. Both of these explanations increase risk-neutral volatility relative to observed volatility and therefore are capable of replicating the observed data. In reality, both estimation risk and jump risk premiums are likely important, and therefore an explanation combining aspects of both would be even more plausible.²² Moreover, as shown by Santa-Clara and Saretto (2007), bid-ask spreads on index options and margin requirements are substantial, and incorporating these would significantly decrease (in absolute value) the observed option returns, making it even easier for models incorporating jump risk premiums or estimation risk to explain the observed patterns.

6. Conclusion

In this paper, we propose a new methodology to evaluate the significance of index option returns. To avoid the pitfalls of using average option returns, CAPM alphas, Sharpe ratios, and asymptotic distributions, we rely on standard

²⁰ Here we compute a bid-ask spread as the difference between an option valued at the theoretical volatility value and an option valued at the adjusted volatility value.

²¹ As discussed earlier, CAPM alphas and Sharpe ratios provide no additional information, even for straddles or delta-hedged returns, and so they are not included.

²² We note that the challenge of providing a formal equilibrium explanation that fits consumption, dividends, stock, and option prices still remains.

Table 8
Returns for at-the-money and crash-neutral straddles

Strategy data, %		ATMS	CNS
		-15.7	-9.9
Jump risk premiums	$E^{\mathbb{P}}$, %	-11.1	-4.6
	p -val, %	8.3	6.9
Estimation risk	$E^{\mathbb{P}}$, %	-11.0	-7.7
	p -val, %	12.4	17.5

The table reports sample average returns for at-the-money and crash-neutral straddles, denoted by ATMS and CNS, respectively. Population expected returns and finite-sample p -values are computed from the SVJ model for two configurations of \mathbb{Q} -measure parameters. The p -values are computed using the finite-sample distributions of the respective statistics. The distributions were constructed from 25,000 simulated paths, each with 215 monthly observations.

option-pricing models to compute analytical expected options returns and to construct finite-sample distributions of average option returns using Monte Carlo simulation. When implementing these models, we constrain the equity premium and volatility of stock returns to be equal to the values historically observed, a reasonable assumption when trying to understand option returns (and not equity returns).

We present a number of interesting findings. First, we find that individual put option returns are not particularly informative about potential option mispricing. The finite-sample distributions are extremely dispersed, due to the difficulty in estimating the equity premium and the highly skewed return distributions generated by put options. In fact, we find that one of the biggest puzzles in the literature, the very large (in absolute value) returns to deep OTM options, is, in fact, not inconsistent with the Black-Scholes or Heston stochastic volatility models. Second, we find little added benefit from using CAPM alphas or Sharpe ratios as diagnostic tools because the results are similar to those from average option returns.

Third, we provide evidence that option portfolios, especially straddles, are far more informative because they are approximately neutral to movements in the underlying. Unlike returns on individual option positions, straddle returns are shown to be inconsistent with the Black-Scholes and SV models with no risk premiums beyond an equity premium. Finally, we find that option portfolio returns are consistent with explanations such as estimation risk or jump risk premiums that arise in the context of models with jumps in prices.

Our results are silent on the actual economic sources of the gaps between the \mathbb{P} and \mathbb{Q} measures. It is important to test potential explanations that incorporate investor heterogeneity, discrete trading, model misspecification, or learning. For example, Garleanu, Pedersen, and Poteshman (2005) provide a theoretical model incorporating both investor heterogeneity and discrete trading. It would be interesting to study formal parameterizations of this model to see if it can quantitatively explain the observed straddle returns. We leave these questions for future work.

Appendix A: Previous Research on Option Returns

Before discussing our approach and results, we provide a brief review of the existing literature analyzing index option returns.²³ The market for index options developed in the mid- to late 1980s. The Black-Scholes implied volatility smile indicates that OTM put options are expensive relative to the ATM puts, and the issue is to then determine if these put options are in fact mispriced.

Jackwerth (2000) documents that the risk-neutral distribution computed from S&P 500 index put options exhibits a pronounced negative skew after the crash of 1987. Based on a single-factor model, he shows that utility over wealth has convex portions, interpreted as evidence of option mispricing. Investigating this further, Jackwerth (2000) analyzes monthly put trading strategies from 1988 to 1995 and finds that put writing strategies deliver high returns, in both absolute and risk-adjusted levels, with the most likely explanation being option mispricing.

In a related study, Ait-Sahalia, Wang, and Yared (2001) report a discrepancy between the risk-neutral density of S&P 500 index returns implied by the cross-section of options versus the time series of the underlying asset returns. The authors exploit the discrepancy to set up “skewness” and “kurtosis” trade portfolios. Depending on the current relative values of the two implicit densities, the portfolios were long or short a mix of ATM and OTM options. The portfolios were rebalanced every three months. Ait-Sahalia, Wang, and Yared (2001) find that during the period from 1986 to 1996, such strategies generated Sharpe ratios two to three times larger than those of the market.

