The Pricing of Volatility and Jump Risks in the Cross-Section of Index Option Returns*

Guanglian Hu
University of Sydney

Yuguo Liu
University of Houston

September 16, 2019

Abstract

In the data, out-of-the-money (OTM) S&P 500 call and put options both have puzzling low average returns. Existing studies relate these results to models with non-standard preferences. We argue that the low returns on OTM index options are primarily due to the pricing of market volatility risk. When volatility risk is priced, expected option returns match the average returns of call and put options across all strikes as well as returns of option portfolios. Consistent with the differential impact of the volatility risk premium on expected option returns, we also find that the market volatility risk premium is positively related to future index option returns and this relationship is stronger for OTM options and ATM straddles. Lastly, we find some portion of OTM put option returns are attributable to the jump risk premium.

JEL classification: G12 G13

Keywords: volatility risk premium; jump risk premium; expected option returns; the cross-section of index option returns

*We thank Anandi Banerjee, David Bates (discussant), Christian Dorion, Hitesh Doshi, Neal Galpin, Quan Gan, Bing Han, Christopher Jones, Praveen Kumar, Hamish Malloch, Neil Pearson, Sang Byung Seo, Longfei Shang, Aurelio Vasquez, James Yae, seminar participants at the University of Houston, the University of Sydney, Monash University, the 2016 FMA PhD Student Session, the IFSID Fifth Conference on Derivatives, 2019 Derivative Markets Conference, and especially Kris Jacobs for their helpful discussions and comments. We are responsible for all remaining errors and omissions. Please send correspondence to Guanglian Hu, Discipline of Finance, the University of Sydney Business School, the University of Sydney, NSW 2006, Australia; telephone: +61 2 8627 9431. E-mail: guanglian.hu@sydney.edu.au.

1 Introduction

One of the most enduring puzzles of the asset pricing literature is that out-of-the-money (OTM) index put options are associated with large negative average returns (e.g., Jackwerth, 2000; Santa-Clara and Saretto, 2009; Bondarenko, 2014). While an index put option is a negative beta asset and thus is expected to have a negative rate of return, the magnitudes in the data seem too large to be consistent with standard models (Chambers, Foy, Liebner, and Lu, 2014). On the other hand, Bakshi, Madan, and Panayotov (2010) document that the average returns of OTM index call options are also negative and declining with the strike price. This stylized fact is somewhat less known, but is perhaps even more puzzling because it contradicts the prediction from standard theories that expected call option returns should be positive and increase with the strike price (Coval and Shumway, 2001).[1]

Previous research relates these large negative OTM call and put option returns to models featuring non-standard preferences. For instance, Polkovnichenko and Zhao (2013) consider a rank-dependent utility model with a particular probability weighting function to explain the data. Baele, Driessen, Ebert, Londono, and Spalt (2018) show that a model with cumulative prospect theory preferences is able to generate the otherwise puzzling index option return patterns. The low returns on OTM call and put options can also be explained with theories of skewness/lottery preferences and leverage constraints (Barberis and Huang, 2008; Brunnermeier, Gollier, and Parker, 2007; Mitton and Vorkink, 2007; Frazzini and Pedersen, 2012). OTM options are often associated with substantial skewness and embedded leverage, which make them particularly attractive for investors who have skewness preferences or face leverage constraints. Demand pressure will drive up prices and consequently lead to low returns in equilibrium (Gârleanu, Pedersen, and Poteshman, 2009).

This paper investigates whether the low returns on OTM index options can be consistent with the pricing of market volatility and jump risks. Options are sensitive to changes in volatility

[1] Related, Constantinides and Jackwerth (2009) and Constantinides et al. (2011) document widespread violations of stochastic dominance in OTM index and index futures options.

and price jumps, therefore their expected returns should critically depend on investor's attitudes towards volatility and jump risks. To study how the pricing of volatility and jump risks affects the cross-section of index option returns, we follow Broadie, Chernov, and Johannes (2009) and compare historical realized option returns with the expected returns implied from option pricing models. We first show that the low returns on OTM call and put options would appear puzzling to standard option pricing models in which volatility and jump risks are not priced, as models with only an equity risk premium are inconsistent with the empirical index option return patterns. However, when market volatility risk is priced, the implied expected option returns match the average returns of call and put options across all strikes as well as the average returns of different option portfolios. Consistent with the data, the pricing of volatility risk implies a steep relationship between expected put option returns and the strike price, with OTM put options earning a large negative rate of return. It also implies an overall decreasing relation between expected call option returns and the strike price, with OTM call options earning negative expected returns. Finally, we find that the pricing of jump risk implies that OTM put options have large negative expected returns with magnitudes very close to the data. But the jump risk premium would also imply the expected call option return is an increasing function of the strike price and OTM calls should earn large positive expected returns, which is contrary to the data. Our results are robust to different parameterizations of stochastic volatility and jumps.

Option pricing theory not only predicts that the pricing of volatility risk results in lower expected option returns, but also predicts that the effect of the volatility risk premium is stronger for OTM options and at-the-money (ATM) straddles. Confirming these predictions, we find that the volatility risk premium is positively related to future index option returns: A more negative volatility risk premium in a given month is associated with low option returns in the subsequent month. Moreover, this relationship is indeed stronger for OTM options and ATM straddles. Our findings cannot be explained by the underlying return predictability by the volatility risk premium (Bollerslev, Tauchen, and Zhou, 2009), and are robust to different empirical implementations and controlling for other variables. Lastly we find that the jump risk premium is significantly related to future returns on OTM put options, but its relationship with call option and straddle returns is insignificant.

Taken together, our results suggest that the low returns on OTM index options are primarily due to the pricing of market volatility risk, although the jump risk premium also accounts for some portion of OTM put option returns.[2] Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014) compare historical returns of put options and a number of option portfolios with those implied from option pricing models, finding that index option returns can be explained by a jump risk premium.[3] The key difference between these papers and the current study is that their focus is on OTM index put options, while our paper aims to understand not only OTM index put options but also OTM index call options. Studying index call options is important because any theory put forward to explain the low returns on OTM put options should also fit call option returns. Studying call options is also important because call options, which are claims on the upside, are critical for disentangling the volatility risk premium from the jump risk premium as these two risk premiums have drastically different implications on expected call option returns. We confirm the results of Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014) that the jump risk premium fits put option data well, but we also show that the jump risk premium fails to match call option returns. In contrast, the volatility risk premium is able to match the low returns on OTM call and put options simultaneously.

The rest of the paper is organized as follows. Section 2 discusses related literature. Section 3 compares expected option returns implied from option pricing models to historical S&P 500 option returns, with a particular focus on the effect of volatility and jump risk premiums. Section 4 studies

[2]In bad times, investors have concerns about both tails (variance) and OTM call options are also priced with a significant premium. For example, buying a 1-month 5% OTM call in February 2009 and holding it to maturity generated a return of −54%, despite the fact that the underlying index actually went up by 6.2% over the same period. In contrast, a same 5% OTM call yielded a positive return of 841% from October 2004 to November 2004 during which the S&P 500 index went up by 6.3%.

[3]The two papers have different conclusions about whether index put option returns are consistent with standard option pricing models with only equity risk premium (e.g., volatility and jump risks are not priced). Our analysis confirms the results in Chambers et al. (2014) that the hypothesis of no additional risk premiums can be rejected in general.

the time series relationship between the volatility and jump risk premiums and future index option returns. Section 5 contains robustness results, and Section 6 concludes the paper.

2 Related Literature

The bulk of the index option literature focuses on the behavior of *option prices*. For example, it is well known that in the equity index options market implied volatilities from OTM put options have been consistently higher than their ATM counterparts since the 1987 market crash (Rubinstein, 1994). This stylized fact is often referred to as the implied volatility skew or volatility smirk, and it contradicts the prediction of the Black-Scholes-Merton model that the implied volatility is constant across strikes.[4] The presence of a pronounced volatility skew has inspired many subsequent studies. For example, there is an extensive literature that demonstrates stochastic volatility and jumps are needed in order to fit rich option price dynamics, although the empirical evidence is somewhat mixed regarding the relative importance of these additional factors as well as their pricing. For important contributions, see Bakshi, Cao, and Chen (1997), Bates (2000), Chernov and Ghysels (2000), Pan (2002), Jones (2003), Eraker (2004), Broadie, Chernov, and Johannes (2007), and Andersen, Fusari, and Todorov (2015).[5] Our paper differs from this literature in that we examine *option returns* rather than *option prices*. Understanding option returns is also important because option returns contain additional information not spanned by option prices. For example, the low returns on OTM call and OTM put options suggest that both are problematic, whereas one might wrongly conclude that only OTM put options are problematic by observing the volatility skew only. We show that a simple stochastic volatility model in which volatility risk is priced describes the average option

[4]Closely related, Aït-Sahalia and Lo (1998), Jackwerth and Rubinstein (1996), and Jackwerth (2000) document that the risk-neutral distribution inferred from option prices is not log-normal and systematically skewed more to the left.

[5]Another strand of literature addresses the implied volatility skew in equilibrium models (e.g., Benzoni, Collin-Dufresne, and Goldstein, 2011; Du, 2011; Seo and Wachter, 2017). Existing studies also suggest that the implied volatility skew might be related to demand pressure (Bollen and Whaley, 2004; Gârleanu, Pedersen, and Poteshman, 2009), aversion to model uncertainty (Liu, Pan, and Wang, 2005), and investor sentiment (Han, 2007).

returns reasonably well. This result is somewhat surprising because we know this model is not rich enough to capture the behavior of option prices. Our results somewhat echo the findings of Cochrane and Piazzesi (2005) for the bond market that although multiple factors are needed to describe empirical patterns in bond prices, a single factor summarizes nearly all information about returns/risk premiums. Johnson (2017) also reports similar results in the VIX market.

Our paper is closely related to an expanding literature that investigates index option returns. Early studies usually focus on put options, finding surprisingly low returns for OTM index puts (e.g., Bondarenko, 2014; Jackwerth, 2000). Coval and Shumway (2001) show that index call option returns are positive and increase with the strike price, which is consistent with standard asset pricing theories. On the other hand, Bakshi, Madan, and Panayotov (2010) document that the average returns of OTM index call options are negative and decreasing with the strike price, and they relate this otherwise puzzling finding to a U-shaped pricing kernel that arises in a model featuring short-selling and heterogeneity in investors' beliefs about return outcomes. We also find low returns on OTM call options over our sample period.[6] Related, several papers use factor models to gain a better understanding of index option returns. See, among others, Jones (2006), Cao and Huang (2007), and Constantinides, Jackwerth, and Savov (2013). Israelov and Kelly (2017) propose a method for constructing the conditional distribution for index option returns. Driessen and Maenhout (2007) and Faias and Santa-Clara (2017) analyze index option returns from a portfolio allocation perspective. Santa-Clara and Saretto (2009) focus on the impact of margin requirements on option trading strategies. Chaudhuri and Schroder (2015a) develop model-free tests of stochastic discount factor monotonicity based on option returns.

There is a large body of literature on the pricing of volatility and jump risks. The pricing of aggregate volatility and jump risks has been examined extensively in the cross-section of stock returns.[7] See, among others, Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008)

[6] Duarte, Jones, and Wang (2019) show that after correcting microstructure biases, expected call option returns decrease with the strike price and deep OTM calls have negative returns.

[7] A number of studies examine the volatility risk premium using data on variance swaps. See, among others, Egloff,

and Cremers, Halling, and Weinbaum (2015). Our paper is more closely related to studies that focus on the pricing of aggregate volatility and jump risks in the equity index options market. Index options market, where stochastic volatility and jump risks play a prominent role, contains rich economic information about the pricing of these risk factors. For example, Coval and Shumway (2001) report that zero-beta at-the-money straddle positions produce large losses and they interpret it as evidence that systematic stochastic volatility is priced in option returns. Bakshi and Kapadia (2003) find that delta-hedged option portfolios have negative average returns, which indicates the volatility risk premium is negative. Our results are consistent with the findings of Coval and Shumway (2001) and Bakshi and Kapadia (2003) that the volatility risk premium is negative in the index options market. The key difference between the above studies and this paper is that their emphasis is on using option portfolios to infer the existence and sign of the volatility risk premium, while this paper aims to assess the impact of the volatility risk premium on the cross-section of *unhedged* index option returns. We also characterize the effect of the jump risk premium on expected option returns.

We also contribute to the variance risk premium literature. Carr and Wu (2009) quantify the variance risk premiums on equity indexes and a set of individual stocks. Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), and Eraker (2012) study the equilibrium determinants of the variance risk premium. Furthermore, existing studies find that the volatility risk premium is a strong predictor of short term equity index returns (e.g., Bollerslev et al., 2009). Related, Bali and Hovakimian (2009), Goyal and Saretto (2009), and Della Corte, Ramadorai, and Sarno (2016) investigate the role of the volatility risk premium in predicting the cross-section of asset returns. Our paper contributes to this literature by documenting that the volatility risk premium contains predictive information about future option returns. It is important to note that the index

Leippold, and Wu (2010), Aït-Sahalia, Karaman, and Mancini (2015), and Dew-Becker et al. (2017). Another strand of literature provides additional evidence on the market volatility risk premium by comparing option implied volatility with realized volatility. See, among others, Lamoureux and Lastrapes (1993), Fleming, Ostdiek, and Whaley (1995), and Christensen and Prabhala (1998).

option return predictability cannot be attributed to the underlying stock return predictability by the volatility risk premium. Instead, both the sign and pattern of index option return predictability are consistent with the impact of the volatility risk premium on expected option returns, as suggested by option pricing theory.

3 The Volatility Risk Premium, the Jump Risk Premium and Expected Option Returns

In this section, we begin by examining historical returns of S&P 500 index options across a wide range of strikes, as well as the returns of a number of option portfolios. We then evaluate average option returns relative to what would have been obtained in option pricing models. We investigate whether index option returns are consistent with the pricing of volatility and jump risks.

3.1 Historical S&P 500 Index Option Returns

This paper focuses on historical returns from holding S&P 500 index options. We download S&P 500 index options (SPX) data from OptionMetrics through WRDS. The sample period for our analysis is from March 1998 to August 2015.[8] In particular, on the first trading day after the monthly option expiration date, we collect SPX options that will expire over the next month. These options are the most frequently traded options in the marketplace and they have maturities ranging from 25 to 33 calendar days. Prior to February 2015, the expiration day for index options is the Saturday immediately following the third Friday of the expiration month. Starting in February

[8] OptionMetrics data starts from January 1996. However, the settlement values (SET) for SPX options required to compute holding-to-maturity returns are only available from April 1998. As a result, we start sampling options in March 1998. The settlement values for S&P 500 index options are calculated using the opening sales price in the primary market of each component security on the expiration date and are obtained from the CBOE. We also extend our sample to 1996 by using the closing price of the index as a proxy for the settlement price. The results are similar.

2015, the option expiration day is the third Friday of the month.[9] We also apply standard filters to option data and relegate the details to Appendix A. Table A1 in the Online Appendix reports the summary statistics of our sample. Table A1 shows that OTM options account for the majority of the trading volume in S&P 500 index options, and OTM call options are as actively traded as OTM put options.

