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

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Abstract

In the data, out-of-the-money (OTM) S&P 500 call and put options both have large negative average returns, and these results are at odds with standard asset pricing theory. We show that these negative OTM option returns are primarily due to the pricing of market volatility risk. With a negative volatility risk premium, expected option returns implied from a stochastic volatility model are consistent with average call and put option returns across all strikes. The volatility risk premium also predicts future option returns. The index option return predictability is statistically and economically significant and is not due to the underlying index return predictability afforded by the volatility risk premium. 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; option return predictability

1 Introduction

One of the most enduring puzzles of 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 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 suggests several explanations for these large negative OTM option returns. For example, Broadie, Chernov, and Johannes (2009) conclude that the presence of a jump risk premium or estimation risk is consistent with historical put option returns. Bakshi, Madan, and Panayotov (2010) relate negative OTM call option returns to a U-shaped pricing kernel that arises in a model featuring short-selling and heterogeneity in investors' belief about return outcomes. Polkovnichenko and Zhao (2013) consider a rank-dependent utility model with a particular probability weighting function to explain the data. Baele et al. (2018) show that a model with Cumulative Prospect Theory preferences is able to generate the otherwise puzzling low returns on OTM options. Negative OTM option returns 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 makes them particularly attractive for investors who have skewness preferences or face leverage constraints. The demand pressure will drive up prices and

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

consequently lead to low returns in equilibrium (Gârleanu, Pedersen, and Poteshman, 2009).

This paper argues that the low returns on OTM index options are primarily due to the pricing of market volatility risk. Options are volatility-sensitive assets, and therefore their expected returns will critically depend on investor's attitudes towards volatility risk. We find that with a negative volatility risk premium, expected option returns implied from a stochastic volatility model match the average returns of call and put options across all strikes as well as the average returns of all the option portfolios that we consider. In particular, consistent with the data, not only does the pricing of volatility risk imply a steep relationship between expected put option returns and the strike price with OTM put options earning large negative rate of returns, it also implies a non-monotonic relation between expected call option returns and the strike price with OTM call options earning large negative expected returns. These results are robust to different parameterizations of the stochastic volatility process and also hold in the presence of a variance-dependent pricing kernel of Christoffersen, Heston, and Jacobs (2013).

Further corroborating the volatility risk premium hypothesis, we document that the volatility risk premium positively predicts future index option returns with OTM options and ATM straddles exhibit the strongest return predictability. Both the sign and patterns of index option return predictability are in line with the impact of the volatility risk premium on expected option returns in a stochastic volatility model. The index option return predictability is not due to the underlying return predictability by the volatility risk premium (Bollerslev, Tauchen, and Zhou, 2009). It is robust to different empirical implementations as well as to controlling for other predictors. We also show that the index option return predictability is economically significant and can be translated into large economic gains. We propose an option selling strategy that exploits option return predictability. The new strategy significantly outperforms a benchmark strategy that writes index options every month.

Lastly, we study the relationship between the pricing of price jump risk and expected option returns. We consider a stochastic volatility jump model (SVJ) that incorporates a compensation for price jump risk, reflecting investors' crash fear. Consistent with Broadie, Chernov, and Johannes (2009), we find that when jump risk is priced, the SVJ model yields large negative expected returns on OTM put options with magnitudes very close to the data. While the jump risk premium fits put option returns extremely well, it fails to match the average returns of OTM calls. In particular, the presence of a jump risk premium would imply an increasing relation between expected call option returns and the strike price with OTM calls earning large positive expected returns, which is contrary to the data. Our results about the jump risk premium are robust to different parameterizations. On the empirical side, we find that the jump risk premium significantly predicts future returns on OTM put options, but it does not predict call option and straddle returns.

Taken together, the evidence leads us to conclude that the negative average OTM index option returns 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] Overall our results suggest that the pricing of volatility risk has a first-order effect on the cross-section of index option returns. The rest of the paper is organized as follows. Section 2 discusses related literature. Section 3 investigates relative roles of the volatility and jump risk premiums in fitting historical S&P 500 option returns. Section 4 studies the index option return predictability. Section 5 contains robustness results, and Section 6 concludes the paper.

2 Related Literature

The bulk of 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 are consistently higher than their ATM counterparts following 1987 market crash (Rubinstein, 1994).

[2] OTM call options are priced with a significant premium during crisis periods. For example, buying 1-month 5% OTM call in February 2009 and holding it to maturity generates a return of -54%, despite the fact that the S&P 500 actually went up by 6.2% over the month. By contrast, a similar episode during normal times would be associated with a large positive return. For example, the rate of return for a same 5% OTM call is 841% from October 2004 to November 2004 during which the S&P 500 index went up by 6.3%. This premium reflects investors' concerns about both tails (variance), not just the crash risk.

This stylized fact is often referred to as the implied volatility skew or volatility smirk, and it contradicts the prediction of the BSM model that implied volatility is constant across strikes.[3] 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 the 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).[4] Our paper differs from this literature in that we model *option returns* rather than *option prices*. Our analysis suggests that the pricing of volatility risk has a first-order effect on the cross-section of index option returns.

Our paper is closely related to the expanding literature that investigates index option returns. Previous studies usually focus on put options and they find surprisingly low returns for OTM index put options (e.g., Bondarenko, 2014; Jackwerth, 2000). Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014) formally compare historical put option returns to option pricing models, and their results suggest that index put options are likely embedded with a jump risk premium.[5] We extend their analysis to include call options. Understanding index call option returns is important for two reasons. First, Bakshi, Madan, and Panayotov (2010) document that average returns of OTM index call options are negative and decreasing with the strike price. Their findings about call options are puzzling because under general economic conditions, Coval and Shumway (2001) show

[3]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.

[4]Another strand of literature addresses the implied volatility skew relying on 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), or investor sentiment (Han, 2007).

[5]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.

that expected call option returns should be positive and increase with the strike price. Therefore any theory that tries to explain why OTM put options have large negative returns should also explain the puzzling returns patterns observed on OTM call options. 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 we will show in the next section, the volatility and jump risk premiums have drastically different predictions on expected OTM call option returns. Consistent with Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014), we find that expected put option returns computed with the jump risk premium are consistent with the observed data. However, the jump risk premium would also imply that expected OTM call option returns are positive and increasing with the strike price, which is contrary to the data. In contrast, we show that expected option returns computed with the volatility risk premium match the low OTM call and put option returns simultaneously. Related, several papers use factor-based approaches to gain a better understanding of index option returns. Examples include Jones (2006), Cao and Huang (2007), and Constantinides, Jackwerth, and Savov (2013). Israelov and Kelly (2017) propose a method for constructing conditional distribution for index option returns. Driessen and Maenhout (2007) and Faias and Santa-Clara (2017) study index option returns from portfolio allocation perspective. Santa-Clara and Saretto (2009) investigate the impact of margin requirements on option trading strategies.