Coval and Shumway (2001) analyze weekly option and straddle returns from 1986 to 1995. They find that put returns are too negative to be consistent with a single-factor model, and that beta-neutral straddles still have significantly negative returns. Importantly, they conclude that those options are mispriced but rather that the evidence points toward additional priced risk factors.

Bondarenko (2003) computes monthly returns for S&P 500 index futures options from August 1987 to December 2000. Using a novel test based on equilibrium models, Bondarenko finds significantly negative put returns that are inconsistent with single-factor equilibrium models. His test results are robust to risk adjustments, peso problems, and the underlying equity premium. He concludes that puts are mispriced and that there is a “put pricing anomaly.” Bollen and Whaley (2003) analyze monthly S&P 500 option returns from June 1988 to December 2000 and reach a similar conclusion. Using a unique dataset, they find that OTM put returns were abnormally large over this period, even if delta hedged. Moreover, the pricing of index options is different than individual stock options, which were not overpriced. The results are robust to transaction costs.

Santa-Clara and Saretto (2007) analyze returns on a wide variety of S&P 500 index option portfolios, including covered positions and straddles, in addition to naked option positions. They argue that the returns are implausibly large and statistically significant by any metric. Further, these returns may be difficult for small investors to achieve due to margin requirements and potential margin calls.

Most recently, Jones (2006) analyzes put returns, departing from the literature by considering daily option (as opposed to monthly) returns and a nonlinear multifactor model. Using data from 1987 to September 2000, Jones finds that deep OTM put options have statistically significant alphas, relative to his factor model. Both in- and out-of-sample, simple put-selling strategies deliver attractive Sharpe ratios. He finds that the linear models perform as well as, or better than, nonlinear models. Bates (2008) reviews the evidence on stock index option pricing and concludes that options do not price risks in a manner consistent with current option-pricing models.

Given the large returns to writing put options, Driessen and Maenhout (2004a) assess the economic implications for optimal portfolio allocation. Using closing prices on the S&P 500

²³ Prior to the development of markets on index options, a number of articles analyzed option returns on individual securities. These articles include Merton, Scholes, and Gladstein (1978, 1982); Gastineau and Madansky (1979); and Bookstaber and Clarke (1984). The focus is largely on returns to various historical trading strategies assuming that the Black-Scholes model is correct. Sheikh and Ronn (1994) document market microstructure patterns of option returns on individual securities.

futures index from 1987 to 2001, they estimate expected utility using realized returns. For a wide range of expected and nonexpected utility functions, investors optimally short put options, in conjunction with long equity positions. Since this result holds for various utility functions and risk-aversion parameters, their finding introduces a serious challenge to explanations of the put-pricing puzzle based on heterogeneous expectations, since a wide range of investors find it optimal to sell puts.

Driessen and Maenhout (2004b) analyze the pricing of jump and volatility risk across multiple countries. Using a linear factor model, they regress ATM straddle and OTM put returns on a number of index- and index-option-based factors. They find that individual national markets have priced jump and volatility risk but find little evidence of an international jump or volatility factor that is priced across countries.

Appendix B: Expected Instantaneous Option Returns

In this appendix, we develop some intuition about the signs, magnitudes, and determinants of instantaneous EORs. First, we apply arguments similar to those used by Black and Scholes to derive their option pricing model for the more general SVJ model. Then we discuss the single-factor Black-Scholes model and its extensions incorporating stochastic volatility and jumps.

B.1 Instantaneous expected excess option returns

The pricing differential equation for a derivative price $f(S_t, V_t)$ in the SVJ model is

$$\begin{aligned} \frac{\partial f}{\partial t} + \frac{\partial f}{\partial S_t} (r - \delta - \lambda^{\mathbb{Q}} \bar{\mu}^{\mathbb{Q}}) S_t + \frac{\partial f}{\partial V_t} \kappa (\theta^{\mathbb{Q}} - V_t) \frac{1}{2} \frac{\partial^2 f}{\partial S_t^2} V_t S_t^2 + \frac{\partial^2 f}{\partial S_t \partial V_t} \rho \sigma_v V_t S_t + \frac{1}{2} \frac{\partial^2 f}{\partial V_t^2} \sigma_v^2 V_t \\ + \lambda^{\mathbb{Q}} E_t^{\mathbb{Q}} [f(S_t e^Z, V_t) - f(S_t, V_t)] = r f, \end{aligned} \quad (\text{B1})$$

where Z is the jump size and the usual boundary conditions are determined by the type of derivative (e.g., Bates 1996). We denote the change in the derivative's prices at a jump time, τ_j , as

$$\Delta f_{\tau_j} = f(S_{\tau_j} e^{Z_j}, V_t) - f(S_{\tau_j-}, V_t)$$

and $F_t = \sum_{j=1}^{N_t} \Delta f_{\tau_j}$.