Following the existing literature, we construct time-series of monthly holding-to-maturity returns to S&P 500 index options for fixed moneyness, ranging from 0.96 to 1.08 for calls, and 0.92 to 1.04 for puts with an increment of 2%.[10] Moneyness is defined as the strike price over the underlying index: K/S. We do not investigate options that are beyond 8% OTM or 4% ITM because of potential data issues (e.g., low price or low trading volume or missing observations).

We also compute returns on a number of option portfolios, including at-the-money straddles (ATMS), put spreads (PSP), crash-neutral spreads (CNS), and call spreads (CSP). ATMS involves the simultaneous purchase of a call option and a put option with $K/S = 1$. PSP consists of a short position in a 6% OTM put and a long position in an ATM put. CNS consists of a long position in an ATM straddle and a short position in a 6% OTM put. Finally, CSP combines a long position in an ATM call with a short position in a 6% OTM call. When computing option returns, we use the mid-point of bid-ask quotes as a proxy for option price, and we calculate option payoff at maturity based on the index settlement values. Notice that Broadie, Chernov, and Johannes (2009) and a subsequent study by Chambers et al. (2014) focus on index put options and several option portfolios. We extend their analysis to include call options. Call options are claims on the upside, which will be critical for differentiating the volatility risk premium from the jump risk premium. In contrast, separately identifying the volatility and jump risk premiums using put option returns can be challenging.

[9]This means we usually select options on Mondays. If Monday is an exchange holiday (e.g., Martin Luther King Day or President's Day), we use Tuesday data.

[10]Options have large bid-ask spreads, and monthly holding-to-maturity returns mitigate this problem because they only incur the trading cost at initiation. Holding-to-maturity returns also have some analytical advantages and avoid a number of theoretical and statistical issues associated with high frequency option returns (Broadie et al., 2009).

Table 1 reports the average monthly returns for the cross-section of index call and put options with different strikes, as well as the average returns for different option portfolios. Panel A of Table 1 shows that the average returns of call options tend to decline with the strike price, with OTM calls earning a negative rate of return. For example, the average return of ATM calls is 6.5% per month, and it drops monotonically to –25.05% for 8% OTM calls. Our results confirm the findings of Bakshi, Madan, and Panayotov (2010), who study 1%, 3%, and 5% OTM S&P 500 call options from 1988 to 2007. The call option return pattern is puzzling because under general economic conditions Coval and Shumway (2001) show that the expected call option return is an increasing function of the strike price and OTM call options should have positive returns.

Panel B of Table 1 presents the well-documented stylized fact that index put options, especially OTM puts, have large negative average returns. For example, over our sample period, buying a 6% OTM put and a 8% OTM put would, on average, lose 45.02% and 52.07% per month, respectively. It is of course not surprising that put options have negative average returns as they are negative beta assets. However, as shown in the next section, the magnitudes of OTM put option returns are too large to be explained by standard option pricing models (e.g., the Black-Scholes-Merton model).

Panel C reports average returns on option portfolios. Coval and Shumway (2001) find that zero-beta straddles have negative average returns. We do not investigate zero-beta straddles as in Coval and Shumway (2001), because constructing a zero-beta straddle would require a model to determine the portfolio weights. Nevertheless, confirming their results, we find that simple ATM straddles on average lose 8.47% per month over our sample period. Also notice that the average return for call spreads is 13.56% per month. Call spreads earn high returns because both the long position in ATM calls and the short position in 6% OTM calls generate positive returns as shown in Panel A.

In summary, confirming existing studies, we show that OTM call options and OTM put options are both associated with low average returns. In the next section, we investigate if these low option returns can be explained by option pricing models. In addition, we also examine if our models can fit option portfolio returns. This is important because, as demonstrated in Broadie, Chernov, and Johannes (2009), option portfolios are more informative than individual option returns and therefore provide more powerful tests.

3.2 Analytical Framework for Expected Option Returns

Statistical inference on option returns is in general difficult because option returns are highly non-normal, which makes the standard linear models inappropriate. To overcome these statistical difficulties, we apply the methodology developed in Broadie, Chernov, and Johannes (2009) (henceforth BCJ). In particular, we compare the average returns in the data with expected option returns implied by various option pricing models estimated over the same period. We also simulate each model to form a finite sample distribution for testing statistical significance.

We consider a standard affine jump diffusion framework with mean-reverting stochastic volatility and jumps in stock price. The model is commonly referred to as the SVJ model (Bates, 1996) and nests the Black-Scholes-Merton model (Black and Scholes, 1973; Merton, 1973), the Heston stochastic volatility model (Heston, 1993), and the Merton jump diffusion model (Merton, 1976) as special cases. The SVJ model says the index level (S_t) and its spot variance (V_t) have the following dynamics under the physical measure ($\mathbb{P}$):

$$
\begin{aligned}
dS_t &= (\mu + r - d)S_t dt + S_t\sqrt{V_t}dW_1 + (e^Z - 1)S_t dN_t - \lambda\overline{\mu}S_t dt \\
dV_t &= \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_2
\end{aligned}
$$

where μ is the equity risk premium, r is the risk-free rate, d is the dividend yield, N_t is a $\mathbb{P}$-measure Poisson process with a constant intensity λ, $Z \sim N(\mu_z, \sigma_z^2)$, $\overline{\mu}$ is the mean jump size with $\overline{\mu} = \exp(\mu_z + \frac{1}{2}\sigma_z^2) - 1$, θ is the long-run mean of variance, κ is the rate of mean reversion, σ is volatility of volatility, and W_1 and W_2 are two correlated Brownian motions with $\mathbb{E}[dW_1 dW_2] = \rho dt$. The dynamics under the risk-neutral measure ($\mathbb{Q}$) are given by:

$$dS_t = (r-d)S_t + S_t\sqrt{V_t}dW_1^{\mathbb{Q}} + (e^{Z^{\mathbb{Q}}}-1)S_t dN_t^{\mathbb{Q}} - \lambda^{\mathbb{Q}}\overline{\mu}^{\mathbb{Q}}S_t dt$$
$$dV_t = [\kappa(\theta - V_t) - \eta V_t]dt + \sigma\sqrt{V_t}dW_2^{\mathbb{Q}}$$

where η is the price of volatility risk, $N_t^{\mathbb{Q}} \sim \text{Poisson}(\lambda^{\mathbb{Q}}t)$, $Z^{\mathbb{Q}} \sim N(\mu_z^{\mathbb{Q}}, (\sigma_z^{\mathbb{Q}})^2)$ and $\overline{\mu}^{\mathbb{Q}} = \exp(\mu_z^{\mathbb{Q}} + \frac{1}{2}(\sigma_z^{\mathbb{Q}})^2) - 1$. Throughout the paper, risk neutral quantities will be denoted with $\mathbb{Q}$ and all other quantities are taken under the physical measure. Note that there are three types of risk premiums in this model: the equity risk premium (μ), the volatility risk premium (ηV_t), and the jump risk premium (price jump has different distributions under $\mathbb{P}$ and $\mathbb{Q}$ probability measures).

Expected option returns can be computed analytically within the above framework.[11] This analytical tractability is particularly useful as we can quantify the impact of different risk premiums on expected option returns. We first compute expected call and put option returns as well as expected returns on option portfolios using models with only an equity risk premium, including the Black-Scholes-Merton model (BSM), a Heston model in which volatility risk is not priced (SV), and a stochastic volatility jump model in which neither volatility risk nor jump risk is priced (SVJ). As we will see, these models will not be able to fit index option return data as they only have the equity risk premium. In light of these results, we further investigate if option pricing models with additional volatility and jump risk premiums can lead to a better fit. In particular, we also examine a stochastic volatility model in which volatility risk is priced (SV+), but otherwise identical to the SV model. To study the effect of the jump risk premium, we extend the SVJ model to incorporate a risk premium for jump risk (SVJ+). Note that in the SVJ+ model, volatility risk is not priced. By setting the volatility risk premium to zero ($\eta = 0$), we can isolate the effect of the jump risk

[11] The intuition is that since physical dynamics are also affine, expected option payoffs and consequently expected returns can be computed analytically. For models with stochastic volatility and jumps, the conditional expected option return is a function of spot variance which has a gamma distribution. We take a numerical integration over gamma distribution to obtain unconditional expected option returns.

premium. In total, we calculate expected option returns for five different option pricing models: Three with the equity risk premium only (BSM, SV, and SVJ), one with the additional volatility risk premium (SV+), and one with the additional jump risk premium (SVJ+).

Following BCJ, we also simulate each model to form a finite-sample distribution of average option returns, from which we can test whether realized historical option returns are significant relative to a model (e.g., how likely it is to observe historical returns in a given model). Specifically, we simulate 25000 sample paths of the index, with each path having 210 months (the sample length of our data). For each sample path, we compute one set of average option returns using simulated data. The p-values are then calculated as the percentile of historical option returns in the 25000 simulated options returns. If the percentile is higher than 0.5, we report the p-value as 1 minus the percentile.

We estimate model parameters in two steps as in BCJ. We first infer physical measure parameters by calibrating the models to fit the behavior of index returns over the same sample period for which option returns are available.[12] Specifically, we calibrate the equity risk premium, the risk-free rate, and the dividend yield based on those realized over our sample period. We use particle filtering to estimate the remaining $\mathbb{P}$-measure parameters from the time-series of index returns. Appendix B describes the details. Second, we obtain estimates of the volatility and jump risk premiums by observing that in a standard power utility framework (e.g., Bakshi and Kapadia, 2003; Broadie, Chernov, and Johannes, 2009; Christoffersen, Heston, and Jacobs, 2013; Naik and Lee, 1990), the risk adjustment for volatility risk is given by:

$$\eta V_t = Cov(\gamma \frac{dS_t}{S_t}, dV_t) \Longrightarrow \eta = \gamma \sigma \rho \tag{1}$$

[12] Realized option returns are highly dependent on the sample, and therefore it is necessary to estimate a model over the same period for which a model is asked to explain option returns.

and the risk adjustment for price jump risk is given by:

$$\begin{aligned}\lambda^{\mathbb{Q}} &= \lambda \exp(-\mu_z\gamma + \frac{1}{2}\gamma^2\sigma_z^2) \\ \mu_Z^{\mathbb{Q}} &= \mu_z - \gamma\sigma_z^2.\end{aligned} \tag{2}$$

where γ is relative risk aversion of the agent. For our benchmark analysis, we follow BCJ and assume a risk aversion of 10. Note that we do not use option data to estimate model parameters because as BCJ point out, this approach might be problematic for our purpose because we would be explaining option returns using information extracted from option prices in the first place.

Table 2 reports (annualized) parameter values that we use for computing expected option returns and simulations. Our parameter estimates are within the reasonable range reported in the literature. For the BSM model, the constant volatility parameter is set equal to the square root of the long run mean of stock variance (θ) in the SV model ($\sigma_{BSM} = 19.05\%$). For the volatility risk premium, given a risk aversion of 10 and a negative ρ, equation (1) indicates that the volatility risk premium parameter η must be negative and is equal to –4.347. Pan (2002) finds that the magnitudes of the volatility risk premium needed to reconcile time-series and option-based spot volatility measures imply explosive risk-neutral volatility dynamics ($\kappa + \eta < 0$). In contrast, our calibration does not have this issue: The volatility process under the risk neutral measure remains mean-reverting ($\kappa + \eta > 0$). Consistent with the notion that investors fear large adverse price jumps, the risk corrections in equation (2) indicate that price jumps occur more frequently and more severely under the risk-neutral measure. Our estimates imply about 1.50 jumps per year on average ($\lambda^{\mathbb{Q}} = 1.4969$) and a mean jump size of –6.67% ($\mu_z^{\mathbb{Q}} = -0.0667$) under $\mathbb{Q}$ probability measure, and about 0.97 jumps per year on average ($\lambda = 0.9658$) with a mean jump size of –2.09% ($\mu_z = -0.0209$) under $\mathbb{P}$ probability measure. We perform an extensive sensitivity analysis with respect to the parameterizations of stochastic volatility and jumps, and the risk aversion parameter in Section 5.1.

3.3 Results

Table 3 compares expected option returns implied from models with only an equity risk premium (BSM, SV, and SVJ) to data. Realized historical option returns taken from Table 1 are denoted by "Data". Expected option returns computed analytically are labeled as "$\mathbb{E}^p$". We also report the average simulated option returns, denoted by "Simulation". Not surprisingly, these two are very close to each other.

First of all, confirming the results of Chambers, Foy, Liebner, and Lu (2014), Panel B shows that models with only an equity risk premium can be rejected by OTM put option returns. While these models do imply a correct pattern that returns become more negative as put options move further away from the money, the magnitudes seem too small to be consistent with the data. For example, a 4% OTM put has an average return of –37.86% in the data, which is much larger than the expected returns implied from the three models: –12.24% (BSM), –10.20% (SV), and –9.16% (SVJ).[13] The return differences are also statistically significant at 10% with a p-value of 0.04, 0.08, and 0.07. A p-value of 0.04 means that only 4% of the 25000 simulated average put returns are less than the realized return –37.86%.

Panel A of Table 3 shows that option pricing models with the equity risk premium only are also inconsistent with the empirical call option return pattern. Specifically, all three models predict an overall increasing relationship between call option returns and the strike price with OTM calls earning large positive returns, which is contrary to the data. Interestingly, despite the return differences for OTM calls being large between data and the models, p-values indicate that only the BSM model can be rejected (based on 6% and 8% OTM calls). Broadie, Chernov, and Johannes (2009) show that the statistical uncertainty is substantial for put returns. Our analysis further suggests that statistical uncertainty is even greater for call returns.

[13] Expected put option returns in the SV and SVJ models are actually less negative than those in the BSM model, despite the fact that the two models are able to generate a volatility skew. In other words, the volatility skew per se does not imply large negative returns unless the skew is driven by risk premiums (e.g., volatility and jump risks are priced).

Panel C reports results based on option portfolio returns. Returns on option portfolios are more informative and provide stronger tests. For example, while the SV model and the SVJ model cannot be rejected by ATM calls or ATM puts individually, they can be rejected based on ATM straddles which consist of ATM calls and ATM puts. Furthermore, the SV model and the SVJ model are also rejected by crash neutral spread returns.

In summary, we conclude that option pricing models with only an equity risk premium are not consistent with the observed index option returns and therefore index option returns would appear puzzling to those models.

Table 4 reports expected option returns for the SV+ model in which volatility risk is priced. When a volatility risk premium is incorporated, expected option returns are able to match the average returns of call and put options across all strikes as well as the average returns of option portfolios. In particular, consistent with the data, the pricing of volatility risk implies that the expected call option return tends to decrease with the strike price, especially over the out-of-the-money range. For example, the expected return drops monotonically from 5.14% per month for ATM calls to –22.54% for 8% OTM calls. This result sharply contrasts with models with only an equity risk premium where the expected call option return is an increasing function of the strike price. On the put option side, we find that expected put option returns are more negative in the presence of the volatility risk premium, which again is consistent with the data. Finally, Panel C shows that the pricing of volatility risk is also consistent with option portfolio returns. The p-values suggest that in all cases realized historical average option returns are not statistically significantly different from those generated by the SV+ model.

