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

Online Appendix

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I. Overview

In this online appendix, we provide additional results that complement the analysis in the paper. Section II discusses the data, Section III describes particle filtering estimation, Section IV proposes a trading strategy that exploits option return predictability afforded by the volatility risk premium, Section V presents the results for predictive regressions of future index option returns on the jump risk premium, Section VI investigates the sensitivity of expected option returns with respect to jump parameters, and Section VII contains additional robustness results.

II. Data

This paper focuses on returns to holding S&P 500 index options. We download S&P 500 index options (SPX) data from OptionMetrics through WRDS. OptionMetrics data starts from January 1996. However, because the settlement values (SET) for SPX options required to compute holding-to-maturity returns are only available from April 1998, we start sampling options in March 1998 and our sample ends in August 2015.[1] In particular, on the first trading day after the monthly option expiration date, we collect SPX options that will expire over the next month. These options are the most frequently traded options in the marketplace and they have maturities ranging from 25 to 33 calendar days. Prior to February 2015, the expiration day for index options is the Saturday immediately following the third Friday of the expiration month. Starting in February 2015, the option expiration day is the third Friday of the month.[2] We also apply standard filters and require an option to meet all of the following requirements to be included in

[1]The settlement values for S&P 500 index options are calculated using the opening sales price in the primary market of each component security on the expiration date and are obtained from the CBOE. We also extend our sample to 1996 by using the closing price of the index as a proxy for the settlement price. The results are similar.

[2]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 sample:

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

2. Option 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 expiration day is standard.

6. Settlement is standard.

7. Implied volatility is not missing.

8. Secid = 108105.

Table A1 reports the summary statistics of our sample. Table A1 shows that out-of-the-money (OTM) options account for the majority of the trading volume in S&P 500 index options, and OTM call options are as actively traded as OTM put options.

Figure A1 plots realize volatility, the VIX, and the volatility risk premium over our sample period.

III. Particle Filtering Using Returns

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

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

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

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

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

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

Step 1: Simulating the State Forward

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

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

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

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

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

Step 2: Computing and Normalizing the Weights

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

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

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

IV. Option Trading Strategies

To assess the economic significance of the predictive relationship between the volatility risk premium and future option returns, we propose a trading strategy that exploits option return predictability in the context of selling index options. Writing index options is popular because historically it tends to yield higher returns by collecting the volatility risk premium. Since the volatility risk premium is positively associated with future option returns, a simple strategy would be to sell options only in months when the volatility risk premium is negative. This strategy relies only on an ex-ante market signal and does not require investors to estimate any model. Moreover, since return predictability is significant for OTM options and at-the-money (ATM) 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 A2 shows that our new strategy outperforms the benchmark strategy. Taking ATM straddles as an example, following our strategy, one would obtain a monthly average return of 0.106 with a Sharpe ratio of 0.151. In contrast, the average return and Sharpe ratio for the benchmark strategy are 0.085 and 0.115, respectively. Note that with the new trading strategy, one would sell options less often. The last column of Table A2 indicates the number of months in which options are shorted.[3] We also report skewness of different trading strategies. In addition to the improvements in the Sharpe ratio, the new strategy that we propose has a similar or even lower skewness relative to the benchmark strategy. Finally, it should be emphasized that the Sharpe ratio is a poor performance measure of derivatives trading strategies, which often yield highly non-normal payoffs (Goetzmann, Ingersoll, Spiegel, and Welch (2004)). The strategy proposed in this paper is only suitable for institutional investors with deep pockets and a long investment horizon.

Table A2 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

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

options, one mainly collects the volatility risk premium. The divergence between selling calls and puts might also be related to institutional frictions and order flow. For example, it is in general easy to sell calls via covered calls, but difficult to sell naked puts. Moreover, OTM put options can be used as portfolio insurance and therefore attract much more demand than OTM calls.

V. The Jump Risk Premium and Future Option Returns

Table A3 reports the results for regressions of future index option returns against the jump risk premium:

$$\text{OPTION\_RET}^{i}_{t,\,t+1} = \alpha^{i} + \beta^{i}\text{JUMP}_{t} + \epsilon, \quad i \in \{call, put, straddle\} \tag{1}$$

where the jump risk premium (JUMP_t) is computed as the difference in average implied volatilities between OTM and ATM index put options.

Panel A of Table A3 indicates that the jump risk premium is not informative about future call option returns. It is insignificant across all moneyness groups and R^2s are close to zero. Panel B shows that a larger jump risk premium in a given month is associated with lower OTM put option returns in the subsequent month, with a Newey-West t-statistic of –2.94 and an adjusted R^2 of 1.45%. Panel C shows that the jump risk premium does not contain predictive information about straddle returns.