There is a large body of literature on the pricing of volatility and jump risks in the financial markets. The pricing of aggregate volatility and jump risks has been studied extensively in the cross-section of stock returns.[6] See, among others, Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008) and Cremers, Halling, and Weinbaum (2015). Our paper is more related to studies that focus on the pricing of aggregate volatility and jump risks in the equity index options

[6]A number of studies examine the volatility risk premium based on variance swaps. See, among others, Egloff, 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).

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 quantify the impact of the volatility risk premiums on the cross-section of *unhedged* index option returns. We also document that the volatility risk premium predicts future option returns and characterize the effect of the jump risk premium on expected option returns.

We also contribute to the growing literature on the variance risk premium (e.g., Bollerslev, Tauchen, and Zhou, 2009; Carr and Wu, 2009; Drechsler and Yaron, 2011; Eraker, 2012). Existing studies find that the volatility risk premium is a strong predictor of short term U.S. stock index returns (e.g., Bollerslev et al., 2009), and the predictability is also seen in the international data (Bollerslev et al., 2014). This is in contrast to many traditional predictors (e.g., dividend yield) which often operate over long horizons. 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 expands the existing evidence on the predictive power of the volatility risk premium by documenting a significant time-series index return predictability by the volatility risk premium in the S&P 500 index options market. These results are new in the literature. It is important to note that the index option return predictability cannot be attributed to the underlying stock return predictability by the volatility risk premium. Instead, we show the option return predictability is likely due to the time-varying volatility risk premiums embedded in index options.

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

In this section, we begin by reviewing historical returns of S&P 500 index options across a wide range of strikes as well as returns of a number of option portfolios. We then compare these average returns in the data to expected option returns implied by option pricing models. We investigate whether index option returns are consistent with the pricing of volatility risk, or the pricing of price jump risk or both.

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.[7] In particular, on the first trading day after 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 2015, the option expiration day is the third Friday of a month.[8] We also apply standard filters to option data and relegate details to Appendix A. Table A1 in the Online Appendix reports the summary statistics of our sample. As can be seen from Table A1, OTM options account for the majority of

[7]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.

[8]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.

the trading volume of 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, 0.92 to 1.04 for puts with an increment of 2%.[9] 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). As pointed out by Broadie, Chernov, and Johannes (2009), returns on option portfolios are more informative than individual option returns and therefore they provide more powerful tests. 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 index call options. Call options are claims on the upside, which will be critical for differentiating the volatility risk premium from the jump risk premium.

Table 1 reports average monthly returns for the cross-section of index options with different strikes as well as option portfolios. Panel A of Table 1 shows that average returns of OTM index call options are negative and declining with the strike price. For example, the average returns from

[9] The bid-ask spreads in the option market are usually large, and monthly holding-to-maturity option returns mitigate this problem because they only incur the trading cost at initiation. Holding-to-maturity returns are also easy to analyze analytically and avoid a number of theoretical and statistical issues associated with high frequency option returns (Broadie et al., 2009).

buying a 4% OTM call and a 6% OTM call are -1.47% and -18.12% per month, respectively. Our results confirm the findings of Bakshi, Madan, and Panayotov (2010) which study 1%, 3% and 5% OTM S&P 500 call options from 1988 to 2007.

Panel B of Table 1 presents another stylized fact in the equity index option market that put options, especially OTM put options, have very large negative returns. For example, over our sample period, buying a 6% OTM put option would lose about 45% per month on average. These estimates are largely consistent with the existing literature.

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 call and the short position in 6% OTM call generate positive returns as shown in Panel A.

Conducting statistical inference on option returns reported in Table 1 is in general difficult because option returns are highly non-normal. For example, Figure 1 and 2 plot the time series of OTM index call and put option returns. As can be seen from these figures, option returns are often associated with extreme observations, which makes the standard CAPM-type of linear models inappropriate. Broadie, Chernov, and Johannes (2009) propose to evaluate average option returns relative to what would have been obtained in an option pricing model. Their methodology not only automatically takes into account the leverage and kinked payoffs of options, but also anchors hypothesis tests at appropriate null values. Following Broadie, Chernov, and Johannes (2009), we compare historical option returns with those generated by various option pricing models. We are particularly interested in understanding to what extent these negative OTM index option returns are due to the pricing of stochastic volatility risk, or the pricing of price jump risk or both.

3.2 Analytical Framework

To assess the relative roles of the volatility and jump risk premiums in explaining the cross section of index option returns, we consider a standard affine jump diffusion framework with mean-reverting stochastic volatility and Poisson-driven 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:

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

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 the SVJ 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).

Broadie, Chernov, and Johannes (2009) point out that expected option returns can be computed analytically within the above framework. Their insight is particularly useful as it allows one to quantitatively analyze the impact of different risk premiums. To better understand relative effects of the volatility and jump risk premiums on expected option returns, we will focus on three versions of the SVJ model: a benchmark BSM model in which neither volatility nor jump risk is priced (BSM), the Heston stochastic volatility model with a volatility risk premium (SV), and finally a SVJ model in which only jump risk is priced, but stochastic volatility risk is not (SVJ).

Computing model-implied expected option returns requires the knowledge of parameter values of each model. Our approach to infer model parameters is very similar to Broadie, Chernov, and Johannes (2009). In particular, we calibrate the equity risk premium, the risk-free rate and the dividend yield based on those realized over our sample period. The remaining $\mathbb{P}$-measure parameters are estimated from the time-series of index returns.[10] Our estimation is based on particle filtering and Appendix B describes the details. In the robustness analysis, we show our results are robust to different parameterizations of stochastic volatility and jumps.

Moreover, we obtain estimates of the volatility and jump risk premiums by observing that in a standard power utility environment (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:

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

[10] As argued by Broadie, Chernov, and Johannes (2009), while one can estimate these parameters using option data, 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.

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 Broadie, Chernov, and Johannes (2009) and assume a risk aversion of 10. We also perform an extensive sensitivity analysis with respect to risk aversion and those results are contained in Section 5.1.

Table 2 reports (annualized) parameter values that we use to compute expected option returns for different models. 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 SV model, 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: volatility process under the risk neutral measure remains mean-reverting ($\kappa + \eta > 0$). For the SVJ model, we set the volatility risk premium to zero ($\eta = 0$) so that we can focus exclusively on the jump risk premium. 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 ($\lambda = 0.9685$) with a mean jump size of -2.09% ($\mu_z = -0.0209$) under $\mathbb{P}$ probability measure.