By Itô's lemma, the dynamics of the derivative's price under the measure \mathbb{P} are given by

$$\begin{aligned} df = \left[\frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial S_t^2} V_t S_t^2 + \frac{\partial^2 f}{\partial S_t \partial V_t} \rho \sigma_v V_t S_t + \frac{1}{2} \frac{\partial^2 f}{\partial V_t^2} \sigma_v^2 V_t \right] dt + \frac{\partial f}{\partial S_t} dS_t^c \\ + \frac{\partial f}{\partial V_t} dV_t + d \left(\sum_{j=1}^{N_t} \Delta f_{\tau_j} \right), \end{aligned} \quad (\text{B2})$$

where S_t^c is the continuous portion of the index process:

$$\begin{aligned} dS_t^c = (r + \mu - \delta) S_t dt + S_t \sqrt{V_t} dW_t^s - \lambda^{\mathbb{P}} \bar{\mu}^{\mathbb{P}} S_t dt \\ = (r + \mu^c - \delta - \lambda^{\mathbb{Q}} \bar{\mu}^{\mathbb{Q}}) S_t dt + S_t \sqrt{V_t} dW_t^s. \end{aligned} \quad (\text{B3})$$

Substituting the pricing PDE into the drift, we see that

$$\begin{aligned}
 df &= \left[-\frac{\partial f}{\partial S_t}(r - \delta - \lambda^{\mathbb{Q}}\bar{\mu}^{\mathbb{Q}})S_t - \frac{\partial f}{\partial V_t}\kappa(\theta_v^{\mathbb{Q}} - V_t) - \lambda^{\mathbb{Q}}E_t^{\mathbb{Q}}[f(S_t e^Z, V_t) - f(S_t, V_t)] + rf \right] dt \\
 &\quad + \frac{\partial f}{\partial S_t}dS_t^c + \frac{\partial f}{\partial V_t}dV_t + dF_t \\
 &= (rf - \lambda^{\mathbb{Q}}E_t^{\mathbb{Q}}[f(S_t e^Z, V_t) - f(S_t, V_t)])dt + \frac{\partial f}{\partial S_t}[dS_t^c - (r - \delta - \lambda^{\mathbb{Q}}\bar{\mu}^{\mathbb{Q}})S_t dt] \\
 &\quad + \frac{\partial f}{\partial V_t}[dV_t - \kappa(\theta_v^{\mathbb{Q}} - V_t)] + dF_t. \tag{B4}
 \end{aligned}$$

From this expression, we can compute instantaneous EORs. Taking \mathbb{P} -measure expectations,

$$\begin{aligned}
 \frac{1}{dt}E_t^{\mathbb{P}}[df] &= rf + \frac{\partial f}{\partial S_t}\mu^c S_t + \frac{\partial f}{\partial V_t}\kappa(\theta_v^{\mathbb{P}} - \theta_v^{\mathbb{Q}}) + \{\lambda^{\mathbb{P}}E_t^{\mathbb{P}}[f(S_t e^Z, V_t) - f(S_t, V_t)] \\
 &\quad - \lambda^{\mathbb{Q}}E_t^{\mathbb{Q}}[f(S_t e^Z, V_t) - f(S_t, V_t)]\}. \tag{B5}
 \end{aligned}$$

Rearranging, instantaneous excess option returns are given by

$$\begin{aligned}
 \frac{1}{dt}E_t^{\mathbb{P}}\left[\frac{df(S_t, V_t)}{f(S_t, V_t)} - rdt\right] &= \frac{\partial \log[f(S_t, V_t)]}{\partial \log S_t}\mu^c + \frac{1}{f(S_t, V_t)}\frac{\partial f(S_t, V_t)}{\partial V_t}\kappa(\theta_v^{\mathbb{P}} - \theta_v^{\mathbb{Q}}) \\
 &\quad + \frac{\lambda^{\mathbb{P}}E_t^{\mathbb{P}}[f(S_t e^Z, V_t) - f(S_t, V_t)] - \lambda^{\mathbb{Q}}E_t^{\mathbb{Q}}[f(S_t e^Z, V_t) - f(S_t, V_t)]}{f(S_t, V_t)}. \tag{B6}
 \end{aligned}$$