Table 5 reports expected option returns when jump risk is priced but volatility risk is not (SVJ+). Confirming the findings of Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014), Panel B shows that the pricing of jump risk implies that put options have large negative expected returns, which is consistent with the data. While the jump risk premium matches put returns very well, it fails to explain index call option returns. Specifically, Panel A shows that when jump risk is priced, there is an increasing relation between expected call option returns and the strike price with OTM calls earning large positive returns, which is contrary to the data. This finding about the jump risk premium is not due to our parameterization. We also use parameters reported in Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014) and find very similar results. Section 5.1 contains additional discussion. Note that because OTM call options in the SVJ+ model have very large return standard deviations, the model actually cannot be rejected despite the fact that it generates a wrong return pattern. However, portfolio-based evidence in Panel C shows that the SVJ+ model can be rejected by call spread returns. The average monthly return of call spreads is 13.56% in the data, much higher than the model-implied return of 1.46%. The difference is statistically significant with a p-value of 0.04.

Figure 1 summarizes our findings by plotting expected option returns in Tables 3 to 5 against the strike price. For comparison, we also include the average returns in the data. Panel A shows that the volatility and jump risk premiums have drastically different predictions on OTM call options. The jump risk premium implies that expected returns of OTM call options are positive and increasing with the strike price, which is similar to models with the equity risk premium only. In contrast, the volatility risk premium predicts a decreasing relationship between expected returns and the strike price, with OTM calls earning large negative returns. Panel B shows that all models yield similar predictions on puts in that expected put option returns should be negative and increasing with the strike price. However the jump risk premium yields the most negative estimates, followed by the volatility risk premium.

The volatility and jump risk premiums affect expected option returns because they induce changes in the risk-neutral index return distribution under which option prices are determined. A negative volatility risk premium will add probability mass to both tails and thus increase the value of both OTM calls and OTM puts, which leads to lower expected returns. On the other hand, the jump risk premium has two effects on the risk-neutral distribution. First, the presence of a jump risk premium will result in a more negatively-skewed risk neutral distribution. This, in turn, will increase the value of OTM put options and decrease the value of OTM call options. Second, the jump risk premium also tends to fatten both tails. For OTM put options, both effects will lead to a higher valuation and this is the reason expected put option returns are much more negative in the presence of a jump risk premium. On the other hand, for OTM calls, the skewness effect tends to dominate under plausible parameterizations and therefore the presence of the jump risk premium will result in higher expected returns for OTM call options.[14]

Our analysis shows that a simple stochastic volatility model in which volatility risk is priced describes the average option returns reasonably well. This result is somewhat surprising because we know the stochastic volatility model is not rich enough to capture the behavior of option prices.[15] As discussed in Section 2, there is an extensive literature that demonstrates several factors are needed to fit the rich dynamics of option prices. Our results are nevertheless consistent with the findings of Cochrane and Piazzesi (2005) for the bond market that although multiple factors are needed to describe empirical patterns in bond prices, a single factor summarizes nearly all information about risk premium/returns. Johnson (2017) also reports similar results in the VIX market.

3.4 The Effect of the Volatility Risk Premium: Further Investigation

In this section, we analyze how expected option returns vary with respect to changes in the volatility risk premium. Based on the same parameter values reported in Table 2, Figure 2 plots expected returns on call options, put options, and straddles in the SV+ model as a function of risk aversion γ for different moneyness. A higher γ implies a larger volatility risk premium (more negative) as shown in equation (1). Figure 2 reveals several interesting results. First, as γ increases (e.g.,

[14] If one ignores the equilibrium restrictions and allows the variance of jump size to take different values under the physical and risk neutral measures, expected option returns become even more complicated and can exhibit different patterns. See Branger, Hansis, and Schlag (2010) for a related discussion.

[15] The empirical shortcomings of the SV model are of course well-documented. For example, the estimated SV model often generates a steeply upward-sloping term structure of implied volatility, which is incompatible with the observed term structure. Moreover, the model implies the instantaneous change in volatility is Gaussian and homoskedastic, thus unable to capture the sudden and abrupt moves in the observed volatility dynamics. For detailed discussions, see Bates (2003), Broadie, Chernov, and Johannes (2007), and Christoffersen, Jacobs, and Mimouni (2010).

the volatility risk premium becomes more negative), expected returns on calls, puts, and straddles monotonically decrease regardless of moneyness. Again, this is because a negative volatility risk premium makes options more expensive. However, the magnitude of this effect highly depends on the moneyness. In particular, the relation between the volatility risk premium and expected option returns is much stronger for OTM calls and OTM puts with the steepest slope. As options move towards the in-the-money direction, the slope flattens out as expected returns become less sensitive to the volatility risk premium. On the other hand, straddles have their own unique pattern. ATM straddle returns are more sensitive to changes in the volatility risk premium as compared to their ITM and OTM counterparts. We test these predictions in Section 4.

Figure 2 also helps understand why the volatility risk premium fits index option returns well. As discussed, a negative volatility risk premium increases option value, which then leads to a lower expected return. Moreover, this effect is disproportionately stronger for out-of-the-money options. As a result, the pricing of volatility risk is able to generate not only a steeper relation between expected put option returns and the strike price, with OTM put options earning large negative returns, but also a decreasing relation between expected call option returns and the strike price, with OTM calls having negative expected returns.

4 Time Series Analysis

The previous section shows that the presence of a negative volatility risk premium decreases expected option returns. Moreover, the effect of the volatility risk premium is stronger for OTM options and ATM straddles. We formally test these predictions by investigating the time series relationship between the volatility risk premium and future index option returns. We also examine how the jump risk premium is related to future option returns.

4.1 The Volatility Risk Premium and Future Option Returns

To test the differential impact of the volatility risk premium on expected option returns, we estimate the following time-series predictive regressions at monthly frequency:

$$option\_ret^{i}_{t,\,t+1} = \alpha^{i} + \beta^{i}\mathrm{VRP}_t + \epsilon, \quad i \in \{call, put, straddle\} \tag{3}$$

where the dependent variable *option_ret* is the returns from holding call options, put options and straddles from month t to month $t+1$. The analysis in Section 3.4 suggests that options with different moneyness have different sensitivities with respect to the volatility risk premium and therefore we estimate the above regressions separately for different moneyness groups. In particular, for call options, we consider the following three groups: $0.96 <= K/S < 1.00$, $1.00 <= K/S < 1.04$, and $1.04 <= K/S < 1.08$. For put options, we consider $0.92 <= K/S < 0.96$, $0.96 <= K/S < 1.00$, and $1.00 <= K/S < 1.04$. Again we do not investigate options that are beyond 8% OTM or 4% ITM in light of potential data issues. For straddles, we consider the following three moneyness groups: $0.94 <= K/S < 0.98$, $0.98 <= K/S < 1.02$, and $1.02 <= K/S < 1.06$.

Following the definition of the equity risk premium, we define the volatility risk premium as the difference between physical and risk neutral expectations of future realized volatility:

$$\mathrm{VRP}_t = \mathbb{E}_t(RV_{t,t+1}) - \mathbb{E}^{\mathbb{Q}}_t(RV_{t,t+1}).$$

The volatility risk premium is constructed each month on the option selection date and will be used to forecast option returns over the following month. For the baseline results, we follow Bollerslev, Tauchen, and Zhou (2009) and measure the volatility risk premium as the difference between realized volatility and the VIX index:

$$\mathrm{VRP}_t = RV_{t-1,t} - VIX_t$$

where realized volatility is computed based on 5-min log returns on S&P 500 futures over the past

30 days.[16] The VIX index is published by the Chicago Board Options Exchange (CBOE), and it tracks 30-day risk neutral expectation of future realized volatility.[17] In the robustness analysis, we show that our empirical results are not sensitive to the measurement of the volatility risk premium. For example, instead of using realized volatility, we also estimate expected physical volatility and find similar results. Figure A1 in the Online Appendix plots realized volatility, the VIX, and the volatility risk premium throughout our sample period. Consistent with the findings in Todorov (2010) and Carr and Wu (2009), Figure A1 shows that the volatility risk premium, like volatility itself, is also time varying.

Panel A of Table 6 reports regression results for call options. For call options that are between 4% and 8% OTM, the volatility risk premium is positively related to future returns with a statistically significant coefficient. The t-statistic is 2.11 and the adjusted R^2 of the regression is 0.99%. Throughout the paper, t-statistics are computed using Newey-West standard errors with four lags (Newey and West, 1987, 1994). Interestingly, this relationship between the volatility risk premium and call returns weakens as call options move towards the in-the-money direction. The slope coefficient, t-stat, and R^2 all decrease monotonically.

Panel B shows that there is a positive relationship between the volatility risk premium and future index put option returns. Similar to calls, this relation becomes increasingly weak as put options move towards the in-the-money direction, judging by the slope coefficient, statistical significance, and R^2. For example, among put options that are between 4% OTM and 8% OTM, the slope coefficient is estimated to be 8.37 with a Newey-West t-statistic of 2.21 and an adjusted R^2 of

[16] The use of intra-day data is motivated by the realized volatility literature that demonstrates the critical role of high frequency data in volatility measuring and modeling. See, among others, Andersen et al. (2001), Andersen et al. (2003), and Barndorff-Nielsen and Shephard (2002). Following the literature, we focus on 5-min returns to avoid potential microstructure effects. Liu et al. (2015) find that it is difficult to outperform 5-minute realized variance even with more sophisticated sampling techniques. We also treat overnight and weekend returns as an additional 5-min interval.

[17] The CBOE developed the first-ever volatility index in 1993, which then was based on the average implied volatilities of at-the-money S&P 100 options. In 2003, the CBOE started publishing a new index that is calculated using S&P 500 index option prices in a model-free manner. We use the new VIX index. For more details on the model-free approach, see for example Dupire (1994), Neuberger (1994), Britten-Jones and Neuberger (2000), and Jiang and Tian (2005).

2.04%. In contrast, among put options that are between ATM and 4% ITM, the slope coefficient is only 2.70 and not statistically significant.

Panel C shows that the volatility risk premium also exhibits a positive relation with future straddle returns, but with a different pattern. In particular, the relationship between the volatility risk premium and future returns is stronger for at-the-money straddles. As straddles move away from the money, this relation is only marginally significant.

In summary, we find that the volatility risk premium is positively related to future index option returns: A more negative volatility risk premium in a given month is associated with lower option returns in the subsequent month. This positive relationship is consistent with the theoretical prediction that a negative volatility risk premium leads to lower expected option returns. We also find that the relationship between the volatility risk premium and future option returns is stronger for OTM calls, OTM puts, and ATM straddles. This pattern is also consistent with the prediction that the effect of the volatility risk premium varies across moneyeness, and OTM options and ATM straddles are more sensitive to changes in the volatility risk premium. In Appendix C, we show that the positive relationship between the volatility risk premium and future option returns is also economically significant and can be translated into large economic gains.

Bollerslev, Tauchen, and Zhou (2009), among others, document that the volatility risk premium predicts future index returns at short horizons. Therefore, a natural interpretation of our finding is that it is merely a manifestation of the underlying index return predictability afforded by the volatility risk premium. While this explanation appears plausible, it can be ruled out based on the fact that the volatility risk premium forecasts future option returns with the same sign: A more negative volatility risk premium this month is associated with lower option returns in the subsequent month. If option return predictability were caused by stock return predictability, then one would observe opposite signs for calls and puts because the expected call (put) option return increases (decreases) with the expected stock return. Instead we argue that the economic source of option return predictability is due to the time-varying volatility risk premium embedded in index options.

4.2 The Jump Risk Premium and Future Option Returns

We also investigate how the jump risk premium is related to future option returns. Dennis and Mayhew (2002) and Bakshi and Kapadia (2003) establish the link between risk neutral skewness and the slope of the implied volatility curve, and therefore we use the difference in average implied volatilities ($IVOL$) between OTM and ATM put options as a proxy for the jump risk premium:

$$\text{JUMP}_t = IVOL_{OTM,t} - IVOL_{ATM,t} \tag{4}$$

where OTM and ATM refer to put options with $0.90 =< K/S <= 0.94$ and $0.98 =< K/S <= 1.02$, respectively.

Table A2 in the Online Appendix reports the regression results with the jump risk premium. Panel A indicates that the jump risk premium is not informative about future call option returns. It is insignificant across all moneyness groups and R^2s are close to zero. Panel B shows that the jump risk premium is negatively and significantly related to future OTM put option returns with a Newey-West t-statistic of –2.94 and an adjusted R^2 of 1.45%. We find a larger jump risk premium in a given month is associated with lower OTM put option returns in the subsequent month. Panel C shows that the jump risk premium does not contain predictive information about straddle returns.

In summary, we conclude that the jump risk premium is informative about future OTM put option returns, but its relationship with future call and straddle returns is insignificant.

5 Robustness

This section includes several robustness checks. We study how different parameterizations might affect expected option returns. We also investigate the robustness of the empirical relationship between the volatility risk premium and option returns to a number of implementation choices.

5.1 Parameters

Our main analysis shows that the presence of the volatility risk premium implies that both OTM calls and OTM puts should earn large negative expected returns, which is consistent with the data. On the other hand, the jump risk premium implies that OTM put options should have large negative expected returns, whereas OTM call options should have large positive returns. In this section, we assess how these conclusions might be affected by different parameterizations with respect to both physical measure parameters and the risk aversion parameter.

Table 7 recalculates expected option returns in the SV+ model by increasing/decreasing each $\mathbb{P}$-measure parameter by one standard deviation. We continue to assume a risk aversion of 10 when computing expected option returns. The results suggest that expected option returns are not sensitive to changes in $\mathbb{P}$-measure parameters, and overall expected returns are very close to those obtained with our baseline parameterization. For example, it is well-known that the volatility mean reverting parameter κ is notoriously difficult to pin down precisely. However, its impact on expected option returns turns out to be quite small: Decreasing or increasing it by one standard deviation produces very similar expected returns.

Table 8 reports expected option returns in the SV+ model by changing the risk aversion parameter from 0 to 20. For $\mathbb{P}$-measure parameters, we use our baseline estimates reported in Table 2. Table 8 shows that risk aversion (and therefore risk premium) has a much larger effect on expected option returns, especially for OTM options. When risk aversion is equal to zero (e.g., volatility risk is not priced), the SV+ model collapses to the SV model and both expected call and put option returns increase with the strike price. As risk aversion increases, namely the volatility risk premium becomes more negative, expected option returns decrease. Notice that in order for the volatility risk premium to match the data, risk aversion should be relatively high.

We also compute expected option returns using the variance-dependent pricing kernel of Christoffersen, Heston, and Jacobs (2013). Their variance-dependent pricing kernel, when projected onto the stock return, is U-shaped and able to explain a range of option anomalies.[18] With this particular pricing kernel, Christoffersen, Heston, and Jacobs (2013) show that the volatility risk premium has the following two factor structure:

$$\eta = \gamma\sigma\rho - \xi\sigma^2 \tag{5}$$

where the first term is related to risk aversion as before, and the second term originates from variance preferences ξ which, according to Christoffersen, Heston, and Jacobs (2013), should be positive. Table A3 repeats the same exercise in Table 8 but using the new specification of the volatility risk premium in equation (5). With a variance-dependent pricing kernel, risk aversion needed to fit option returns is small.