Based on parameter values reported in Table 2, we compute expected option returns implied from the BSM, SV and SVJ models and compare them to realized average option returns in the data. Following Broadie, Chernov, and Johannes (2009), we also simulate each model to form a finite-sample distribution of average option returns, which allows one to test whether realized option returns are significant relative to a model. Specifically, we simulate 25000 sample paths of the index, with each sample path having 210 months (the sample length of our data). For each sample path, we compute time series average option returns. The p-values are then calculated as the percentile of realized option returns relative to the 25000 simulated options returns. If the percentile is higher than 0.5, we report the p-value as 1 minus the percentile.

3.3 Results

Table 3 contains results for the BSM model. Expected option returns computed analytically are labeled by "Model". We also report the average simulated option returns, denoted by "Simulation". Not surprisingly, those two are very close to each other. Historical option returns taken from Table 1 are denoted by "Data". Table 3 shows that the BSM model cannot account for the empirical option return patterns. First, confirming the results of Chambers, Foy, Liebner, and Lu (2014), we find that the BSM model is rejected by OTM put option returns and ATM straddle returns. For example, according to the BSM model, an ATM straddle should earn 0.71 percent per month. In the data, the monthly average return for ATM straddles is -8.47 percent with a p-value of 0.03. The p-value of 0.03 means that only 3% of the 25000 simulated average straddle returns are less than the -8.47 percent realized return in the data. Furthermore, we find that the BSM model is also unable to explain OTM call option returns. In particular, the model predicts that expected call option return is an increasing function of the strike price with OTM call options earning large positive return, which is contrary to the data.[11] The difference between the BSM model implied returns and the data is statistically significant for 6% and 8% OTM calls as indicated by p-values.

Table 4 shows that the stochastic volatility model is able to quantitatively match average returns

[11] In the BSM model, a call option is effectively a levered position in the underlying asset. Moreover, the embedded leverage is an increasing function of the strike price. Because the underlying asset (i.e., the index) typically has a positive expected return that is higher than the risk-free rate, the expected call option return should be greater than the expected return of the underlying, and it is increasing with the strike price.

of call and put options across all strikes as well as average returns of all option portfolios. In particular, consistent with the data, the model implies that expected returns of OTM call options are negative and decreasing with the strike price. The expected monthly return decreases monotonically from 1.89 percent for ATM calls to -25.05 percent for 8% OTM calls. This property of the stochastic volatility model sharply contrasts with the Black-Scholes-Merton model where the expected call option return is monotonically increasing function of the strike price. In regards to put options, the stochastic volatility model predicts more negative expected returns on OTM put options relative to the BSM model, which again is consistent with the data. The p-values suggest that realized average option returns are not significantly different from those generated by the stochastic volatility model. Finally, Panel C shows that the SV model is also consistent with returns on all option portfolio that we consider. The fact that a simple stochastic volatility model describes average option returns remarkably well is somewhat surprising given it is a clearly misspecified model for option prices.[12] As discussed in Section 2, there is an extensive literature that demonstrates several factors are required to fit the rich dynamics of option prices. Our results somewhat echo the findings of Cochrane and Piazzesi (2005) in 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.

Table 5 contains results for the SVJ model. Confirming the findings of Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014), Panel B shows that the presence of a jump risk premium is consistent with observed put option returns; the SVJ model predicts very large negative expected returns on OTM put options. While the jump risk premium matches put returns almost perfectly, it fails to explain the large negative average returns of OTM calls. For example, Panel A shows that the SVJ model actually predicts an increasing relation between expected call option returns and the strike price with OTM call options earning large positive returns, which is

[12] 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 homoskedasticity, which is 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).

contrary to the data. It is important to note that this result about the SVJ model is not due to our parameterization. We also use SVJ parameters reported in Broadie, Chernov, and Johannes (2009) and Chambers et al. (2014) and find very similar results. Also see Section 5.1 for additional discussion. Interestingly, despite the return difference between the data and the model is quite large for OTM call options, the p-values actually indicate that the SVJ model is not rejected. The reason is that OTM call option returns have very large standard deviations, which makes them less informative as compared to portfolio returns. Portfolio-based evidence in Panel C indeed shows that the SVJ model is rejected by call spreads. The monthly average return of call spreads is 13.56 percent, much higher than the model-implied return which is only 1.46 percent. The difference is statistically significant with a p-value of 0.04.

To summarize our findings, we plot expected option returns computed in Tables 3 to 5 against the strike price in Figure 3: Panel A for call options and Panel B for put options. Panel A shows that the volatility and jump risk premiums have drastically different predictions on OTM call options. The SVJ model implies that expected returns of OTM call options are positive and increasing with the strike price, which is qualitatively similar to the BSM model. In contrast, the SV model predicts a decreasing relationship between expected returns and the strike price with OTM calls earning large negative returns. Panel B shows that the three models yield similar predictions on put options in that expected put returns should be negative. The SVJ model yields the most negative estimates, followed by the SV model.

3.4 Discussion

The above section shows that when volatility risk is priced, a stochastic volatility model is able to match the average returns of both OTM call and put options. On the other hand, when the jump risk is priced, a SVJ model is able to match the average returns of OTM put options. It is important to note that the presence of the volatility and jump risk premiums is critical for the SV and SVJ models to fit the data. In unreported results, we find that when volatility and jump risks are not priced, expected option returns implied from the SV and SVJ models are similar to those in the BSM model, and both models will be rejected.

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 call and put options, 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 because it also introduces a wedge between risk neutral and physical variance. For OTM put options, both effects will lead to a higher valuation and this is the reason why the SVJ model yields most negative OTM put option returns. On the other hand, for OTM call options, the skewness effect tends to dominate and therefore a presence of the jump risk premium will result in higher expected returns for OTM call options.[13]

We also analyze how expected option returns vary with respect to changes in the volatility risk premium in the SV model. Based on the same parameter values reported in Table 2, we plot in Figure 4 expected returns on call options, put options and straddles in the SV model against risk aversion γ for different moneyness. A higher γ means a larger volatility risk premium (more negative). Figure 4 reveals several interesting results. First, as γ increases (meaning 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 valuable. However, the magnitude of the effect of the volatility risk premium on expected returns crucially depends on the moneyness of an option. In particular, the relation

[13]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. See Branger, Hansis, and Schlag (2010) for a related discussion.

between the volatility risk premium and the expected option return is much stronger for OTM call and put options with the steepest slope. As options move towards the in-the-money direction, expected returns become less sensitive to the volatility risk premium and the slope flattens out. 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. In Section 4, we show these theoretical results are consistent with our findings on index option return predictability.