B.2 The Black-Scholes model

In the Black and Scholes (1973) model, the link between instantaneous returns on a derivative, $f(S_t)$, and excess index returns is

$$\frac{df(S_t)}{f(S_t)} = rdt + \frac{S_t}{f(S_t)}\frac{\partial f(S_t)}{\partial S_t}\left[\frac{dS_t}{S_t} - (r - \delta)dt\right].$$

This expression displays two crucial features of the Black-Scholes model. First, instantaneous changes in the derivative's price are *linear* in the index returns, dS_t/S_t . Second, *instantaneous* option returns are conditionally normally distributed. This linearity and normality motivated Black and Scholes to assert a "local" CAPM-style model:

$$\frac{1}{dt}E_t^{\mathbb{P}}\left[\frac{df(S_t)}{f(S_t)} - rdt\right] = \frac{\partial \log[f(S_t)]}{\partial \log(S_t)}\mu.$$

In the Black-Scholes model, this expression shows that EORs are determined by the equity premium and the option's elasticity, which, in turn, are functions primarily of moneyness and volatility.

This instantaneous CAPM is often used to motivate an approximate CAPM model for finite holding period returns,

$$E_t^{\mathbb{P}}\left[\frac{f(S_{t+T}) - f(S_t)}{f(S_t)} - rT\right] \approx \beta_t \mu T,$$

and the model is often tested via an *approximate* linear factor model for option returns:

$$\frac{f(S_{t+T}) - f(S_t)}{f(S_t)} = \alpha_T + \beta_t \left(\frac{S_{t+T} - S_t}{S_t} - rT\right) + \varepsilon_{t,T}.$$

As reviewed above, a number of authors use this as a statistical model of returns and point to findings that $\alpha_T \neq 0$ as evidence of either mispricing or risk premiums.

This argument, however, has a serious potential problem since the CAPM does not hold over finite time horizons. Option prices are convex functions of the underlying price, and therefore linear regressions of option returns and underlying returns are generically misspecified. This implies, for example, that α could depend on the parameters (S_t , K , t , T , σ , μ) and is not zero in population. Since the results hold in continuous time, the degree of bias depends on the length of the holding period. Since option returns are highly skewed, the errors $\varepsilon_{t,T}$ are also highly skewed, bringing into question the applicability of ordinary least squares. We show below that even the simple Black-Scholes model generates economically large alphas for put options. These results also bring into question the practice of computing alphas for multifactor specifications such as the Fama-French model.

B.3 Stochastic volatility and jumps

Consider next the case of the Heston mean-reverting SV model. As derived in Appendix B.1, instantaneous realized option returns are driven by both factors,

$$\frac{df(S_t, V_t)}{f(S_t, V_t)} = rdt + \beta_t^s \left[\frac{dS_t}{S_t} - (r - \delta)dt \right] + \beta_t^v [dV_t - \kappa_v^{\mathbb{P}}(\theta_v^{\mathbb{Q}} - V_t)], \quad (B7)$$

and expected excess returns are given by

$$\frac{1}{dt} E_t^{\mathbb{P}} \left[\frac{df(S_t, V_t)}{f(S_t, V_t)} - rdt \right] = \beta_t^s \mu + \beta_t^v \kappa_v^{\mathbb{P}} (\theta_v^{\mathbb{P}} - \theta_v^{\mathbb{Q}}), \quad (B8)$$

where

$$\beta_t^s = \frac{\partial \log [f(S_t, V_t)]}{\partial \log S_t} \quad \text{and} \quad \beta_t^v = \frac{\partial \log [f(S_t, V_t)]}{\partial V_t}.$$

Since β_t^v is positive for all options and priced volatility risk implies that $\theta_v^{\mathbb{P}} < \theta_v^{\mathbb{Q}}$, expected put returns are more negative with priced volatility risk.

Equations (B7) and (B8) highlight the shortcomings of standard CAPM regressions, even in continuous time. Regressions of excess option returns on excess index returns will potentially generate negative alphas for two reasons. First, if the volatility innovations are omitted, then α will be negative to capture the effect of the volatility risk premium. Second, because dS_t/S_t is highly correlated with dV_t , CAPM regressions generate biased estimates of β and α due to omitted variable bias. As in the Black-Scholes case, discretizations will generate biased coefficient estimates.