Tables A4 and A5 in the Online Appendix report the corresponding results for the SVJ+ model. Tables A4 investigates if expected option returns are sensitive to our characterization of jump process under the physical measure by increasing or decreasing each jump parameter by one standard deviation. We only focus on jump-related parameters because, as already demonstrated, expected option returns do not vary much with parameters associated with stochastic volatility. Overall, we find the return patterns are similar to our benchmark case. Specifically, the jump risk premium would imply very large negative expected returns for OTM put options, which is consistent with the data. However, it would also imply that expected OTM call option returns are positive and increasing with the strike price, which is not consistent with the data.

Table A5 reports the effect of risk aversion on expected option returns in the SVJ+ model. An increase in risk aversion leads to a larger jump risk premium, meaning price jumps occur more

[18] Many papers find that the pricing kernel is not a monotonically decreasing function of index returns. See, among others, Aït-Sahalia and Lo (1998), Jackwerth (2000), Rosenberg and Engle (2002), and Chaudhuri and Schroder (2015b). On the other hand, Linn, Shive, and Shumway (2018) point out potential biases in the existing estimates of the pricing kernel. After properly accounting for the conditioning information, they show the pricing kernel is monotonically decreasing with index returns.

frequently and more severely under the risk neutral measure. Overall Table A5 shows that while the jump risk premium is able to match put option returns easily, its implications on call options are in general inconsistent with the data. For example, across a wide range of risk aversion values, expected returns on OTM calls are positive and increasing with the strike price. If risk aversion is high enough (e.g., 20), it is possible to observe negative expected returns on OTM calls. However, a very large risk aversion would also imply that ATM and ITM calls have negative expected returns, which is not consistent with the data.

5.2 The Measurement of the Volatility Risk Premium

In the main analysis, we measure the volatility risk premium as the difference between realized volatility and the VIX. In other words, we assume that volatility follows a random walk and lagged realized volatility is an unbiased estimate of expected volatility. To ensure our empirical results are not driven by this assumption, we also estimate expected physical volatility using the heterogeneous autoregressive model (the HAR model) proposed by Corsi (2009). In particular, we obtain conditional forecasts of future volatility by projecting realized volatility onto lagged realized volatilities computed over difference frequencies:

$$\log RV_{t,t+1} = \delta_0 + \delta_1 \log RV_{t-1,t} + \delta_2 \log RV_t^W + \delta_3 \log RV_t^D + \epsilon$$

where $RV_{t-1,t}$ is realized volatility over the past month, and RV_t^W and RV_t^D denote realized volatilities over the past week and day, respectively. Because realized volatilities are approximately log-normally distributed (Andersen et al., 2001), it is more appropriate to forecast the logarithmic of realized volatilities with linear models. The log specification also ensures that volatility forecasts always remain positive. We estimate the above model based on the full sample and take the fitted values as expectations of future realized volatility:

$$\mathbb{E}_t(RV_{t,t+1}) = \exp(\delta_0 + \delta_1 \log RV_{t-1,t} + \delta_2 \log RV_t^W + \delta_3 \log RV_t^D + \frac{1}{2}\sigma_\epsilon^2).$$

Finally we compute the difference between $\mathbb{E}_t(RV_{t,t+1})$ and the VIX to obtain the volatility risk premium estimates.

Table 9 contains results with this new measure of the volatility risk premium. Consistent with our benchmark findings, the volatility risk premium is positively related to future option returns, and this relationship is stronger for OTM options and ATM straddles. We also find similar results when using daily returns to compute physical volatility or using the average option implied volatility as a proxy for risk neutral volatility.

5.3 Controlling for Other Variables

Our main analysis documents a positive relationship between the volatility risk premium and future option returns in univariate regressions. In this section, we investigate if the volatility risk premium is robust to controlling for other variables including the jump risk premium and the level of volatility. Given the results are stronger for OTM options and ATM straddles, we will focus on these options only.

Table 10 reports the results for multivariate regressions. Specification (1) controls for the jump risk premium. After including the jump risk premium as a control, we find the volatility risk premium remains statistically significant. We also find that the volatility risk premium does not subsume the jump risk premium: The jump risk premium is still negatively and significantly related to future OTM put option returns. This suggests that the volatility and jump risk premiums are both informative about OTM put option returns.

Specification (2) of Table 10 controls for the level of volatility. Including volatility as a control does not change our results. The volatility risk premium remains significant in all cases. Note that volatility itself is also related to future option returns. Specifically, volatility is negatively related to future straddle returns and call returns, but positively related to future put returns, although the relationship is not always statistically significant. These results are broadly consistent with the analysis in Hu and Jacobs (2017).

Specification (3) shows that our findings remain robust when including both controls. Finally, Table A6 in the Online Appendix shows that the positive relationship between the volatility risk premium and future option returns is also robust to controlling for option betas.

In the main analysis, we study the predictive relation between the volatility risk premium and holding-to-maturity index option returns. Table A7 examines if our empirical findings persist to other holding periods. In particular, instead of holding options to maturity, we consider a holding period of half month (15 calendar days). We find very similar results with holding-period option returns.

6 Conclusion

Out-of-the-money S&P 500 index call and put options are both associated with large negative average returns. We argue that the low returns on OTM options are primarily due to the pricing of market volatility risk. When volatility risk is priced, expected option returns are consistent with realized historical index option returns across all strikes as well as the returns of a number of option portfolios. Further corroborating the volatility risk premium hypothesis, we document that the volatility risk premium is positively related to future option returns, and this relationship is stronger for OTM options and ATM straddles. These findings are consistent with the differential effect of the volatility risk premium on expected option returns. Overall, our results suggest that the pricing of volatility risk has a first-order effect on the cross-section of index option returns. On the jump risk premium side, we find that the pricing of jump risk is also important and some portion of OTM put option returns are related to the jump risk premium.

This paper can be extended in several ways. First, in our theoretical analysis we assume there is only one factor that drives time-varying stochastic volatility. In the data, volatility dynamics are much more complex and our analysis can be extended to take this into account.[19] Second, we have focused on the one-month maturity and extensions to investigating the term structure would be useful. Third, we consider index option returns in the U.S. market, and it may prove interesting to extend our analysis to international data. We plan to address these in future research.

[19]Existing studies find that two factors are needed in order to characterize the volatility dynamics. See, among others, Alizadeh, Brandt, and Diebold (2002), Engle and Rangel (2008), and Christoffersen, Heston, and Jacobs (2009). Another strand of literature emphasizes the importance of incorporating jumps into the volatility dynamics. See, among others, Broadie, Chernov, and Johannes (2007) and Eraker, Johannes, and Polson (2003).

Appendix A: Sampling Index Option Data

An option is included in the sample if it meets all of the following requirements.

1) The best bid price is positive and the best bid price is smaller than the best offer price.

2) The price does not violate no-arbitrage bounds: For call options we require that the price of the underlying exceeds the best offer, which is in turn higher than $max(0, S - K)$. For put options we require that the exercise price exceeds the best bid, which is in turn higher than $max(0, K - S)$.

3) Open interest is positive.

4) Volume is positive.

5) The bid-ask spread exceeds \$0.05 when the option price is below \$3, and \$0.10 when the option price is higher than \$3.

6) The expiration day is standard.

7) Settlement is standard.

8) Implied volatility is not missing.

9) Secid = 108105.

Appendix B: Particle Filtering Using Returns

In this appendix, we discuss the estimation of the SVJ model. The estimation of the SV model follows accordingly by ignoring the jump component. We first time-discretize the SVJ model. Applying Euler discretization and Ito's lemma, we can rewrite the SVJ model as:

$$R_{t+1} = ln(\frac{S_{t+1}}{S_t}) = \mu + r - d - V_t/2 + \sqrt{V_t} z_{1,t+1} + J_{t+1} B_{t+1}$$

$$V_{t+1} - V_t = \kappa(\theta - V_t) + \sigma \sqrt{V_t} z_{2,t+1}$$

where $z_{1,t+1}$ and $z_{2,t+1}$ are standard normal shocks. B_{t+1} and J_{t+1} are the jump occurrence and jump size. We implement the discretized model using daily S&P 500 index returns.

We have two sets of unknowns: 1) parameters $\Theta(\kappa, \theta, \sigma, \rho, \lambda, \mu_z, \sigma_z)$ and 2) latent states $\{V_t\}$. We use particle filtering to filter the latent states and adaptive Metropolis-Hastings sampling to perform the parameter search.

The particle filtering algorithm relies on the approximation of the true density of the state V_t by a set of N discrete points or particles that are updated iteratively through variance process. Throughout the estimation, we use $N = 10,000$ particles. Below we outline how Sequential Importance Resampling (SIR) particle filtering is implemented using the return data.

Step 1: Simulating the State Forward

For $i = 1 : N$, we first simulate all shocks from their corresponding distribution:

$$(z_{1,t+1}, z_{2,t+1}, B_{t+1}, J_{t+1})^i$$

where the correlation between the innovations is taken into account. Then, new particles are simulated according to the equation below:

$$V_t = V_{t-1} + \kappa(\theta - V_{t-1}) + \sigma\sqrt{V_{t-1}}z_{2,t}.$$

Note that period $t+1$ shocks affect R_{t+1} and V_{t+1}, and thus to simulate V_t, we in fact need $z_{2,t}$ from the previous period. We record $z_{2,t+1}$ for the next period for each particle.

Step 2: Computing and Normalizing the Weights

Now we compute the weights according to the likelihood for each particle $i = 1 : N$:

$$\omega_{t+1}^{i} = f(R_{t+1}|V_t^i)$$
$$= \frac{1}{\sqrt{2\pi V_t^i}} \exp\left\{ -\frac{1}{2} \frac{\left[R_{t+1} - (\mu + r - d - \frac{1}{2}V_t^i - \lambda\bar{\mu} + J_{t+1}B_{t+1})\right]^2}{V_t^i} \right\}$$

The normalized weights π_{t+1}^{i} are calculated as:

$$\pi_{t+1}^{i} = \omega_{t+1}^{i} / \sum_{j=1}^{N} \omega_{t+1}^{j}$$

Step 3: Resampling

The set $\left\{\pi_{t+1}^{i}\right\}_{i=1}^{N}$ can be viewed as a discrete probability distribution of V_t from which we can resample. The resampled $\{V_t^i\}_{i=1}^{N}$ as well as its ancestors are stored for the next period.

The filtering for period $t+1$ is now done. The filtering for period $t+2$ starts over from step 1 by simulating new particles based on resampled particles and shocks from period $t+1$. By repeating these steps for all $t = 1 : T$, particles that are more likely to generate the observed return series tend to survive till the end, yielding a discrete distribution of filtered spot variances for each day.

Appendix C: Option Trading Strategies

To assess the economic significance of the predictive relationship between the volatility risk premium and future option returns, we propose a trading strategy that exploits option return predictability in the context of selling index options. Writing index options is popular because historically it tends to yield higher returns by collecting the volatility risk premium. Since the volatility risk premium is positively associated with future option returns, a simple strategy would be to sell options only in months when the volatility risk premium is negative. This strategy relies only on an ex-ante market signal and does not require investors to estimate any model. Moreover, since return predictability is significant among out-of-the-money options and at-the-money straddles, we will test the performance of the new trading strategy in the context of selling a 4% OTM call, a 6% OTM call, a 4% OTM put, a 6% OTM put, and an ATM straddle. As a benchmark, we consider a strategy that writes options in every month of the sample. The new strategy is called "VRP < 0", and the benchmark strategy is called "Always". The performance of the S&P 500 over the same period is also included for comparison.

Table A8 in the Online Appendix shows that our new strategy outperforms the benchmark strategy. Taking ATM straddles as an example, following our strategy, one would obtain a monthly average return of 0.106 with a Sharpe ratio of 0.151. In contrast, the average return and Sharpe ratio for the benchmark strategy are 0.085 and 0.115, respectively. Note that with the new trading strategy, one would sell options less often. The last column of Table A8 indicates the number of months in which options are shorted.[20] We also report skewness of different trading strategies. In addition to the improvements in the Sharpe ratio, the new strategy that we propose has a similar or even lower skewness relative to the benchmark strategy. Finally, it should be emphasized that the Sharpe ratio is a poor performance measure of derivatives trading strategies, which often yield highly non-normal payoffs (Goetzmann et al., 2004). The strategy proposed in this paper is only suitable for institutional investors with deep pockets and a long investment horizon.

Table A8 also shows that overall writing OTM put options tends to be more profitable than writing OTM call options. As our analysis suggests, one potential explanation is that selling OTM put options earns both the volatility and jump risk premiums. In contrast, by selling OTM call options, one mainly collects the volatility risk premium. The divergence between selling calls and puts might also be related to institutional frictions and order flow. For example, it is in general easy to sell calls via covered calls, but difficult to sell naked puts. Moreover, OTM put options can be used as portfolio insurance and therefore attract much more demand than OTM calls.

[20]The number differs for different trading strategies due to missing data. For example, certain options might not exist in some months.

References

Adrian, Tobias, and Joshua Rosenberg, 2008, Stock Returns and Volatility: Pricing the Long-Run and Short-Run Components of Market Risk, *Journal of Finance* 63, 2997–3030.

Aït-Sahalia, Yacine, Mustafa Karaman, and Loriano Mancini, 2015, The Term Structure of Variance Swaps and Risk Premia, *Working Paper, Princeton University* .

Aït-Sahalia, Yacine, and Andrew W. Lo, 1998, Nonparametric Estimation of State-Price Densitites Implicit in Financial Asset Prices, *Journal of Finance* 53, 499–547.

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold, 2002, Range-Based Estimation of Stochastic Volatility Models, *Journal of Finance* 57, 1047–1091.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Heiko Ebens, 2001, The Distribution of Realized Stock Return Volatility, *Journal of Financial Economics* 61, 43–76.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2003, Modeling and Forecasting Realized Volatility, *Econometrica* 71, 579–625.

Andersen, Torben G., Nicola Fusari, and Viktor Todorov, 2015, Parametric Inference and Dynamic State Recovery From Option Panels, *Econometrica* 83, 1081–1145.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259–299.

Baele, Lieven, Joost Driessen, Sebastian Ebert, Juan M. Londono, and Oliver Spalt, 2018, Cumulative Prospect Theory, Option Returns, and the Variance Premium, *Review of Financial Studies, Forthcoming* .

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 1997, Empirical Performance of Alternative Option Pricing Model, *Journal of Finance* 52, 2003–2049.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-Hedged Gains and the Negative Market Volatility Risk Premium, *Review of Financial Studies* 16, 527–566.

Bakshi, Gurdip, Dilip Madan, and George Panayotov, 2010, Returns of Claims on the Upside and the Viability of U-Shaped Pricing Kernels, *Journal of Financial Economics* 97, 130–154.

Bali, Turan G., and Armen Hovakimian, 2009, Volatility Spreads and Expected Stock Returns, *Management Science* 55, 1797–1812.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as Lotteries: The Implication of Probability Weighting for Security Prices, *American Economic Review* 98, 2066–2100.

Barndorff-Nielsen, Ole E., and Neil Shephard, 2002, Econometric Analysis of Realised Volatility and Its Use in Estimating Stochastic Volatility Models, *Journal of the Royal Statistical Society* 64, 253–280.