Figure 4 also helps understand why the volatility risk premium fits option return data 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, a negative volatility risk premium 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 OTM call option returns and the strike price.

4 Predicting Index Option Returns

In this section, we investigate whether the volatility and jump risk premiums can forecast future index option returns. If options were embedded with time-varying volatility and jump risk premiums, then one might observe some predictability of option returns by these risk premiums. Indeed, we find that the volatility risk premium predicts subsequent index option returns. The index option return predictability is both statistically and economically significant, and is not due to the underlying return predictability afforded by the volatility risk premium. We also find that the jump risk premium predicts future OTM put option returns.

4.1 Predicting Option Returns: the Volatility Risk Premium

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:

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

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:

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

where realized volatility is computed as the square-root of the sum of squared 5-min log returns on S&P 500 futures over the past 30 days.[14] The VIX index is published by the Chicago Board Options Exchange (CBOE), and it tracks 30-day risk neutral expectation of future realized volatility inferred from option prices.[15] In the robustness analysis, we show that our empirical results are not sensitive to how we measure the volatility risk premium. For example, instead of using realized volatility, we also estimate expected volatility and find similar results. Figure 5 plots realized volatility, the VIX and the volatility risk premium throughout our sample period. Consistent with findings in Todorov (2010) and Carr and Wu (2009), Figure 5 shows that the volatility risk premium, like volatility

[14] The use of intra-day data is motivated by the realized volatility literature which 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) argue 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-minute interval.

[15] The CBOE developed the first-ever volatility index in 1993, which then was based on the average implied volatilities of at-the-money options on S&P 100. In 2003, the CBOE started publishing a new index that is calculated using S&P 500 index option prices in a model-free approach. We uses 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).

itself, fluctuates substantially over time.

To investigate whether the volatility risk premium predicts future index option returns, we run 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 returns from holding call options, put options and straddles from month t to month $t+1$. The analysis in Section 3.4 shows that options with different moneyness have different sensitivities with respect to the volatility risk premium and therefore we run predictive 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 because 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 $1.02 <= K/S < 1.06$.

Panel A of Table 6 reports predictive regression results for call options. The volatility risk premium significantly predicts future returns with a positive and statistically significant coefficient for call options that are between 4% and 8% OTM. 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).[16] Interestingly, the forecasting power of the volatility risk premium, in terms of the slope estimates, statistical significance and R^2, decreases monotonically as call options move towards the in-the-money direction.

Panel B shows that the volatility risk premium also positively predicts future index put option returns. Similar to calls, return predictability however becomes increasingly weak as put options move towards the in-the-money direction, judging by the predictive coefficient, statistical signifi-

[16]Results with OLS standard errors are stronger. To be conservative, we report only Newey-West t-stats.

cance as well as R^2. Specifically, among put options that are between 4% OTM and 8% OTM, the volatility risk premium significantly predicts subsequent returns, with a Newey-West t-statistic of 2.21 and an adjusted R^2 of 2.04%. The predictability, however, becomes insignificant for other groups.

Panel C shows that straddle has its own distinct pattern. In particular, the volatility risk premium exhibits the most significant forecasting power over at-the-money straddles. As straddles move away from the money, the predictive power of the volatility risk premium drops substantially and is only marginally significant.

To sum up, we document that the volatility risk premium positively forecasts future option returns. Moreover, this index option return predictability exhibits an interesting dependence on the moneyness, with OTM options and ATM straddles having the strongest predictability.

4.2 The Economic Significance of Index Option Return Predictability

To assess the economic significance of the index option return predictability that we document above, this section proposes 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, the simplest 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 7 reports the results. First, by comparing the benchmark strategy "Always" to the S&P 500 index, it appears that writing index options is more profitable than investing in the S&P 500. For example, over our sample period, average returns and Sharpe ratios from selling put options and straddles are higher than those obtained with the S&P 500. Selling OTM call options is also more profitable than just buying the index, but it has very large standard deviation which actually makes the Sharpe ratio lower than the S&P 500.

More importantly, Table 7 shows that our new strategy outperforms the benchmark strategy. Taking ATM straddles as an example, following the new 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 sells options less often. The last column of Table 7 indicates the number of months in which options are shorted. We also report skewness of different trading strategies. Despite 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 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 long investment horizon.

Table 7 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 collects mainly 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.

4.3 Option Return Predictability and Index Return Predictability

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 option return predictability 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 all in the same direction: 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 on the predictive coefficients for calls and puts because the expected stock return has differential impacts on call and put returns. In particular, the expected call (put) option return increases (decreases) with the expected stock return.

On the other hand, both the sign of predictive coefficients and the predictability patterns are consistent with the impact of the volatility risk premium on expected option returns in a stochastic volatility model. Section 3.4 shows that as the volatility risk premium becomes more negative, expected option returns decrease, which is consistent with a positive predictive coefficient. Furthermore, as also discussed in Section 3.4, OTM options and ATM straddles are most sensitive to changes in the volatility risk premium. These predictions are in line with our empirical findings that OTM options and ATM straddles exhibit strongest return predictability. This suggests that the economic source of option return predictability is likely due to the time varying volatility risk premium embedded in index options.

4.4 Predicting Option Returns: the Jump Risk Premium

We also investigate whether the jump risk premium can predict future option returns. Dennis and Mayhew (2002) and Bakshi and Kapadia (2003) establish the links between risk neutral skewness and the slope of the implied volatility curve, and therefore we use the difference in average implied volatilities 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 reports predictability regression results with the jump risk premium. Panel A indicates that the jump risk premium does not contain predictive information on 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 negatively forecasts future OTM put option returns, with a highly significant Newey-West t-statistic of -2.94 and an adjusted R^2 of 1.45%. The predictability, however, becomes insignificant for other moneyness groups. Lastly, Panel C shows that the jump risk premium does not predict straddle returns.

Overall, we conclude that the jump risk premium significantly predicts future OTM put option returns, but it does not seem to be a significant predictor for other options.

5 Robustness

This section includes several robustness checks. We study how different parameterizations might affect expected option returns in the SV and SVJ models. We also investigates the robustness of option return predictability results 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 call and put options 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 expected returns. In this section, we assess how these results might be affected by different parameterizations with respect to both physical measure parameters and risk aversion parameter. We first discuss the volatility risk premium and subsequently the jump risk premium.

Table 8 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 particularly 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 small: decreasing or increasing it by one standard deviation produces very similar expected returns.