Next, consider the impact of jumps in prices via the Merton (1976) model. Here, the link between option and index returns is far more complicated:

$$\begin{aligned} \frac{df(S_t)}{f(S_t)} = & rdt + \frac{\partial \log(f(S_t))}{\partial \log(S_t)} \left[\frac{dS_t^c}{S_t} - (r - \delta - \lambda^{\mathbb{Q}} \bar{\mu}^{\mathbb{Q}})dt \right] + \left[\frac{f(S_t - e^Z) - f(S_t)}{f(S_t)} \right] \\ & - \lambda^{\mathbb{Q}} \frac{E_t^{\mathbb{Q}} [f(S_t e^Z) - f(S_t)]}{f(S_t)} dt, \end{aligned}$$

where dS_t^c denotes the continuous portion of the sample path increment and $S_t = S_{t-} e^Z$. The first line is similar to the expressions given earlier, with the caveat that excess index returns contain only the continuous portion of the increment. The second line captures the effect of discrete jumps. Expected returns are given by

$$\frac{1}{dt} E_t^{\mathbb{P}} \left[\frac{df(S_t)}{f(S_t)} - rdt \right] = \beta_t \mu^c + \frac{\lambda^{\mathbb{P}} E_t^{\mathbb{P}} [f(S_t e^Z) - f(S_t)] - \lambda^{\mathbb{Q}} E_t^{\mathbb{Q}} [f(S_t e^Z) - f(S_t)]}{f(S_t)}.$$

Because option prices are convex functions of the underlying, $f(S_{t-}e^Z) - f(S_{t-})$ cannot be linear in the jump size, e^Z , and thus even instantaneous option returns are not linear in index returns. This shows why linear factor models are fundamentally not applicable in models with jumps in prices. For contracts such as put options and standard forms of risk premiums (e.g., $\mu_z^Q < \mu_z^P$), $E_t^P[f(S_t e^Z)] < E_t^Q[f(S_t e^Z)]$, which implies that expected put option returns are negatively impacted by any jump size risk premiums. As in the case of stochastic volatility, a single-factor CAPM regression, even in continuous time, is inappropriate. Moreover, negative alphas are fully consistent with jump risk premiums and are not indicative of mispricing.

Appendix C: Details of the Options Dataset

In this appendix, we provide a discussion of major steps taken to construct our options dataset. There are two primary choices to construct a dataset of option prices for multiple strikes: using closing prices or by sampling options over a window of time. Due to microstructure concerns with closing prices, we followed the latter approach. For each trading day, we select put and call transactions that could be matched within one minute to a futures transaction, typically producing hundreds of matched options-futures transactions. With these matched pairs, we compute Black-Scholes implied volatilities using a binomial tree to account for the early exercise feature of futures options. Broadie, Chernov, and Johannes (2007) show that this produces accurate early exercise adjustments in models with stochastic volatility and jumps in prices.

To reduce the dimension of our dataset and to compute implied volatilities for specific strikes, we fit a piecewise quadratic function to the implied volatilities. This allows us to combine an entire day's worth of information and compute implied volatilities for exact moneyness levels. Figure C1 shows a representative day, and Broadie, Chernov, and Johannes (2007) discuss the accuracy of the method. For each month, we select the day that is exactly one month to maturity (28 or 35 calendar days) and compute implied volatilities and option prices for fixed moneyness (in increments of 0.02), measured by strike divided by the underlying.

Appendix D: High-Frequency Data Issues

First, it is important to note the advantage of using monthly returns: every month, an option with exactly one month to maturity exists. This is not the case for weekly returns. This implies that either a single weekly option is used every month (which severely reduces sample sizes), or weekly returns can be computed by holding a longer-dated option for one week (for example, hold a four-week maturity option for one week, a three-week option for one week, a two-week option for one week, and finally, a one-week maturity option until maturity). This strategy has often been utilized in the literature, but it presents an important theoretical complication in this context since weekly return characteristics vary by maturity. A one-week return on a five-week option is theoretically different from a one-week return on a one-week option, generating an "apples and oranges" comparison problem for weekly returns that is not present in monthly returns.

Second, the option "roll" strategies described above also generate particularly acute data problems for deep OTM options. The 6% OTM strike is a relatively actively traded strike for options with one month to maturity. For shorter maturity options, a 6% movement is much less likely, and, therefore, there is less trading and there are larger bid-ask spreads. In fact, for one-week options, it is often the case that there is virtually no trading in deep OTM strikes. This implies that weekly option returns will generate data availability problems and may also seriously vary in terms of liquidity. For this reason, researchers who construct daily or weekly returns typically allow for moneyness and maturity windows. This strategy adds more data points but also introduces noise because time to maturity and moneyness vary from one period to another. By using monthly returns, we are able to largely mitigate these issues.