Bates, David S., 1996, Jumps and Stochastic Volatility: Exchange Rate Processes Implicit in Deutschemark Options, *Review of Financial Studies* 9, 69–107.

Bates, David S., 2000, Post-'87 Crash Fears in the S&P 500 Futures Option Market, *Journal of Econometrics* 94, 181–238.

Bates, David S., 2003, Empirical Option Pricing: A Retrospection, *Journal of Econometrics* 116, 387–404.

Benzoni, Luca, Pierre Collin-Dufresne, and Robert S. Goldstein, 2011, Explaining Asset Pricing Puzzles Associated with the 1987 Market Crash, *Journal of Financial Economics* 101, 552–573.

Black, Fischer, and Myron Scholes, 1973, The Pricing of Options and Corporate Liabilities, *Journal of Political Economy* 81, 637–654.

Bollen, Nicolas P.B., and Robert E. Whaley, 2004, Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?, *Journal of Finance* 59, 711–753.

Bollerslev, Tim, James Marrone, Lai Xu, and Hao Zhou, 2014, Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence, *Journal of Financial and Quantitative Analysis* 49, 633–661.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected Stock Returns and Variance Risk Premia, *Review of Financial Studies* 22, 4463–4492.

Bondarenko, Oleg, 2014, Why are Put Options So Expensive?, *Quarterly Journal of Finance* 4, 1450015.

Branger, Nicole, Alexandra Hansis, and Christian Schlag, 2010, Expected Option Returns and the Structure of Jump Risk Premia, *Working Paper, University of Muenster* .

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option Prices, Implied Price Processes, and Stochastic Volatility, *Journal of Finance* 55, 839–866.

Broadie, Mark, Mikhail Chernov, and Michael Johannes, 2007, Model Specification and Risk Premia : Evidence from Futures Options, *Journal of Finance* 62, 1453–1490.

Broadie, Mark, Mikhail Chernov, and Michael Johannes, 2009, Understanding Index Option Returns, *Review of Financial Studies* 22, 4493–4529.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker, 2007, Optimal Beliefs, Asset Prices, and the Preference for Skewed Returns, *American Economic Review* 97, 159–165.

Cao, Charles, and Jing-Zhi Huang, 2007, Determinants of S&P 500 Index Option Returns, *Review of Derivatives Research* 10, 1–38.

Carr, Peter, and Liuren Wu, 2009, Variance Risk Premiums, *Review of Financial Studies* 22, 1311–1341.

Chambers, Donald R., Matthew Foy, Jeffrey Liebner, and Qin Lu, 2014, Index Option Returns: Still Puzzling, *Review of Financial Studies* 27, 1915–1928.

Chaudhuri, Ranadeb, and Mark Schroder, 2015a, Monotonicity of the stochastic discount factor and expected option returns, *The Review of Financial Studies* 28, 1462–1505.

Chaudhuri, Ranadeb, and Mark Schroder, 2015b, Monotonicity of the Stochastic Discount Factor and Expected Option Returns, *Review of Financial Studies* 28, 1462–1505.

Chernov, Mikhail, and Eric Ghysels, 2000, A Study Towards a Unified Approach to the Joint Estimation of Objective and Risk Neutral Measures for the Purpose of Options Valuation, *Journal of Financial Economics* 56, 407–458.

Christensen, Bent J., and Nagpurnanand R. Prabhala, 1998, The Relation Between Implied and Realized Volatility, *Journal of Financial Economics* 50, 125–150.

Christoffersen, Peter, Steven Heston, and Kris Jacobs, 2009, The Shape and Term Structure of the Index Option Smirk: Why Multifactor Stochastic Volatility Models Work So Well, *Management Science* 55, 1914–1932.

Christoffersen, Peter, Steven Heston, and Kris Jacobs, 2013, Capturing Option Anomalies with a Variance-Dependent Pricing Kernel, *Review of Financial Studies* 26, 1962–2006.

Christoffersen, Peter, Kris Jacobs, and Karim Mimouni, 2010, Volatility Dynamics for the S&P500: Evidence from Realized Volatility, Daily Returns, and Option Prices, *Review of Financial Studies* 23, 3141–3189.

Cochrane, John H., and Monika Piazzesi, 2005, Bond Risk Premia, *American Economic Review* 95, 138–160.

Constantinides, George M., Michal Czerwonko, Jens Carsten Jackwerth, and Stylianos Perrakis, 2011, Are Options on Index Futures Profitable for Risk-Averse Investors? Empirical Evidence, *Journal of Finance* 66, 1407–1437.

Constantinides, George M., and Jens Carsten Jackwerth, 2009, Mispricing of S&P 500 Index Options, *Review of Financial Studies* 22, 1247–1277.

Constantinides, George M., Jens Carsten Jackwerth, and Alexi Savov, 2013, The Puzzle of Index Option Returns, *Review of Asset Pricing Studies* 3, 229–257.

Corsi, Fulvio, 2009, A Simple Approximate Long-Memory Model of Realized Volatility, *Journal of Financial Econometrics* 7, 174–196.

Coval, Joshua D., and Tyler Shumway, 2001, Expected Option Returns, *Journal of Finance* 56, 983–1009.

Cremers, Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns, *Journal of Finance* 70, 577–614.

Della Corte, Pasquale, Tarun Ramadorai, and Lucio Sarno, 2016, Volatility Risk Premia and Exchange Rate Predictability, *Journal of Financial Economics* 120, 21–40.

Dennis, Patrick, and Stewart Mayhew, 2002, Risk-Neutral Skewness: Evidence from Stock Options, *Journal of Financial and Quantitative Analysis* 37, 471–493.

Dew-Becker, Ian, Stefano Giglio, Anh Le, and Marius Rodriguez, 2017, The Price of Variance Risk, *Journal of Financial Economics* 123, 225–250.

Drechsler, Itamar, and Amir Yaron, 2011, What's Vol Got to Do with It, *Review of Financial Studies* 24, 1–45.

Driessen, Joost, and Pascal Maenhout, 2007, An Empirical Portfolio Perspective on Option Pricing Anomalies, *Review of Finance* 11, 561–603.

Du, Du, 2011, General Equilibrium Pricing of Options with Habit Formation and Event Risks, *Journal of Financial Economics* 99, 400–426.

Duarte, Jefferson, Christopher Jones, and Junbo Wang, 2019, Very noisy option prices and inferences regarding option returns, *Working Paper* .

Dupire, Bruno, 1994, Pricing with a Smile, *Risk* 7, 1–10.

Egloff, Daniel, Markus Leippold, and Liuren Wu, 2010, The Term Structure of Variance Swap Rates and Optimal Variance Swap Investments, *Journal of Financial and Quantitative Analysis* 45, 1279–1310.

Engle, Robert F., and Jose Gonzalo Rangel, 2008, The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes, *Review of Financial Studies* 21, 1187–1222.

Eraker, Bjørn, 2004, Do Stock Prices And Volatility Jump? Reconciling Evidence From Spot And Option Prices, *Journal of Finance* 59, 1–37.

Eraker, Bjørn, 2012, The Volatility Premium, *Working Paper, University of Wisconsin* .

Eraker, Bjørn, Michael S. Johannes, and Nicholas G. Polson, 2003, The Impact of Jumps in Volatility and Returns, *Journal of Finance* 58, 1269–1300.

Faias, José Afonso, and Pedro Santa-Clara, 2017, Optimal Option Portfolio Strategies: Deepening the Puzzle of Index Option Mispricing, *Journal of Financial and Quantitative Analysis* 52, 277–303.

Fleming, Jeff, Barbara Ostdiek, and Robert E. Whaley, 1995, Predicting Stock Market Volatility: A New Measure, *Journal of Futures Markets* 15, 265–302.

Frazzini, Andrea, and Lasse H. Pedersen, 2012, Embedded Leverage, *Working Paper, New York University* .

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-Based Option Pricing, *Review of Financial Studies* 22, 4259–4299.

Goetzmann, William, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch, 2004, Sharpening Sharpe Ratios, *Working Paper, Yale University* .

Goyal, Amit, and Alessio Saretto, 2009, Cross-Section of Option Returns and Volatility, *Journal of Financial Economics* 94, 310–326.

Han, Bing, 2007, Investor Sentiment and Option Prices, *Review of Financial Studies* 21, 387–414.

Heston, Steven L., 1993, A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options, *Review of Financial Studies* 6, 327–343.

Hu, Guanglian, and Kris Jacobs, 2017, Volatility and Expected Option Returns, *Working Paper, University of Houston* .

Israelov, Roni, and Bryan Kelly, 2017, Forecasting the Distribution of Option Returns, *Working Paper, University of Chicago* .

Jackwerth, Jens Carsten, 2000, Recovering Risk Aversion from Option Prices and Realized Returns, *Review of Financial Studies* 13, 433–451.

Jackwerth, Jens Carsten, and Mark Rubinstein, 1996, Recovering Probability Distributions from Contemporaneous Security Prices, *Journal of Finance* 51, 1611–1631.

Jiang, George J., and Yisong S. Tian, 2005, The Model-Free Implied Volatility and Its Information Content, *Review of Financial Studies* 18, 1305–1342.

Johnson, Travis L., 2017, Risk Premia and the VIX Term Structure, *Journal of Financial and Quantitative Analysis* 52, 2461–2490.

Jones, Christopher S., 2003, The Dynamics of Stochastic Volatility: Evidence from Underlying and Options Markets, *Journal of Econometrics* 116, 181–224.

Jones, Christopher S., 2006, A Nonlinear Factor Analysis of S&P 500 Index Option Returns, *Journal of Finance* 61, 2325–2363.

Lamoureux, Christopher G., and William D. Lastrapes, 1993, Forecasting Stock-Return Variance: Toward an Understanding of Stochastic Implied Volatilities, *Review of Financial Studies* 6, 293–326.

Linn, Matthew, Sophie Shive, and Tyler Shumway, 2018, Pricing Kernel Monotonicity and Conditional Information, *Review of Financial Studies* 31, 493–531.

Liu, Jun, Jun Pan, and Tan Wang, 2005, An Equilibrium Model of Rare-Event Premia and Its Implication for Option Smirks, *Review of Financial Studies* 18, 131–164.

Liu, Lily Y., Andrew J. Patton, and Kevin Sheppard, 2015, Does Anything Beat 5-Minute RV? A Comparison of Realized Measures across Multiple Asset Classes, *Journal of Econometrics* 187, 293–311.

McKeon, Ryan, 2019, Time variation in options expected returns, *Working Paper* .

Merton, Robert C., 1973, Theory of Rational Option Pricing, *Bell Journal of Economics and Management Science* 4, 141–183.

Merton, Robert C., 1976, Option Pricing when Underlying Stock Returns are Discontinuous, *Journal of Financial Economics* 3, 125–144.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium Underdiversification and the Preference for Skewness, *Review of Financial Studies* 20, 1255–1288.

Naik, Vasanttilak, and Moon Lee, 1990, General Equilibrium Pricing of Options on the Market Portfolio with Discontinuous Returns, *Review of Financial Studies* 3, 493–521.

Neuberger, Anthony, 1994, The Log Contract, *Journal of Portfolio Management* 20, 74–80.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–727.

Newey, Whitney K., and Kenneth D. West, 1994, Automatic Lag Selection in Covariance Matrix Estimation, *Review of Economic Studies* 61, 631–653.

Pan, Jun, 2002, The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study, *Journal of Financial Economics* 63, 3–50.

Polkovnichenko, Valery, and Feng Zhao, 2013, Probability Weighting Functions Implied in Options Prices, *Journal of Financial Economics* 107, 580–609.

Rosenberg, Joshua V., and Robert F. Engle, 2002, Empirical pricing kernels, *Journal of Financial Economics* 64, 341–372.

Rubinstein, Mark, 1994, Implied Binomial Trees, *Journal of Finance* 49, 771–818.

Santa-Clara, Pedro, and Alessio Saretto, 2009, Option Strategies: Good Deals and Margin Calls, *Journal of Financial Markets* 12, 391–417.

Seo, Sang Byung, and Jessica A. Wachter, 2017, Option Prices in a Model with Stochastic Disaster Risk, *Working Paper, University of Pennsylvania* .

Todorov, Viktor, 2010, Variance Risk-Premium Dynamics: The Role of Jumps, *Review of Financial Studies* 23, 345–383.

Table 1: Average Monthly Returns of S&P 500 Index Options

			Panel A: Call Option				
K/S	0.96	0.98	1.00	1.02	1.04	1.06	1.08
Ret	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
			Panel B: Put Option				
K/S	0.92	0.94	0.96	0.98	1.00	1.02	1.04
Ret	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
			Panel C: Option Portfolio				
	ATMS	PSP	CNS	CSP			
Ret	-8.47	-18.54	-3.93	13.56			

Notes: This table reports the average monthly returns of S&P 500 call and put options with different moneyness (defined as the strike price over the index: K/S), as well as the average monthly returns of several option portfolios. For option portfolios, we consider an at-the-money straddle (ATMS) that consists of a long position in an ATM call and a long position in an ATM put, a put spread (PSP) that consists of a short position in a 6% OTM put and a long position in an ATM put, a crash neutral spread (CNS) that consists of a long position in an ATM straddle and a short position in a 6% OTM put, and a call spread (CSP) that consists of a long position in an ATM call and a short position in a 6% OTM call. Returns are reported in percent per month. The sample period is March 1998 to August 2015.

Table 2: Parameters

	BS	SV	SVJ	SV+	SVJ+
μ	0.0506	0.0506	0.0506	0.0506	0.0506
r	0.0201	0.0201	0.0201	0.0201	0.0201
d	0.0174	0.0174	0.0174	0.0174	0.0174
σ_{BSM}	0.1905				
κ		6.4130	5.9859	6.4130	5.9859
		(0.923)	(0.909)	(0.923)	(0.909)
θ		0.0363	0.0358	0.0363	0.0358
		(0.004)	(0.004)	(0.004)	(0.004)
σ		0.5472	0.5423	0.5472	0.5423
		(0.033)	(0.035)	(0.033)	(0.035)
ρ		-0.7944	-0.8015	-0.7944	-0.8015
		(0.026)	(0.028)	(0.026)	(0.028)
λ			0.9658		0.9658
			(0.114)		(0.114)
μ_z			-0.0209		-0.0209
			(0.007)		(0.007)
σ_z			0.0677		0.0677
			(0.009)		(0.009)
η		0.0000	0.0000	-4.3470	0.0000
$\lambda^{\mathbb{Q}}$			0.9658		1.4969
$\mu_z^{\mathbb{Q}}$			-0.0209		-0.0667

Notes: This table reports parameter values that we use to compute expected option returns. We first consider three option pricing models with only an equity risk premium: the Black-Scholes-Merton model (BSM), a stochastic volatility model in which volatility risk is not priced (SV), and a stochastic volatility jump model in which neither volatility nor jump risk is priced (SVJ). To study the effect of the volatility and jump risk premiums, we further consider a stochastic volatility model in which volatility risk is priced (SV+) and a stochastic volatility jump model in which jump risk is priced but volatility risk is not (SVJ+). The equity risk premium (μ), risk-free rate (r), and dividend yield (d) are calibrated to match those observed in our sample. For the BSM model, the constant volatility parameter (σ_{BSM}) is equal to the square root of the long-run variance (θ) in the SV model. We use particle filtering to estimate the remaining $\mathbb{P}$-measure parameters and report standard errors of those estimates in the parentheses. The volatility risk premium (η) and $\mathbb{Q}$-measure jump parameters ($\lambda^{\mathbb{Q}}$ and $\mu_z^{\mathbb{Q}}$) are obtained according equations (1) and (2) with a risk aversion of 10. All parameters are reported in annual terms.