Table 9 reports expected option returns in the SV model with different values of risk aversion ranging from 0 to 20. For $\mathbb{P}$-measure parameters, we use our baseline estimates reported in Table 2. Table 9 shows that risk aversion 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), return patterns in the SV model are actually similar to the BSM model: both expected call and put option returns increase with the strike price. In this case, confirming the results in Chambers et al. (2014), we find the SV model is rejected. As risk aversion increases, namely the volatility risk premium becomes more negative, expected option returns decrease. Notice that in order for the SV model to match the data quantitatively, the value of risk aversion should be around 8-12.

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.[17] With this particular

[17]Many papers find that the pricing kernel is not a monotonically decreasing function of index return. See, among others, Aït-Sahalia and Lo (1998), Jackwerth (2000), Rosenberg and Engle (2002) and Chaudhuri and Schroder (2015). On the other hand, Linn, Shive, and Shumway (2018) point out potential biases in the existing estimates

pricing kernel, Christoffersen, Heston, and Jacobs (2013) show that the volatility risk premium is given by:

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

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. We assume $\xi = 10$. Table 10 repeats the same exercise in Table 9 using the above new specification of the volatility risk premium. With the variance-dependent pricing kernel, expected option returns are lower than those in Table 9 because the volatility risk premium now has an extra component resulting from variance preferences ξ. Also notice that the variance-dependent pricing kernel implies that the risk aversion value needed for the SV model to fit option returns is small.

Tables A3 and A4 in the Online Appendix report the corresponding results for the SVJ model. Tables A3 investigates if our results about the jump risk premium are sensitive to our characterization of jump process under the physical measure by increasing or decreasing each of the jump parameters by one standard deviation. We only focus on jump-related parameters since 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 implies very large negative expected returns for OTM put options which is consistent with the data. However, it also implies that expected OTM call option returns are positive and increasing with the strike price, which is inconsistent with the data.

Table A4 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 that price jumps occur more frequently and more severely under the risk neutral measure. Overall Table A4 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,

of the pricing kernel. After properly accounting for the conditioning information, they show the pricing kernel is monotonically decreasing with index returns.

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 for the SVJ model to yield negative expected returns on OTM calls. However, a very large risk aversion also implies that ATM and ITM calls should earn negative expected returns which is inconsistent 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 use realized volatility as a proxy for the expected future volatility under the physical measure. 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 logarithmic of realized volatilities with linear models. The log specification also ensures that we will always obtain positive volatility forecasts. 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.

Table 11 contains results of predictive regressions based on this new measure of the volatility risk premium. Consistent with our benchmark results, the volatility risk premium positively predicts futures option returns, with OTM calls, OTM puts and ATM straddles exhibiting the strongest return predictability. We also estimate the volatility risk premium simply as the difference between 30-day historical volatility based on daily returns and the average option implied volatility and find very similar results.

5.3 Controlling for Other Predictors

So far we have only focused on univariate predictive regression. In this section, we evaluate the performance of the volatility risk premium in predicting future option returns controlling for other factors including the jump risk premium and the level of volatility. Given return predictability is concentrated among OTM options and ATM straddles, we will focus on these options only.

The results of multivariate predictive regressions are summarized in Table 12. Specification (1) considers both the volatility risk premium and the jump risk premium as predictors. After including the jump risk premium as a control, we find the predictive power of the volatility risk premium remains statistically significant. We also find that the volatility risk premium does not subsume the jump risk premium. While the jump risk premium does not predict returns on calls and straddles, it remains a significant predictor over future OTM put option return. This suggests that both the volatility and jump risk premiums are important for OTM put options.

Specification (2) of Table 12 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 has some forecasting power over future option returns. Specifically, volatility negatively predicts future straddle and call option returns and positively predicts future put option returns, but the predictability is not always statistically significant. These results are broadly consistent with the analysis in Hu and Jacobs (2017).

Finally, specification (3) includes all three variables into the predictive regression. Including both volatility and the jump risk premium as controls does not affect the predictive power of the volatility risk premium. The volatility risk premium remains significant in forecasting future option returns. Finally, we also find that the predictive power of the volatility risk premium is robust to controlling for option betas (e.g., loadings on price, volatility and jump risks), and these results are summarized in Table A5.

5.4 Holding-Period Option Returns

In the main analysis, we study the predictive relation between the volatility risk premium and holding-to-maturity index option returns. Table A6 examines if our empirical findings persist to other holding periods. In particular, instead of holding options to maturity, we consider a holding period of 15 calendar days. 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. Overall, we find similar results when using the volatility risk premium to predict holding-period option returns.

6 Conclusion

Both out-of-the-money S&P 500 index call and put options are associated with large negative average returns. This paper investigates how these negative returns are related to the pricing of stochastic volatility and jump risks. We show that the low returns on OTM option are primarily due to the pricing of market volatility risk. A stochastic volatility model in which volatility risk is negatively priced is able to match average returns of call and put options across all strikes as well as returns of a number of option portfolios. Further corroborating the volatility risk premium hypothesis, we document a statistically and economically significant index option return predictability by the volatility risk premium. 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, our analysis suggests 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.[18] Second, we have focused on the volatility risk premium and extensions to investigating the impact of higher moment (e.g., skewness and kurtosis) risk premiums on expected option returns would be useful. Third, we consider the predictability of 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.

[18]Existing studies find that at least 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, the SVJ model becomes:

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

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

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. Here 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 needs to be taken into account. Then, new particles are simulated according to 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 $i = 1 : N$:

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

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 based on resampled particles and shocks for 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.

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

Panel A: Call Option							
K/S	0.96	0.98	1	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	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 average monthly returns of S&P 500 call and put options for different moneyness (defined as the strike price over the index: K/S), as well as average monthly returns of several option portfolios. For option portfolios, we consider an at-the-money straddle (ATMS), 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

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

Notes: This table reports parameter values that we use to compute expected option returns for different models. 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. For the SV and SVJ models, 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 based on equations (1) and (2) with a risk aversion of 10. All parameters are reported in annual terms.

Table 3: Expected Option Returns: the Black-Scholes-Merton Model

Panel A: Call Option							
K/S	0.96	0.98	1	1.02	1.04	1.06	1.08
Data	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
Model	7.25	8.67	10.30	12.13	14.12	16.27	18.54
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
Panel B: Put Option							
K/S	0.92	0.94	0.96	0.98	1	1.02	1.04
Data	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
Model	-16.01	-14.07	-12.24	-10.54	-8.99	-7.61	-6.40
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
Panel C: Option Portfolio							
Portfolio	ATMS	PSP	CNS	CSP			
Data	-8.47	-18.54	-3.93	13.56			
Model	0.71	-8.03	1.97	8.88			
Simulation	0.67	-7.99	1.93	8.77			
p-value	0.03	0.09	0.11	0.29			

Notes: This table compares average option returns in the data reported in Table 1 with expected option returns implied from the Black-Scholes-Merton model (BSM). "Model" represents expected option returns computed analytically using BSM 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 percentage of the 25000 simulated option returns that is less than realized option returns. Sample paths are simulated based on the same parameters used for computing expected option returns.