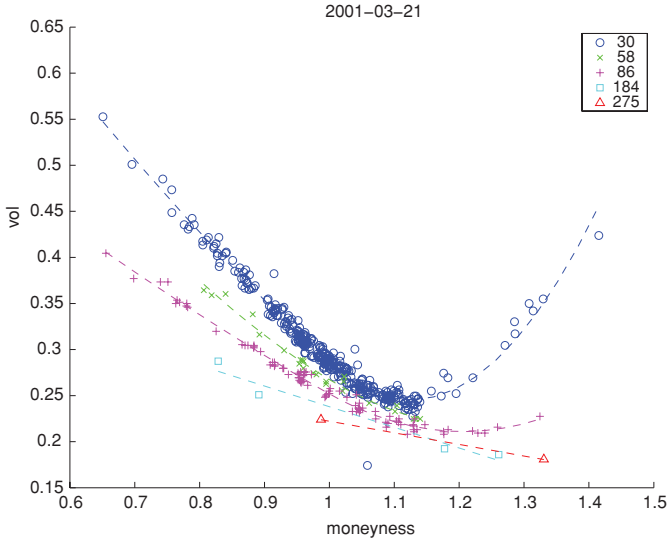


Figure C1
Implied volatility smiles

The figure shows representative implied volatility smiles that we construct. Circles represent the actual transactions. The solid line is the interpolated smile.

Third, as one considers weekly or daily trading, transaction costs start playing a much more important role than in the monthly buy-and-hold case. The roll strategy is expected to generate inordinate transaction costs. For example, bid-ask spreads are currently on the order of 3% to 5% of the option price for ATM index options, and are often more than 10% for deep OTM strikes. Moreover, because of liquidity issues mentioned above, transaction costs tend to increase for OTM short-maturity options. We avoid these costs by holding an option throughout the entire month.

Fourth, since our goal is to estimate averages, the insight of Merton (1980) implies that the total time span of data is the key for estimating means rather than the sampling frequency. On the one hand, this would suggest that there is little difference between weekly and monthly returns, at least after they are properly compounded (see Rubinstein 1984). On the other hand, intuition from the continuous-time dynamics of an option price (2) in the main text would suggest that the statistical properties of option returns would improve for higher frequencies.

We analyze this issue by comparing the finite-sample distribution of returns in the Black-Scholes and Merton models. We use Monte Carlo simulation to explore whether an increasing frequency of option returns helps in reducing statistical uncertainty of average returns. Simulation analysis is attractive for two reasons. First, we can construct finite-sample distributions of average returns and directly compare these distributions under various data sampling scenarios. Second, an idealized simulation setting allows us to abstract from real-life challenges such as transaction costs and additional uncertainty generated by varying maturities and strikes, which are inevitable at frequencies higher than monthly. We can focus directly on the impact of higher frequency.

We simulate from the Black-Scholes and the Merton models many paths, each corresponding to 215 months of observations matching the actual sample. Along each path, we compute average put returns according to two scenarios. First, we replicate the monthly frequency that we use in our dataset. We compute average buy-and-hold returns on a one-month maturity put option. Second, we evaluate a weekly “roll” strategy. We purchase a one-month option and sell it one week later. Then, we take a new option that has one week less left to maturity and has the same moneyiness

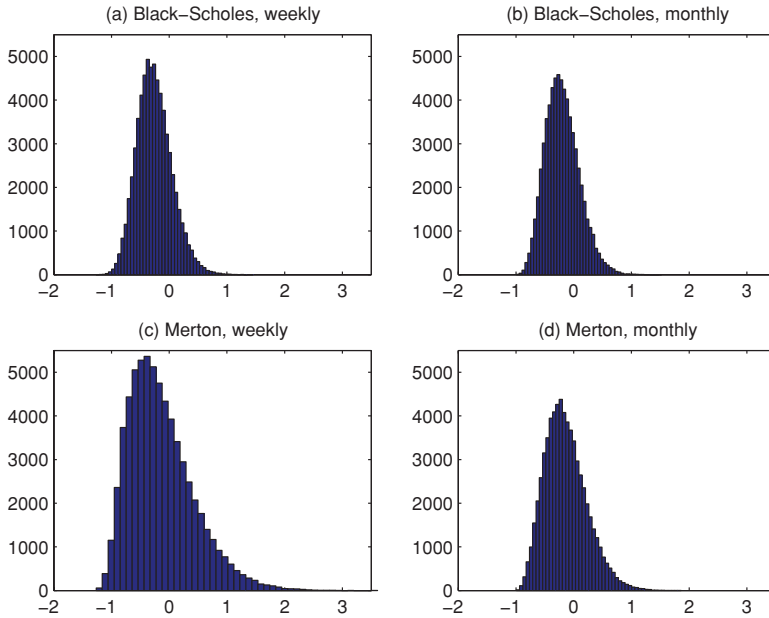


Figure D1
Finite-sample distributions
 The figure displays finite-sample distribution of average option returns.

as the first one. As a result, we construct 860 (four times 215) weekly returns. We compute an average of these returns.