Table 3: Expected Option Returns with the Equity Risk Premium Only

Panel A: Call Option								
Moneyness		0.96	0.98	1.00	1.02	1.04	1.06	1.08
Data		6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
	$\mathbb{E}^p$	7.25	8.67	10.30	12.13	14.12	16.27	18.54
BS	Simulation	7.18	8.58	10.19	12.00	14.01	16.18	18.53
	p-value	(0.45)	(0.42)	(0.37)	(0.23)	(0.19)	(0.07)	(0.08)
	$\mathbb{E}^p$	7.51	9.78	13.46	20.06	31.11	43.26	53.63
SV	Simulation	7.52	9.81	13.53	20.22	31.64	44.39	52.50
	p-value	(0.42)	(0.35)	(0.24)	(0.10)	(0.11)	(0.16)	(0.38)
	$\mathbb{E}^p$	7.32	9.45	12.80	18.10	22.14	21.35	19.62
SVJ	Simulation	7.28	9.41	12.78	18.15	22.36	21.61	19.76
	p-value	(0.44)	(0.37)	(0.27)	(0.14)	(0.20)	(0.22)	(0.33)
Panel B: Put Option								
Moneyness		0.92	0.94	0.96	0.98	1.00	1.02	1.04
Data		-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
	$\mathbb{E}^p$	-16.01	-14.07	-12.24	-10.54	-8.99	-7.61	-6.40
BS	Simulation	-15.92	-13.99	-12.19	-10.49	-8.94	-7.56	-6.35
	p-value	(0.10)	(0.05)	(0.04)	(0.06)	(0.06)	(0.12)	(0.12)
	$\mathbb{E}^p$	-11.08	-10.67	-10.20	-9.66	-9.02	-8.20	-7.08
SV	Simulation	-11.34	-10.76	-10.23	-9.67	-9.02	-8.20	-7.09
	p-value	(0.13)	(0.09)	(0.08)	(0.11)	(0.12)	(0.20)	(0.19)
	$\mathbb{E}^p$	-9.65	-9.41	-9.16	-8.85	-8.44	-7.84	-6.88
SVJ	Simulation	-9.53	-9.29	-9.06	-8.76	-8.37	-7.78	-6.83
	p-value	(0.09)	(0.07)	(0.07)	(0.10)	(0.11)	(0.19)	(0.19)
Panel C: Option Portfolio								
Portfolio		ATMS	PSP	CNS	CSP			
Data		-8.47	-18.54	-3.93	13.56			
	$\mathbb{E}^p$	0.71	-8.03	1.97	8.88			
BS	Simulation	0.67	-7.99	1.93	8.77			
	p-value	(0.03)	(0.09)	(0.11)	(0.29)			
	$\mathbb{E}^p$	2.30	-8.56	3.70	12.11			
SV	Simulation	2.33	-8.56	3.73	12.16			
	p-value	(0.02)	(0.16)	(0.05)	(0.44)			
	$\mathbb{E}^p$	2.24	-8.08	3.74	11.59			
SVJ	Simulation	2.27	-8.02	3.74	11.58			
	p-value	(0.03)	(0.14)	(0.06)	(0.41)			

Notes: This table compares realized historical index option returns in Table 1 with expected option returns implied from models with only an equity risk premium. "$\mathbb{E}^p$" represents expected option returns computed analytically using parameters from Table 2. We also simulate 25000 sample paths of the index from which we report the average simulated option returns (denoted by "Simulation") and p-values. The p-values are calculated as the percentile of realized option returns relative to the 25000 simulated options returns. Sample paths are simulated based on the same parameters used for computing expected option returns. Returns are reported in percent per month.

Table 4: The Volatility Risk Premium and Expected Option Returns

			Panel A: Call Option				
K/S	0.96	0.98	1.00	1.02	1.04	1.06	1.08
Data	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
$\mathbb{E}^p$	4.82	5.10	5.14	4.50	1.12	-8.53	-22.54
Simulation	4.90	5.24	5.38	4.94	1.78	-7.99	-21.34
p-value	(0.40)	(0.40)	(0.44)	(0.41)	(0.48)	(0.50)	(0.30)
			Panel B: Put Option				
K/S	0.92	0.94	0.96	0.98	1.00	1.02	1.04
Data	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
$\mathbb{E}^p$	-30.43	-26.69	-22.96	-19.29	-15.74	-12.39	-9.40
Simulation	-30.54	-26.77	-23.03	-19.33	-15.76	-12.42	-9.42
p-value	(0.22)	(0.19)	(0.18)	(0.26)	(0.26)	(0.34)	(0.28)
			Panel C: Option Portfolio				
Portfolio	ATMS	PSP	CNS	CSP			
Data	-8.47	-18.54	-3.93	13.56			
$\mathbb{E}^p$	-5.24	-12.33	-2.52	6.74			
Simulation	-5.13	-12.37	-2.41	6.94			
p-value	(0.24)	(0.25)	(0.36)	(0.20)			

Notes: This table compares realized historical index option returns in Table 1 with expected option returns implied from the SV+ model in which volatility risk is priced. "$\mathbb{E}^p$" represents expected option returns computed analytically using parameters reported in Table 2. We also simulate 25000 sample paths of the index from which we report the average simulated option returns (denoted by "Simulation") and p-values. The p-values are calculated as the percentile of realized option returns relative to the 25000 simulated options returns. Sample paths are simulated based on the same parameters used for computing expected option returns. Returns are reported in percent per month.

Table 5: The Jump Risk Premium and Expected Option Returns

Panel A: Call Option							
K/S	0.96	0.98	1.00	1.02	1.04	1.06	1.08
Data	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
$\mathbb{E}^p$	2.96	2.70	2.32	2.34	7.31	29.39	64.09
Simulation	3.01	2.74	2.35	2.39	7.63	29.65	64.05
p-value	(0.26)	(0.26)	(0.30)	(0.50)	(0.40)	(0.25)	(0.29)
Panel B: Put Option							
K/S	0.92	0.94	0.96	0.98	1.00	1.02	1.04
Data	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
$\mathbb{E}^p$	-41.93	-35.61	-29.10	-22.71	-16.85	-11.95	-8.38
Simulation	-42.22	-35.93	-29.40	-22.98	-17.05	-12.09	-8.46
p-value	(0.32)	(0.31)	(0.29)	(0.35)	(0.30)	(0.33)	(0.24)
Panel C: Option Portfolio							
Portfolio	ATMS	PSP	CNS	CSP			
Data	-8.47	-18.54	-3.93	13.56			
$\mathbb{E}^p$	-7.21	-9.30	-2.45	1.46			
Simulation	-7.30	-9.47	-2.50	1.49			
p-value	(0.41)	(0.16)	(0.38)	(0.04)			

Notes: This table compares realized historical index option returns in Table 1 with expected option returns implied from the SVJ+ model in which jump risk is priced, but volatility risk is not. "$\mathbb{E}^p$" represents expected option returns computed analytically using parameters reported in Table 2. We also simulate 25000 sample paths of the index from which we report the average simulated option returns (denoted by "Simulation") and p-values. The p-values are calculated as the percentile of realized option returns relative to the 25000 simulated options returns. Sample paths are simulated based on the same parameters used for computing expected option returns. Returns are reported in percent per month.

Table 6: The Volatility Risk Premium and Future Option Returns

	Panel A: Call Option		
	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$	$1.04 <= K/S < 1.08$
Intercept	0.11	0.27	1.28
	(1.66)	(1.57)	(1.50)
VRP	-0.06	4.35	24.44
	(-0.04)	(1.70)	(2.11)
Adj. R^2	-0.06%	0.37%	0.99%
	Panel B: Put Option		
	$0.92 <= K/S < 0.96$	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$
Intercept	-0.23	-0.12	-0.09
	(-1.21)	(-0.83)	(-0.72)
VRP	8.37	4.38	2.70
	(2.21)	(1.53)	(1.21)
Adj. R^2	2.04%	0.64%	0.55%
	Panel C: Straddle		
	$0.94 <= K/S < 0.98$	$0.98 <= K/S < 1.02$	$1.02 <= K/S < 1.06$
Intercept	0.08	0.04	-0.04
	(1.91)	(0.83)	(-0.50)
VRP	1.47	2.63	2.39
	(1.84)	(2.83)	(1.76)
Adj. R^2	0.87%	1.59%	1.41%

Notes: This table reports results of the following monthly predictive regression:

$$option\_ret^i_{t,\ t+1} = \alpha^i + \beta^i \mathrm{VRP}_t + \epsilon, \quad i \in \{call, put, straddle\}$$

where *option_ret* is monthly holding-to-maturity returns on call options (Panel A), put options (Panel B), and straddles (Panel C). Each month VRP_t is computed as the difference between realized volatility and the VIX. Realized volatility is constructed based on 5-min log returns on S&P 500 futures over the past 30 calendar days. We run predictive regressions for different moneyness groups as indicated by different columns. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

Table 7: Sensitivity Analysis: Stochastic Volatility Parameters

			Panel A: Call Option				
K/S	0.96	0.98	1	1.02	1.04	1.06	1.08
Baseline	4.82	5.10	5.14	4.50	1.12	-8.53	-22.54
$\kappa+$	4.81	5.08	5.03	4.29	1.07	-6.99	-20.07
$\kappa-$	4.97	5.46	5.94	6.12	1.85	-10.64	-26.04
$\theta+$	4.42	4.49	4.23	3.21	0.03	-7.94	-20.06
$\theta-$	5.27	5.85	6.42	6.67	2.81	-9.64	-25.68
$\sigma+$	4.61	4.85	4.86	4.18	0.01	-11.26	-26.08
$\sigma-$	4.96	5.30	5.43	4.99	2.31	-5.89	-18.75
$\rho+$	5.00	5.39	5.58	5.15	1.94	-7.13	-20.14
$\rho-$	4.70	4.91	4.84	4.07	0.50	-10.01	-25.32
			Panel B: Put Option				
K/S	0.92	0.94	0.96	0.98	1	1.02	1.04
Baseline	-30.43	-26.69	-22.96	-19.29	-15.74	-12.39	-9.40
$\kappa+$	-30.18	-26.43	-22.69	-19.03	-15.51	-12.22	-9.31
$\kappa-$	-31.00	-27.26	-23.52	-19.81	-16.19	-12.72	-9.53
$\theta+$	-29.56	-25.88	-22.25	-18.70	-15.29	-12.11	-9.29
$\theta-$	-31.42	-27.61	-23.79	-20.01	-16.30	-12.76	-9.52
$\sigma+$	-30.88	-27.13	-23.39	-19.69	-16.09	-12.67	-9.56
$\sigma-$	-29.85	-26.13	-22.44	-18.83	-15.36	-12.11	-9.23
$\rho+$	-30.21	-26.50	-22.80	-19.16	-15.64	-12.31	-9.33
$\rho-$	-30.77	-26.98	-23.21	-19.50	-15.90	-12.52	-9.48
			Panel C: Option Portfolio				
	ATMS	PSP	CNS	CSP			
Baseline	-5.24	-12.33	-2.52	6.74			
$\kappa+$	-5.28	-12.12	-2.57	6.57			
$\kappa-$	-5.05	-12.87	-2.39	7.55			
$\theta+$	-5.48	-11.68	-2.66	6.06			
$\theta-$	-4.87	-13.13	-2.27	7.80			
$\sigma+$	-5.55	-12.50	-2.74	6.65			
$\sigma-$	-4.90	-12.10	-2.27	6.90			
$\rho+$	-4.96	-12.37	-2.32	7.08			
$\rho-$	-5.47	-12.38	-2.69	6.50			

Notes: This table reports expected option returns for the SV+ model by increasing (+) and decreasing (–) each stochastic volatility parameter by one standard deviation. Expected option returns based on our baseline parameterization are also included for comparison. Returns are in percent per month.

Table 8: Sensitivity Analysis: Risk Aversion

Panel A: Call Option							
$\gamma \backslash K/S$	0.96	0.98	1.00	1.02	1.04	1.06	1.08
0	7.51	9.78	13.46	20.06	31.11	43.26	53.63
2	6.99	8.86	11.76	16.66	24.06	30.17	32.46
4	6.55	8.08	10.36	14.03	18.66	19.58	15.45
6	5.98	7.09	8.60	10.75	12.36	8.94	0.35
8	5.49	6.24	7.11	8.00	7.06	-0.14	-12.30
10	4.82	5.10	5.14	4.50	1.12	-8.53	-22.54
12	4.25	4.15	3.54	1.75	-3.73	-15.87	-31.44
14	3.80	3.38	2.18	-0.72	-8.24	-22.77	-39.74
16	3.01	2.14	0.22	-3.85	-12.88	-28.33	-45.40
18	2.40	1.15	-1.40	-6.53	-17.08	-33.73	-51.12
20	1.87	0.25	-2.90	-9.04	-21.06	-38.81	-56.33
Panel B: Put Option							
$\gamma \backslash K/S$	0.92	0.94	0.96	0.98	1.00	1.02	1.04
0	-11.08	-10.67	-10.20	-9.66	-9.02	-8.20	-7.08
2	-15.34	-14.12	-12.88	-11.63	-10.35	-9.00	-7.52
4	-19.58	-17.61	-15.66	-13.73	-11.83	-9.93	-8.02
6	-23.37	-20.74	-18.15	-15.60	-13.12	-10.72	-8.45
8	-27.16	-23.93	-20.73	-17.58	-14.52	-11.62	-8.94
10	-30.43	-26.69	-22.96	-19.29	-15.74	-12.39	-9.40
12	-33.77	-29.55	-25.32	-21.14	-17.09	-13.28	-9.90
14	-37.16	-32.49	-27.78	-23.09	-18.51	-14.20	-10.42
16	-39.85	-34.85	-29.77	-24.69	-19.73	-15.05	-10.97
18	-42.71	-37.39	-31.94	-26.45	-21.05	-15.96	-11.52
20	-45.56	-39.94	-34.14	-28.24	-22.41	-16.88	-12.06
Panel C: Option Portfolio							
$\gamma \backslash$ Portfolio	ATMS	PSP	CNS	CSP			
0	2.30	-8.56	3.70	12.11			
2	0.78	-9.30	2.45	10.97			
4	-0.66	-10.22	1.25	10.14			
6	-2.19	-10.91	0.00	8.97			
8	-3.64	-11.76	-1.21	8.05			
10	-5.24	-12.33	-2.52	6.74			
12	-6.71	-13.09	-3.74	5.78			
14	-8.10	-14.01	-4.92	4.96			
16	-9.70	-14.53	-6.22	3.80			
18	-11.17	-15.27	-7.46	2.84			
20	-12.60	-16.10	-8.66	1.95			

Notes: This table reports expected option returns for the SV+ model using different values of risk aversion (γ) ranging from 0 to 20. The remaining parameters are based on Table 2. Returns are in percent per month.