Table 4: The Volatility Risk Premium and Expected Option Returns

Panel A: Call Option							
K/S	0.96	0.98	1	1.02	1.04	1.06	1.08
Data	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
Model	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	1.02	1.04
Data	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
Model	-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			
Model	-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 average option returns in the data reported in Table 1 with expected option returns implied from the Heston stochastic volatility model (SV) in which volatility risk is priced. "Model" represents expected option returns computed analytically using SV 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 percentage of the 25000 simulated option returns that is less than realized option returns. Sample paths are simulated based on the same parameters used for computing expected option returns.

Table 5: The Jump Risk Premium and Expected Option Returns

Panel A: Call Option							
K/S	0.96	0.98	1	1.02	1.04	1.06	1.08
Data	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
Model	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	1.02	1.04
Data	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
Model	-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			
Model	-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 average option returns in the data reported in Table 1 with expected option returns implied from the SVJ model in which only jump risk is priced, but volatility risk is not. "Model" represents expected option returns computed analytically using SVJ 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 percentage of the 25000 simulated option returns that is less than realized option returns. Sample paths are simulated based on the same parameters used for computing expected option returns..

Table 6: Predicting Option Returns: 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	0.11	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 option return predictability 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). The predictor 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 7: Descriptive Statistics of Option Trading Strategies

			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, 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. Returns are reported from the perspective of a long investor. The sample period is March 1998 to August 2015.

Table 8: Robustness: 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 $\mathbb{P}$-measure 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 9: The Impact of Risk Aversion: A Sensitivity Analysis

Panel A: Call Option							
$\gamma\backslash K/S$	0.96	0.98	1	1.02	1.04	1.06	1.08
0	7.49	9.74	13.36	19.77	30.47	42.42	52.86
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	1.02	1.04
0	-11.04	-10.62	-10.15	-9.61	-8.96	-8.15	-7.06
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	2.27	-8.51	3.68	11.99			
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 10: The Impact of Risk Aversion: A Variance-Dependent Pricing Kernel

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 for the SV model 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 11: 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 option return predictability 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). The predictor 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.

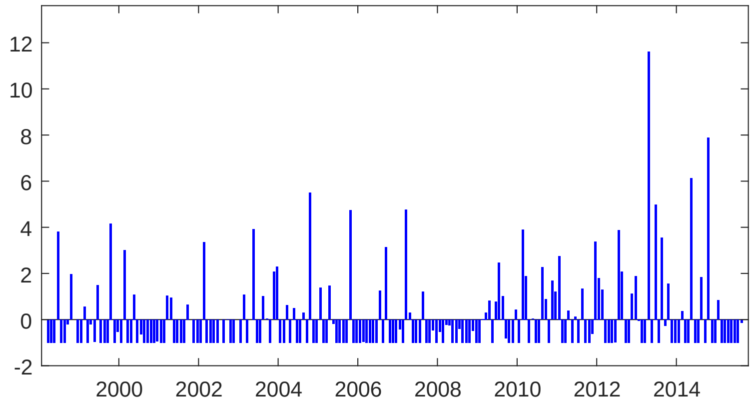
Table 12: Robustness: Controlling for Other Predictors

	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%

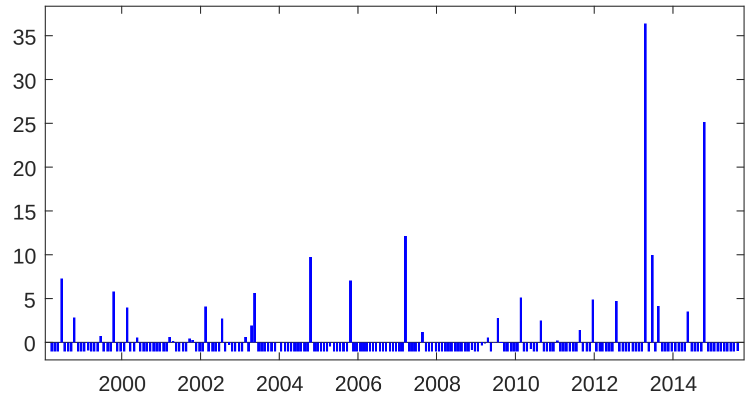
Notes: This table reports results of multivariate predictive regressions. We use realized volatility (RV), the volatility risk premium (VRP) and the jump risk premium (JUMP) to predict future returns on OTM calls ($1.04 <= K/S < 1.08$), OTM puts ($0.92 <= K/S < 0.96$) and ATM straddles ($0.98 <= K/S < 1.02$). 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: The Time Series of OTM Call Option Returns