Figure D1 plots the finite-sample distributions of average 6% OTM put returns obtained based on our simulation strategy. Consistent with Merton (1980), the statistical properties of average returns are the same for the Black-Scholes model as the frequency increases from monthly to weekly returns, indicating no statistical benefit from using high-frequency returns. Moreover, in the case of the Merton model, higher frequency hurts rather than helps. The distribution of weekly average option returns is more noisy and asymmetric than that of the monthly returns. Therefore, detecting potential option mispricing will be even more challenging at the weekly frequency. The intuition for this result is that the presence of jumps in the underlying asset returns introduces kurtosis that is more pronounced over short time periods. Therefore, the impact of jumps will be pronounced at high frequencies and will gradually dissipate over longer horizons due to the central limit theorem.

Table D1 complements Figure D1 by providing statistics describing the finite-sample distributions of average put returns. In the Black-Scholes case, the standard deviation, skewness, and kurtosis do not change appreciably from one frequency to another. In contrast, the Merton model implies that weekly frequency leads to dramatic increases in standard deviation, skewness, and kurtosis of average returns.

Appendix E: Delta Hedging

In this appendix, we discuss delta-hedged returns and, more generally, returns on strategies with data- or model-based portfolio weights. Delta hedging raises a number of issues that, in our view,

Table D1
Finite-sample distributions of 6% OTM

	BSw	BSm	Mw	Mm
Average, %	-25.9	-20.1	-14.3	-13.8
Std Dev, %	30.2	29.2	55.9	36.3
Skew	45.6	51.7	95.6	62.6
Kurt	45.0	35.3	122.4	51.8

The table reports statistics describing finite-sample distribution of average 6% OTM put returns that are measured at different frequencies. BS and M refer to the Black-Scholes and Merton models, respectively. The notations “w” and “m” refer to weekly and monthly frequency of portfolio rebalancing, respectively.

make the interpretation of the delta-hedged returns difficult. The main issue is that hedge ratios, or deltas, can be computed in multiple ways.

Here are three approaches to implementing an option delta-hedging strategy. The first uses a formal option pricing model, e.g., the SV model, to compute the required hedging portfolio weights. The second uses a data-based approach that computes the hedge ratios using the shape of the current implied volatility smile (see Bates 2005). The third, commonly used by practitioners, computes deltas from the Black-Scholes model and substitutes implied volatility for the constant volatility parameter. We discuss each of the approaches in turn.

Model-based hedging requires the knowledge of the spot variance state variable, V_t , and the model parameters. To compute delta-hedged returns using real data, we have to estimate V_t in sample. To do this, we require a formal model, which leads to a joint hypothesis issue and introduces estimation noise. Moreover, estimates of spot volatilities and delta-hedged returns are highly sensitive to the model specification and, in particular, to the importance of jumps in prices. For example, Branger and Schlag (2008) show that delta-hedged errors are not zero if the incorrect model is used or if rebalancing is discrete.

As an alternative, Bates (2005) proposes an elegant model-free technique to establish delta-hedged weights. This approach circumvents the issues mentioned in the previous paragraph. However, the approach assumes that options are priced correctly in the market.²⁴ This concern is particularly relevant in the context of our paper, because we attempt to evaluate whether options are priced correctly.

The most practical approach is to use a Black-Scholes model delta evaluated at the option’s implied volatility. Because of the well-known smile effect in the data, the 6% OTM delta in the Black-Scholes model will be evaluated at an implied volatility that is different from the one used for the ATM delta. This is inconsistent with the Black-Scholes model, which assumes a single volatility that is constant across strikes and over time. However, the deltas computed in this manner are similar to the deltas obtained from more elaborate models and estimation procedures.

Finally, delta hedging requires rebalancing, which increases transaction costs and data requirements.²⁵ Thus, while less attractive from the theoretical perspective, the more practical static delta-hedging strategy should be evaluated. According to this strategy, a delta-hedged position is formed a month prior to an option’s maturity and is not changed through the duration of the option contract.

Because static Black-Scholes-based delta-hedging is reasonable and practical, we use it to compute the results reported in Table E1. Thus a consistent delta-hedging strategy is used for

²⁴ Bates (2005) notes: “While the proposed methodology may be able to infer the deltas . . . perceived by the market, that does not mean the market is correct. If options are mispriced, it is probable that the implicit deltas . . . are also erroneous.”