Table 9: Robustness: Alternative Measures of the Volatility Risk Premium

	Panel A: Call Option		
	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$	$1.04 <= K/S < 1.08$
Intercept	0.10	0.22	1.04
	(1.67)	(1.40)	(1.39)
VRP	-0.37	3.32	20.56
	(-0.31)	(1.41)	(2.05)
Adj. R^2	-0.04%	0.20%	0.73%
	Panel B: Put Option		
	$0.92 <= K/S < 0.96$	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$
Intercept	-0.28	-0.15	-0.11
	(-1.65)	(-1.13)	(-0.98)
VRP	8.03	4.14	2.50
	(2.27)	(1.49)	(1.15)
Adj. R^2	1.98%	0.60%	0.49%
	Panel C: Straddle		
	$0.94 <= K/S < 0.98$	$0.98 <= K/S < 1.02$	$1.02 <= K/S < 1.06$
Intercept	0.07	0.02	-0.07
	(1.68)	(0.38)	(-0.89)
VRP	1.16	2.27	2.02
	(1.52)	(2.48)	(1.52)
Adj. R^2	0.56%	1.24%	1.01%

Notes: This table reports results of the following monthly predictive regression:

$$option\_ret^i_{t,\,t+1} = \alpha^i + \beta^i \text{VRP}_t + \epsilon, \quad i \in \{call, put, straddle\}$$

where *option_ret* is monthly holding-to-maturity returns on call options (Panel A), put options (Panel B), and straddles (Panel C). Each month VRP_t is computed as the difference between expected future realized volatility and the VIX. Expected future realized volatility is estimated using the Heterogeneous Autoregressive Model (the HAR model) of Corsi (2009). We run predictive regressions for different moneyness groups as indicated by different columns. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

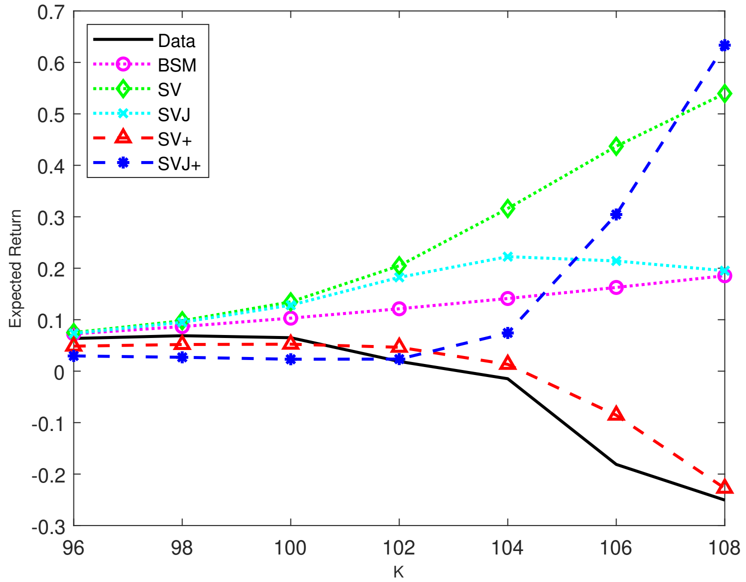
Table 10: Robustness: Controlling for Other Variables

	OTM Call			OTM Put			ATM Straddle		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.05	1.48	0.02	1.13	-0.82	0.31	0.09	0.05	0.11
	(-0.08)	(1.44)	(0.03)	(1.83)	(-5.06)	(0.55)	(0.44)	(0.70)	(0.55)
VRP	24.82	25.31	24.98	7.99	5.71	5.98	2.62	2.67	2.69
	(2.09)	(2.09)	(2.10)	(2.19)	(1.99)	(2.01)	(2.85)	(3.14)	(3.13)
JUMP	18.50		18.12	-18.47		-13.68	-0.63		-0.77
	(1.32)		(1.27)	(-2.89)		(-2.26)	(-0.25)		(-0.31)
RV		-1.02	-0.21		3.16	2.51		-0.04	-0.08
		(-0.53)	(-0.10)		(2.82)	(2.31)		(-0.12)	(-0.22)
Adj. R^2	0.99%	0.93%	0.92%	3.27%	3.48%	4.07%	1.55%	1.53%	1.49%

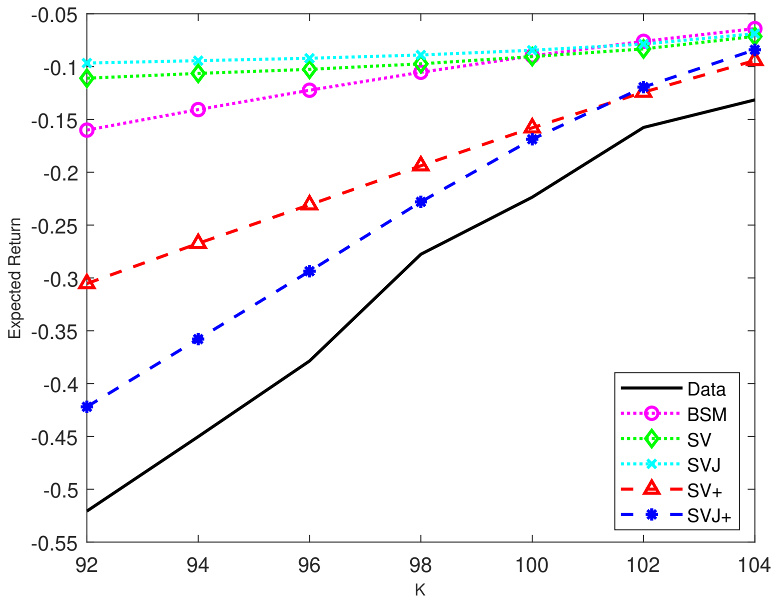
Notes: This table reports the relationship between the volatility risk premium and future returns on OTM calls ($1.04 <= K/S < 1.08$), OTM puts ($0.92 <= K/S < 0.96$) and ATM straddles ($0.98 <= K/S < 1.02$) while controlling for the level of volatility (RV) and the jump risk premium (JUMP). RV is constructed based on 5-min log returns on S&P 500 futures over past 30 calendar days. VRP is computed as the difference between RV and the VIX. JUMP is computed as the difference between the average implied volatility from OTM put options and that from ATM put options. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

Figure 1: Moneyness and Expected Option Returns

Panel A: Expected Call Option Returns



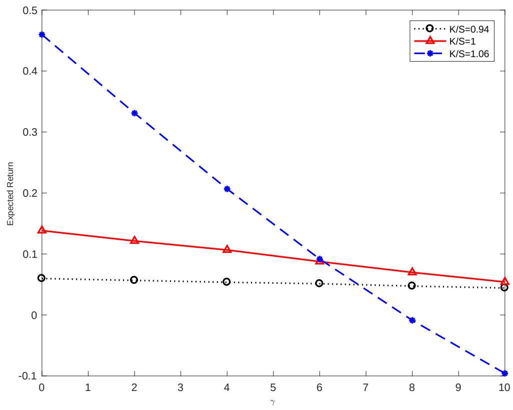
Panel B: Expected Put Option Returns



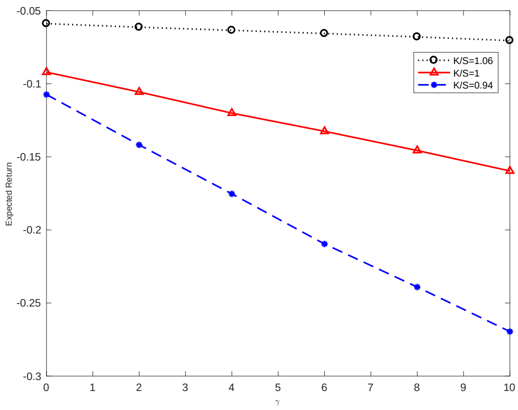
Notes: This figure plots expected option returns as a function of the strike price for three option pricing models with only an equity risk premium (BSM, SV, and SVJ), the SV+ model in which volatility risk is priced, and the SVJ+ model in which jump risk is priced, but volatility risk is not. Panel A is for call options and Panel B for put options. Expected option returns are computed analytically based on parameters reported in Table 2. The realized average option returns are also included (Data).

Figure 2: The Volatility Risk Premium and Expected Option Returns

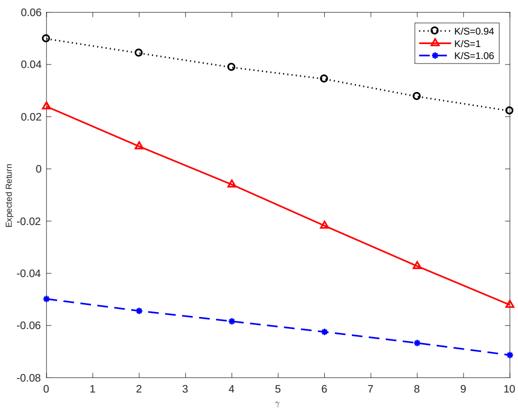
Panel A: Expected Call Option Returns



Panel B: Expected Put Option Returns



Panel C: Expected Straddle Returns



Notes: This figure plots expected option returns against risk aversion coefficient (γ) in the SV+ model: Panel A for calls, Panel B for puts, and Panel C for straddles. A higher γ corresponds to a more negative volatility risk premium. The remaining parameters required for computing expected returns are based on Table 2.

Online Appendix

Table A1: Summary Statistics: S&P 500 Index Options

Panel A: Call Option					
K/S	[0.90-0.94]	(0.94-0.98]	(0.98-1.02]	(1.02-1.06]	(1.06-1.10]
Implied volatility	0.270	0.222	0.190	0.167	0.168
Volume	257	313	2363	3072	2185
Open interest	10444	13511	18349	17667	15797
Delta	0.878	0.764	0.505	0.189	0.057
Theta	-132	-163	-174	-105	-45
Gamma	0.002	0.004	0.007	0.005	0.002
Vega	63	103	134	82	32
Panel B: Put Option					
K/S	[0.90-0.94]	(0.94-0.98]	(0.98-1.02]	(1.02-1.06]	(1.06-1.10]
Implied volatility	0.261	0.223	0.190	0.175	0.220
Volume	3928	3016	2899	422	381
Open interest	22351	22259	16610	9569	12190
Delta	-0.106	-0.225	-0.484	-0.768	-0.886
Theta	-112	-153	-165	-116	-94
Gamma	0.002	0.004	0.007	0.005	0.003
Vega	59	100	134	98	53

Notes: This table reports summary statistics of S&P 500 index options. Panel A and Panel B report, by moneyness, averages of implied volatility, volume, open interest as well as option Greeks for S&P 500 call and put options, respectively. The statistics are first averaged across options in each moneyness group and then averaged across time. Volatilities are stated in annual terms. The sample period is March 1998 to August 2015.

Table A2: The Jump Risk Premium and Future Option Returns

	Panel A: Call Option		
	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$	$1.04 <= K/S < 1.08$
Intercept	-0.06	0.23	-0.38
	(-0.29)	(0.68)	(-0.76)
JUMP	2.19	-1.96	9.55
	(0.75)	(-0.45)	(0.93)
Adj. R^2	0.04%	-0.04%	-0.05%
	Panel B: Put Option		
	$0.92 <= K/S < 0.96$	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$
Intercept	0.90	0.61	0.14
	(1.64)	(1.17)	(0.41)
JUMP	-19.26	-11.76	-4.53
	(-2.94)	(-1.77)	(-0.99)
Adj. R^2	1.45%	0.62%	0.16%
	Panel C: Straddle		
	$0.94 <= K/S < 0.98$	$0.98 <= K/S < 1.02$	$1.02 <= K/S < 1.06$
Intercept	-0.06	0.05	0.04
	(-0.40)	(0.27)	(0.16)
VRP	1.14	-1.42	-2.77
	(0.60)	(-0.58)	(-0.81)
Adj. R^2	-0.01%	0.01%	0.09%

Notes: This table reports results of the following monthly predictive regression:

$$option\_ret^{i}_{t,\ t+1} = \alpha^i + \beta^i \text{JUMP}_t + \epsilon, \quad i \in \{call, put, straddle\}$$

where *option_ret* is monthly holding-to-maturity returns on call options (Panel A), put options (Panel B), and straddles (Panel C). Each month JUMP_t is computed as the difference between the average implied volatility from OTM put options and that from ATM put options. We run predictive regressions for different moneyness groups as indicated by different columns. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

Table A3: Variance-Dependent Pricing Kernel and Expected Option Returns

Panel A: Call Option							
$\gamma\backslash K/S$	0.96	0.98	1	1.02	1.04	1.06	1.08
0	5.69	6.59	7.72	9.12	9.45	4.58	-5.38
2	5.11	5.60	6.01	6.08	3.95	-4.12	-16.75
4	4.57	4.68	4.42	3.23	-1.09	-11.84	-26.63
6	4.11	3.90	3.04	0.76	-5.68	-19.05	-35.54
8	3.47	2.84	1.30	-2.18	-10.39	-25.32	-42.44
10	2.95	1.98	-0.16	-4.71	-14.71	-31.32	-49.06
12	2.34	0.98	-1.79	-7.38	-18.86	-36.51	-54.26
14	1.49	-0.31	-3.75	-10.28	-22.70	-40.52	-57.83
16	0.85	-1.32	-5.35	-12.81	-26.36	-44.80	-61.92
18	0.29	-2.23	-6.83	-15.20	-29.89	-48.90	-65.78
20	-0.50	-3.42	-8.59	-17.73	-33.06	-52.10	-68.51
Panel B: Put Option							
$\gamma\backslash K/S$	0.92	0.94	0.96	0.98	1	1.02	1.04
0	-24.90	-22.01	-19.16	-16.36	-13.64	-11.05	-8.64
2	-28.44	-24.99	-21.57	-18.21	-14.96	-11.89	-9.11
4	-31.91	-27.95	-24.00	-20.10	-16.33	-12.78	-9.62
6	-35.38	-30.95	-26.49	-22.06	-17.76	-13.70	-10.13
8	-38.38	-33.56	-28.68	-23.80	-19.05	-14.57	-10.65
10	-41.45	-36.27	-30.97	-25.65	-20.42	-15.48	-11.17
12	-44.24	-38.75	-33.10	-27.38	-21.73	-16.37	-11.72
14	-46.56	-40.85	-34.94	-28.92	-22.95	-17.28	-12.34
16	-49.10	-43.16	-36.96	-30.60	-24.26	-18.21	-12.93
18	-51.64	-45.50	-39.02	-32.33	-25.59	-19.13	-13.50
20	-53.76	-47.48	-40.81	-33.87	-26.86	-20.09	-14.16
Panel C: Option Portfolio							
$\gamma\backslash$ Portfolio	ATMS	PSP	CNS	CSP			
0	-2.90	-11.15	-0.58	8.36			
2	-4.41	-11.87	-1.83	7.27			
4	-5.89	-12.66	-3.06	6.29			
6	-7.29	-13.57	-4.25	5.47			
8	-8.81	-14.24	-5.50	4.40			
10	-10.23	-15.09	-6.70	3.52			
12	-11.70	-15.82	-7.93	2.56			
14	-13.29	-16.32	-9.23	1.51			
16	-14.75	-17.05	-10.46	0.59			
18	-16.16	-17.88	-11.65	-0.28			
20	-17.68	-18.48	-12.92	-1.21			

Notes: This table reports expected option returns using different values of risk aversion (γ) ranging from 0 to 20. The volatility risk premium is computed based on the variance-dependent pricing kernel of Christoffersen, Heston, and Jacobs (2013). The remaining parameters are based on Table 2. Returns are in percent per month.