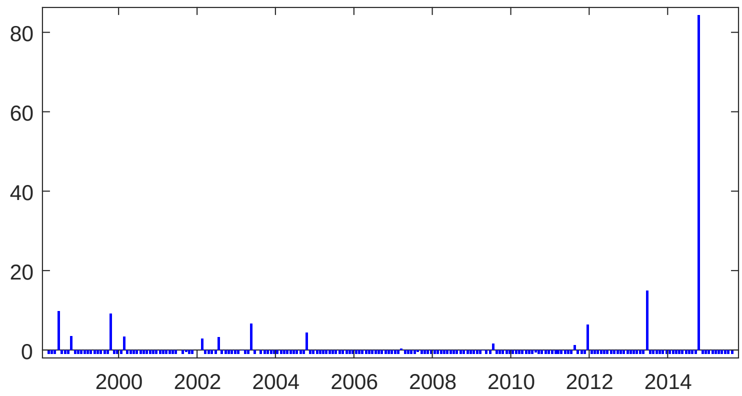
Panel A: 2% OTM Call



Panel B: 4% OTM Call



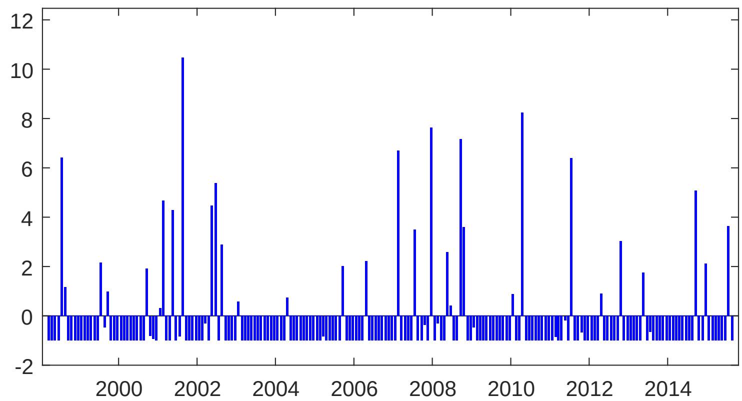
Panel C: 6% OTM Call



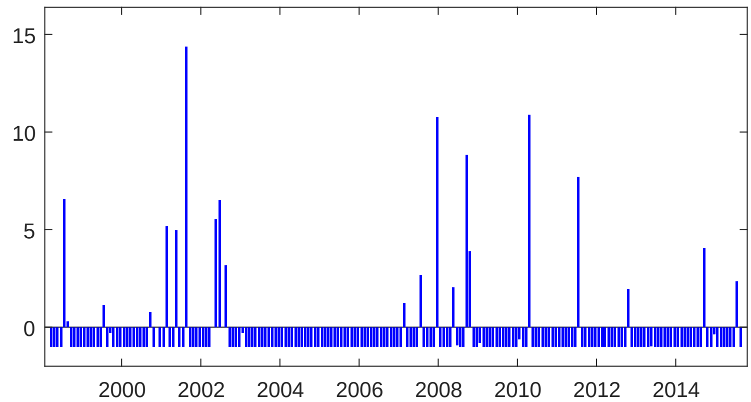
Notes: This figure plots the time series of monthly holding-to-maturity returns of 2% OTM call (Panel A), 4% OTM call (Panel B) and 6% OTM call (Panel C).

Figure 2: The Time Series of OTM Put Option Returns

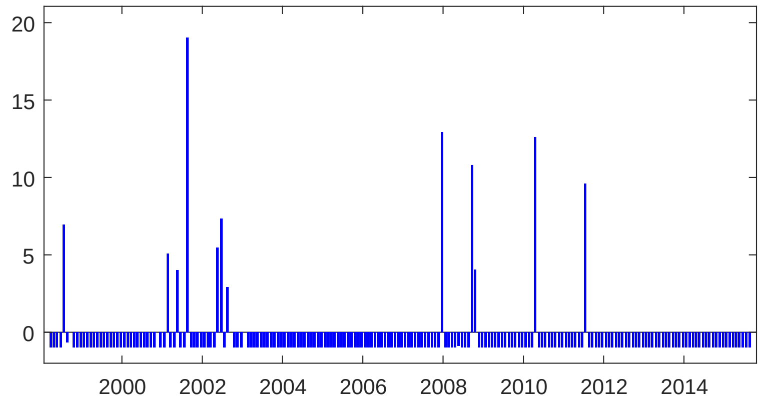
Panel A: 2% OTM Put



Panel B: 4% OTM Put



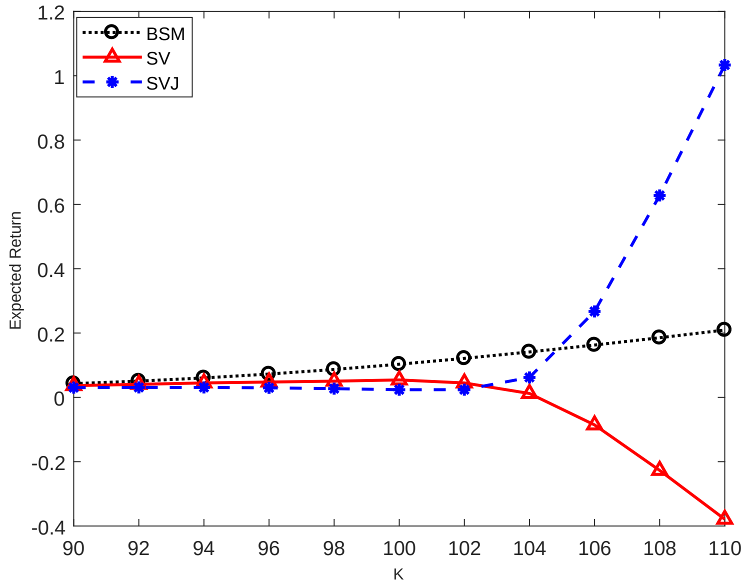
Panel C: 6% OTM Put



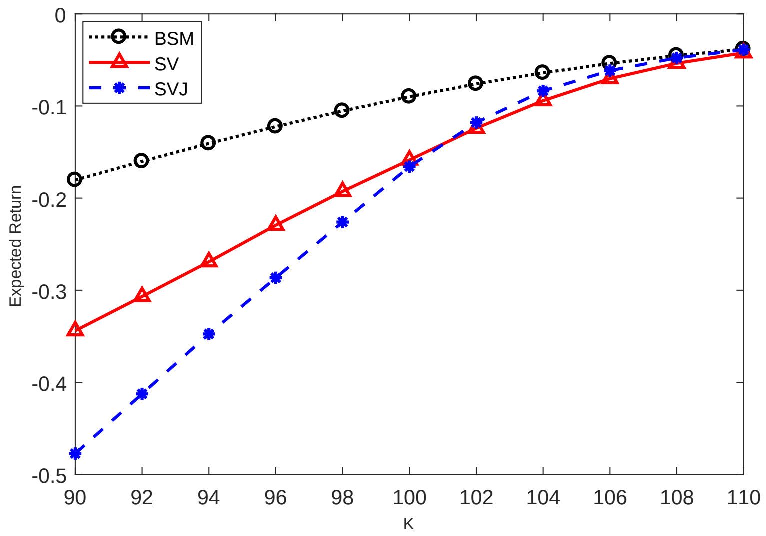
Notes: This figure plots the time series of monthly holding-to-maturity returns of 2% OTM put (Panel A), 4% OTM put (Panel B) and 6% OTM put (Panel C).

Figure 3: Moneyness and Expected Option Returns

Panel A: Expected Call Option Returns



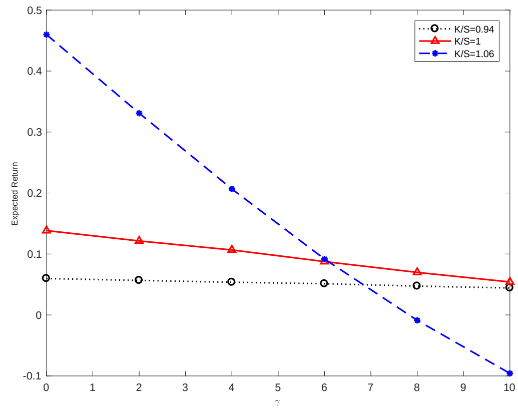
Panel B: Expected Put Option Returns



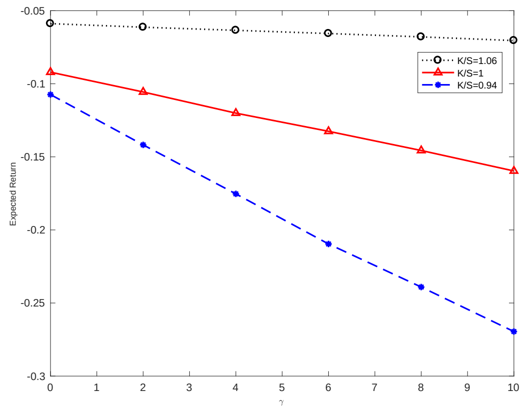
Notes: This figure plots expected option returns against the strike price for a benchmark BSM model, a SV model in which volatility risk is priced and a SVJ model in which jump risk is priced, but volatility risk is not. Panel A is for call options and Panel B for put options. Expected option returns are computed analytically based on parameters reported in Table 2.