²⁵ Bollen and Whaley (2004) is the only paper that considers rebalancing. Because of data demands, they take a shortcut and use the volatility at the time the option position was opened and hold this constant until expiration.

Table E1
Sample average returns for put-based portfolios

Moneyiness		Delta-hedged puts			
		0.94	0.96	0.98	1.00
Data, %		-1.3	-1.2	-1.0	-0.6
BS	$E^{\mathbb{P}}$, %	0.0	0.1	0.0	0.0
	p -val, %	0.0	0.0	0.0	0.0
SV	$E^{\mathbb{P}}$, %	-0.3	-0.1	-0.0	0.1
	p -val, %	0.3	0.0	0.0	0.0
SVJ (jump risk premiums)	$E^{\mathbb{P}}$, %	-1.3	-1.0	-0.7	-0.4
	p -val, %	57.0	35.2	10.9	7.7
SVJ (estimation risk)	$E^{\mathbb{P}}$, %	-0.9	-0.7	-0.6	-0.4
	p -val, %	30.8	18.2	7.6	10.6

The table reports sample average returns for various put-based portfolios based on 215 monthly returns. Population expected returns and finite-sample p -values are computed from the Black-Scholes (BS), stochastic volatility (SV), and stochastic volatility with jumps (SVJ) models using 25,000 artificial histories, 215 observations each, simulated from the respective models. The SVJ results are reported for two configurations of \mathbb{Q} -measure parameters. We assume that volatility risk premiums are equal to zero.

generating the results with historical data and the model-based results using the Black-Scholes, SV, and SVJ models.

As compared to straddle returns in Table 6 of the main text, the magnitude of the delta-hedged returns are much lower, on the order of 1% per month. The corresponding p -values from the Black-Scholes and SV models, computed from the finite-sample distribution as described in Section 1.2.2 of the main text, are approximately zero. In this regard, delta-hedged returns are similar to straddles. The returns on these portfolios are less noisy than for individual option positions and, therefore, are more informative about the potential mispricing. Similarly to straddles, delta-hedged returns are insignificant in the context of the SVJ model.

Appendix E: A Bayesian Perspective on Parameter Uncertainty

One way to see the impact of parameter uncertainty is to consider a standard Bayesian setting for learning about the parameters of the jump distribution, assuming jump times and sizes are observed.²⁶ First, consider uncertainty over the jump mean parameter. Suppose that jump sizes are given by $Z_j = \mu_z + \sigma_z \varepsilon_j$, where $\mu_z \sim \mathcal{N}(\mu_0, \sigma_0^2)$. Then the predictive distribution of Z_{k+1} upon observing k previous jumps is given by

$$p(Z_{k+1} | \{Z_j\}_{j=1}^k) \sim \mathcal{N}(\mu_k, \sigma_k^2),$$

where

$$\mu_k = w_k \mu_0 + (1 - w_k) \bar{Z}_k, \quad \bar{Z}_k = k^{-1} \sum_{j=1}^k Z_k$$

$$\sigma_k^2 = \left(\frac{k}{\sigma_z^2} + \frac{1}{\sigma_0^2} \right)^{-1} + \sigma_z^2, \quad w_k = \frac{\sigma_z^2/k}{\sigma_z^2/k + \sigma_0^2}.$$

²⁶ Benzoni, Collin-Dufresne, and Goldstein (2006) consider uncertainty over the mean parameters with normal priors. Johannes, Polson, and Stroud (2005) consider sequential learning about jump and stochastic volatility parameters in the jump-diffusion setting using historical S&P 500 index returns.

In addition to revising one's beliefs about the location, we also see that $\sigma_k^2 > \sigma_z^2$, implying that estimation risk and learning generates excess volatility. Quantitatively, its impact will be determined by prior beliefs and how many jumps have been observed. In practice, one would expect even more excess volatility, since jump sizes are not perfectly observed.

The impact of uncertainty on σ_z can be even greater. Assuming that μ_z is known, a standard conjugate inverse-gamma prior on the jump variance, $\sigma_z^2 \sim \mathcal{IG}$, implies that the predictive distribution of the jump sizes is t -distributed:

$$p(Z_{k+1} - \mu_z | \{Z_j\}_{j=1}^k) \sim t_\nu,$$

where the degrees of freedom parameter ν depends on the prior parameters and sample size (Zellner 1971, Section 3.2.4). To determine prices, expectations of the form $E(\exp(Z_{k+1}) | \mathcal{F}_k)$ will have to be computed. However, if the jump sizes have a t -distribution, this expectation may not exist because the moment generating function of a t -random variable does not exist. Thus, parameter uncertainty can have a substantial impact on the conditional distribution of S_t , as the two examples demonstrate.

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