Table A4: Sensitivity Analysis: Jump Parameters

Panel A: Call Option							
K/S	0.96	0.98	1	1.02	1.04	1.06	1.08
Baseline	2.96	2.70	2.32	2.34	7.31	29.39	64.09
$\lambda+$	2.50	2.01	1.29	0.78	4.60	24.34	57.93
$\lambda-$	3.45	3.44	3.45	4.06	9.83	31.84	66.93
μ_z+	3.71	3.84	4.12	5.45	13.83	40.22	77.91
μ_z-	2.12	1.43	0.36	-0.87	1.38	20.10	52.98
σ_z+	1.08	0.05	-1.40	-2.81	1.84	28.69	70.76
σ_z-	4.42	4.79	5.33	6.67	12.73	32.07	61.89
Panel B: Put Option							
K/S	0.92	0.94	0.96	0.98	1	1.02	1.04
Baseline	-41.93	-35.61	-29.10	-22.71	-16.85	-11.95	-8.38
$\lambda+$	-42.73	-36.39	-29.84	-23.36	-17.37	-12.29	-8.53
$\lambda-$	-40.67	-34.36	-27.94	-21.75	-16.16	-11.57	-8.24
μ_z+	-39.63	-33.44	-27.17	-21.11	-15.66	-11.19	-7.97
μ_z-	-44.87	-38.40	-31.62	-24.81	-18.40	-12.92	-8.86
σ_z+	-49.35	-42.36	-34.88	-27.21	-19.88	-13.55	-8.96
σ_z-	-35.36	-30.02	-24.63	-19.46	-14.78	-10.91	-8.01
Panel C: Option Portfolio							
	ATMS	PSP	CNS	CSP			
Baseline	-7.21	-9.30	-2.45	1.46			
$\lambda+$	-7.99	-9.30	-3.02	0.55			
$\lambda-$	-6.30	-9.21	-1.79	2.51			
μ_z+	-5.72	-9.08	-1.37	2.70			
μ_z-	-8.97	-9.67	-3.70	0.03			
σ_z+	-10.59	-9.01	-4.43	-2.21			
σ_z-	-4.67	-9.66	-0.99	4.41			

Notes: This table reports expected option returns for the SVJ+ model by increasing (+) and decreasing (–) each $\mathbb{P}$-measure jump parameter by one standard deviation. Expected option returns based on our baseline parameterization are also included for comparison. Returns are in percent per month.

Table A5: Sensitivity Analysis: Jump Risk Premium

Panel A: Call Option							
$\gamma\backslash K/S$	0.96	0.98	1	1.02	1.04	1.06	1.08
0	7.32	9.45	12.80	18.10	22.14	21.35	19.62
2	6.90	8.82	11.89	17.12	23.64	27.79	31.35
4	6.29	7.85	10.39	15.04	22.94	32.59	43.22
6	5.47	6.56	8.33	11.82	20.06	35.25	54.13
8	4.37	4.85	5.65	7.56	14.77	34.00	60.78
10	2.96	2.70	2.32	2.34	7.31	29.39	64.09
12	1.14	-0.03	-1.77	-3.92	-2.31	18.92	60.66
14	-1.32	-3.68	-7.18	-11.93	-13.73	6.81	53.06
16	-4.34	-7.97	-13.22	-20.32	-26.33	-14.43	31.02
18	-8.12	-13.20	-20.29	-29.61	-38.64	-35.29	1.54
20	-12.88	-19.58	-28.58	-39.84	-50.99	-55.13	-34.67
Panel B: Put Option							
$\gamma\backslash K/S$	0.92	0.94	0.96	0.98	1	1.02	1.04
0	-9.65	-9.41	-9.16	-8.85	-8.44	-7.84	-6.88
2	-15.30	-13.59	-12.03	-10.65	-9.41	-8.25	-7.00
4	-21.59	-18.44	-15.51	-12.89	-10.66	-8.79	-7.15
6	-28.30	-23.84	-19.56	-15.65	-12.28	-9.55	-7.42
8	-34.79	-29.33	-23.90	-18.76	-14.22	-10.51	-7.76
10	-41.93	-35.61	-29.10	-22.71	-16.85	-11.95	-8.38
12	-48.66	-41.82	-34.53	-27.10	-19.99	-13.81	-9.22
14	-57.34	-50.10	-42.06	-33.45	-24.74	-16.75	-10.61
16	-63.55	-56.38	-48.17	-39.06	-29.42	-20.08	-12.46
18	-69.35	-62.56	-54.55	-45.30	-35.03	-24.43	-15.11
20	-75.42	-69.16	-61.55	-52.43	-41.82	-30.19	-19.08
Panel C: Option Portfolio							
$\gamma\backslash$ Portfolio	ATMS	PSP	CNS	CSP			
0	2.24	-8.08	3.74	11.59			
2	1.30	-8.21	3.20	10.46			
4	-0.07	-8.37	2.34	8.84			
6	-1.91	-8.59	1.15	6.82			
8	-4.23	-8.82	-0.40	4.36			
10	-7.21	-9.30	-2.45	1.46			
12	-10.83	-9.88	-5.02	-1.96			
14	-15.92	-11.24	-8.77	-6.48			
16	-21.28	-12.53	-12.95	-11.12			
18	-27.63	-14.62	-18.23	-16.31			
20	-35.17	-17.89	-24.87	-22.01			

Notes: This table reports expected option returns for the SVJ+ model using different values of risk aversion (γ) ranging from 0 to 20. The remaining parameters are based on Table 2. Returns are in percent per month.

Table A6: Robustness: Additional Control Variables

	OTM Call			OTM Put			ATM Straddle		
	1	2	3	1	2	3	1	2	3
Intercept	-0.28	0.18	0.50	1.21	0.60	0.51	0.05	0.16	0.16
	(-0.71)	(0.49)	(1.04)	(2.65)	(1.68)	(1.62)	(0.96)	(1.41)	(2.02)
VRP	23.17	23.01	22.92	9.63	9.60	9.96	2.61	2.77	2.89
	(2.14)	(2.17)	(2.14)	(2.75)	(2.59)	(2.72)	(2.81)	(2.94)	(3.14)
$Beta_S$	0.02			0.04			0.00		
	(1.72)			(4.70)			(-1.82)		
$Beta_V$		0.03			-0.05			-0.01	
		(1.42)			(-4.28)			(-1.31)	
$Beta_J$			0.00			-0.00			-0.00
			(1.55)			(-4.80)			(-2.34)
Adj. R^2	1.40%	1.32%	1.27%	7.07%	4.75%	6.38%	1.93%	1.86%	2.58%

Notes: This table examines the relationship between the volatility risk premium (VRP) and future option returns controlling for option betas. $Beta_S$ is computed as index price times delta (O_S) divided by option price: $\frac{SO_S}{O}$. $Beta_V$ is computed as vega (O_V) divided by option price: $\frac{O_V}{O}$. $Beta_J$ is computed as the squared index price times gamma (O_{SS}) divided by option price: $\frac{S^2O_{SS}}{O}$. Option Greeks are based on BSM Greeks provided by OptionMetrics. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

Table A7: Robustness: Holding-Period Option Returns

	Panel A: Call Option		
	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$	$1.04 <= K/S < 1.08$
Intercept	0.04	0.11	0.39
	(0.94)	(1.28)	(1.57)
VRP	0.69	2.86	7.85
	(1.01)	(2.26)	(2.41)
Adj. R^2	0.10%	0.51%	0.80%
	Panel B: Put Option		
	$0.92 <= K/S < 0.96$	$0.96 <= K/S < 1.00$	$1.00 <= K/S < 1.04$
Intercept	-0.21	-0.11	-0.06
	(-2.80)	(-1.84)	(-1.19)
VRP	3.33	2.05	1.18
	(2.33)	(1.91)	(1.31)
Adj. R^2	0.83%	0.36%	0.23%
	Panel C: Straddle		
	$0.94 <= K/S < 0.98$	$0.98 <= K/S < 1.02$	$1.02 <= K/S < 1.06$
Intercept	0.00	-0.01	-0.02
	(0.08)	(-0.21)	(-0.45)
VRP	0.80	1.38	1.40
	(1.77)	(2.76)	(1.73)
Adj. R^2	0.69%	1.63%	1.49%

Notes: This table reports results of the following monthly predictive regression:

$$option\_ret^i_{t,\ t+15} = \alpha^i + \beta^i \mathrm{VRP}_t + \epsilon, \quad i \in \{call, put, straddle\}$$

where *option_ret* is 15-day holding period returns on call options (Panel A), put options (Panel B), and straddles (Panel C). When option liquidation dates land on a holiday (e.g., the New Year and the Fourth of July), we use the option price information the day before and we assume options trade at the mid-point of bid-ask quotes. Each month VRP_t is computed as the difference between realized volatility and the VIX. Realized volatility is constructed based on 5-min log returns on S&P 500 futures over past 30 calendar days. We run predictive regressions for different moneyness groups as indicated by different columns. Newey-West t-statistics with 4 lags are reported in the parentheses. The sample period is March 1998 to August 2015.

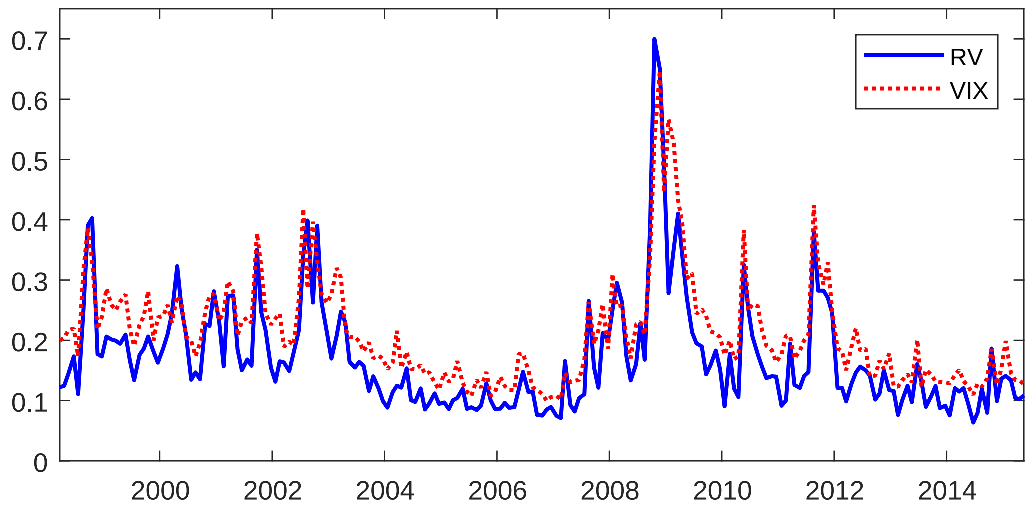
Table A8: Descriptive Statistics of Option Trading Strategies

	Mean	STD	SR	SKEW	Holding-Period
Panel A: Index					
	Mean	STD	SR	SKEW	Holding-Period
S&P 500	0.004	0.045	0.082	-0.639	210
Panel B: 4% OTM Call					
	Mean	STD	SR	SKEW	Holding-Period
Always	-0.015	3.672	-0.004	6.803	209
VRP<0	-0.157	3.272	-0.048	8.146	187
Panel C: 6% OTM Call					
	Mean	STD	SR	SKEW	Holding-Period
Always	-0.181	6.179	-0.029	12.695	206
VRP<0	-0.581	1.873	-0.310	5.605	184
Panel D: 4% OTM Put					
	Mean	STD	SR	SKEW	Holding-Period
Always	-0.379	2.164	-0.175	4.250	207
VRP<0	-0.470	1.973	-0.238	4.792	185
Panel E: 6% OTM Put					
	Mean	STD	SR	SKEW	Holding-Period
Always	-0.450	2.468	-0.182	5.219	206
VRP<0	-0.575	2.216	-0.259	6.221	185
Panel F: ATM Straddle					
	Mean	STD	SR	SKEW	Holding-Period
Always	-0.085	0.739	-0.115	1.430	209
VRP<0	-0.106	0.704	-0.151	1.462	188

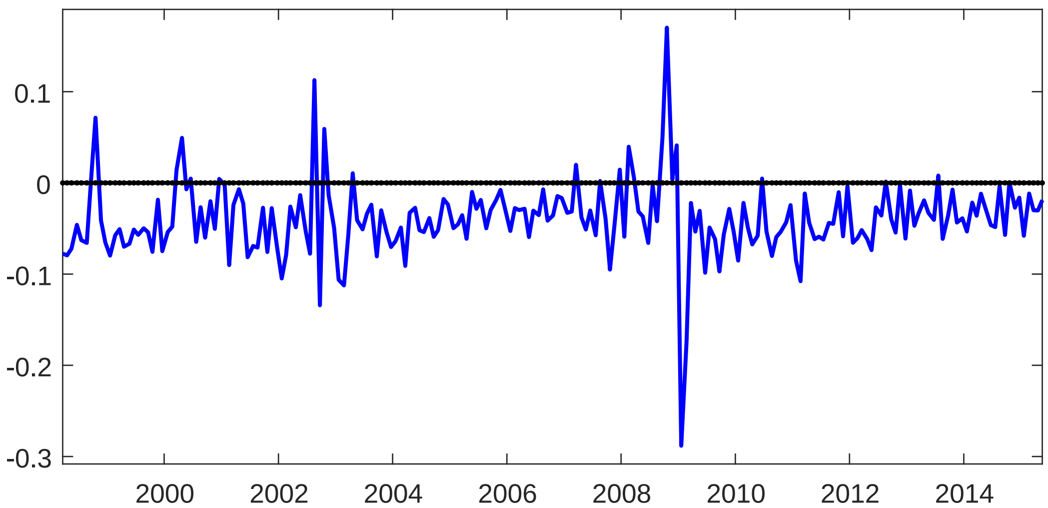
Notes: This table reports mean (Mean), standard deviation (STD), Sharpe ratio (SR) and skewness (SKEW) of returns of several trading strategies. Panel A reports on the S&P 500. Panels B to F report the performance of writing a 4% OTM call, a 6% OTM call, a 4% OTM put, a 6% OTM put, and an ATM straddle. We consider two option selling strategies: "Always" and "VRP <0". "Always" shorts index options in every month. "VRP <0" shorts index options only in months when the observed market volatility risk premium is negative. We report returns to the long side. The sample period is March 1998 to August 2015.

Figure A1: Realized Volatility, the VIX, and the Volatility Risk Premium

Panel A: Realized Volatility and the VIX



Panel B: Volatility Risk Premium



Notes: This figure plots the time series of monthly realized volatility (RV), the VIX (Panel A), and their difference which is the volatility risk premium (Panel B). The sample period is March 1998 to August 2015.