Figure 4: The Volatility Risk Premium and Expected Option Returns

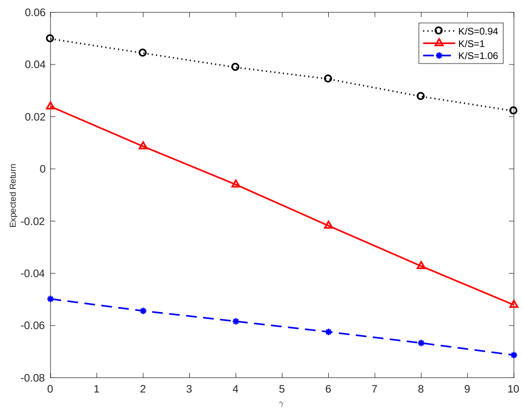
Panel A: Expected Call Option Returns



Panel B: Expected Put Option Returns



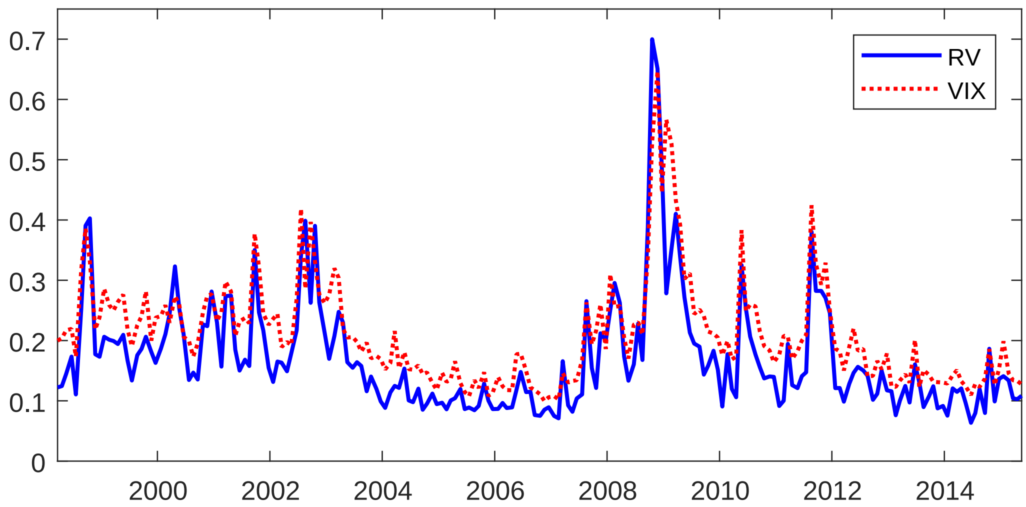
Panel C: Expected Straddle Returns



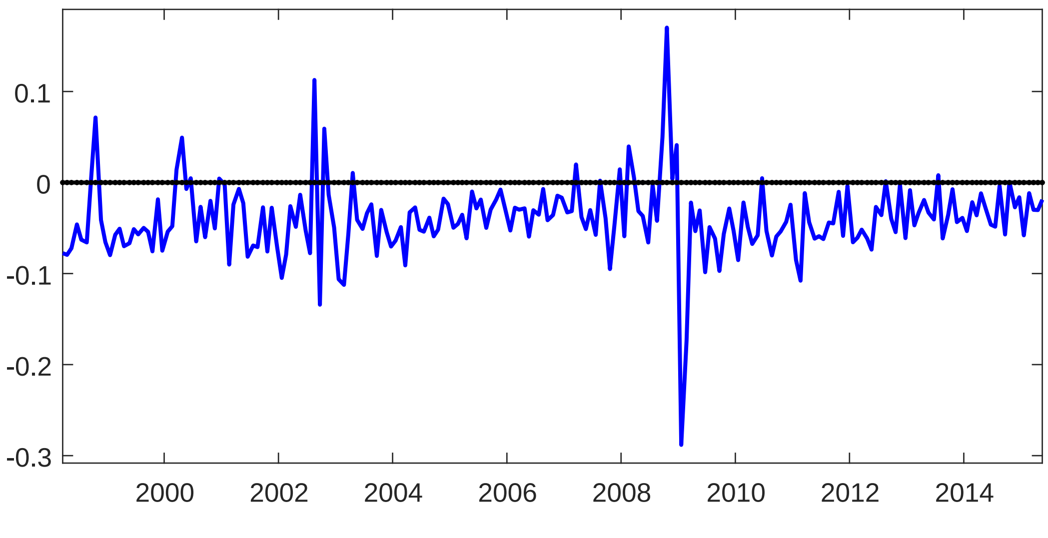
Notes: This figure plots expected option returns against risk aversion coefficient (γ) in the SV model: Panel A for calls, Panel B for puts and Panel C for straddles. A higher γ corresponds to a more negative volatility risk premium. The remaining parameters required for computing expected returns are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

Figure 5: 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) and the VIX (Panel A), as well as their difference which is the volatility risk premium (Panel B). The sample period is March 1998 to August 2015.

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 from March 1998 to August 2015.

Table A2: Predicting Option Returns: the Jump 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	-0.06	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 option return predictability 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). The predictor 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: Robustness: 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 A4: The Impact of Risk Aversion: A Sensitivity Analysis for SVJ Model

Panel A: Call Option							
$\gamma\backslash K/S$	0.96	0.98	1	1.02	1.04	1.06	1.08
0	7.35	9.51	12.93	18.34	22.48	21.44	19.42
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	-9.70	-9.47	-9.22	-8.92	-8.51	-7.90	-6.93
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	2.28	-8.15	3.76	11.75			
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 A5: 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 predictive power of the volatility risk premium (VRP) over 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: $\frac{S^2 O_{SS}}{O}$. 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 A6: Robustness: Predicting 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 option return predictability 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 15-day holding period returns on call options (Panel A), put options (Panel B) and straddles (Panel C). The predictor 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.