VI. Sensitivity Analysis: Jump Parameters

Table A4 investigates if the differential impacts of the jump risk premium on expected OTM call and OTM put returns are sensitive to the characterization of the jump process under the physical measure by increasing or decreasing each physical jump parameter in the SVJ+

model by three standard errors while keeping the jump risk premium unchanged.[4] We only focus on jump-related parameters because, as already demonstrated in the paper, expected option returns do not vary much with parameters associated with stochastic volatility. Confirming our benchmark finding, Table A4 shows that the effect of the jump risk premium on expected option returns is robust to considering alternative $\mathbb{P}$-measure jump parameters. Specifically, the pricing of jump risk implies very large negative expected returns for OTM puts, which is consistent with the data. However, it also implies that expected OTM call returns are in general positive and increasing with the strike price, which is inconsistent with the data. To further demonstrate this finding about the jump risk premium is a general property of option pricing models, we also compute expected option returns using parameter estimates reported in Broadie, Chernov, and Johannes (2009) and Chambers, Foy, Liebner, and Lu (2014), and these results are denoted in Table A4 by "BCJ" and "CFLL", respectively. First, note that we replicate their results very well. For instance, for the CFLL sample, our calculation suggests that the expected returns for the ATMS and the CNS are −24.18% and −12.93% per month, which are very close to those reported in Chambers et al. (2014) (−24.03% and −12.82%).[5] More importantly, Table A4 confirms that the jump parameterizations considered in Broadie et al. (2009) and Chambers et al. (2014) also imply large positive expected return for OTM calls.

Table A5 reports the effect of the jump risk premium on expected option returns in the SVJ+ model by changing the risk aversion parameter from 0 to 20. An increase in risk aversion leads to a larger jump risk premium, meaning price jumps occur more frequently and more severely under the risk neutral measure. Table A5 shows that the jump risk premium is able to match OTM put returns easily, but its implications on call returns are inconsistent with the data. For example, across a wide range of risk aversion values, expected returns on OTM calls are

[4] We fix the jump risk premium by imposing the differences between the risk neutral and physical jump intensity and mean jump size remain the same as those implied by our baseline parameterization.

[5] For the BCJ sample, our results are somewhat different from BCJ but very close to CFLL's replication of BCJ.

positive and increasing with the strike price. If the jump risk premium is high enough (e.g., risk aversion equals 20), it is possible to observe negative expected returns for OTM calls. However, a very large jump risk premium would also imply that ATM and ITM calls have negative expected returns, which is inconsistent with the data.

VII. Additional Robustness Results

This section includes additional robustness results. Table A6 reports the regression results with the new measure of the volatility risk premium as discussed in Section V.B in the paper. Consistent with our benchmark findings, the volatility risk premium positively predicts future OTM option and ATM straddle returns. We also find similar results when using daily returns to compute physical volatility or using the average option implied volatility as a proxy for risk neutral volatility.

Our main analysis documents a positive relationship between the volatility risk premium and future option returns in univariate regressions. We now investigate if the volatility risk premium is robust to controlling for other variables including the jump risk premium and the level of volatility. Given the results are stronger for OTM options and ATM straddles, we will focus on these options only. Table A7 reports the results for multivariate predictive regressions. Specification (1) controls for the jump risk premium. After including the jump risk premium as a control, we find the volatility risk premium remains statistically significant. We also find that the volatility risk premium does not subsume the jump risk premium: The jump risk premium is still negatively and significantly related to future OTM put option returns. This suggests that the volatility and jump risk premiums are both informative about OTM put option returns. Specification (2) of Table A7 controls for the level of volatility. Including volatility as a control does not change our results. The volatility risk premium remains significant in all cases. Note that volatility itself is also related to future option returns. Specifically, volatility is negatively related to future straddle returns and call returns, but positively related to future put returns, although the relationship is not always statistically significant. These results are broadly consistent with the analysis in Hu and Jacobs (2020). Specification (3) shows that our findings remain robust when including both controls. Table A8 further shows that the positive relationship between the volatility risk premium and future option returns is also robust to controlling for option betas.

Table A9 examines if the volatility risk premium can predict holding period option returns. In particular, instead of holding options to maturity, we consider a holding period of half month (15 calendar days). We find very similar results with holding-period option returns.

Table A10 compute option returns by using different ratios of effective spreads to quoted spreads. For comparison, the average returns from Table 1 in the paper are also included and they are labeled as 'Mid-point'. Regardless of the assumption on the effective spread, the average call option returns tend to decrease with the strike price with OTM calls earning large negative average returns, while the average put option returns increase with the strike price, and OTM puts are associated with large negative average returns.

References

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

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

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

Table A2: Descriptive Statistics of Option Trading Strategies

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

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

Table A3: The Jump Risk Premium and Future Option Returns

This table reports results of the following monthly predictive regression:

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

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

	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%

Table A4: Sensitivity Analysis: Jump Parameters

This table reports expected option returns for the SVJ+ model by increasing (+) and decreasing (−) each $\mathbb{P}$-measure jump parameter by three standard errors. Expected option returns based on our baseline parameterization are included for comparison. We also report expected option returns using the parameter estimates in Broadie et al. (2009) and Chambers et al. (2014), denoted by "BCJ" and "CFLL". Returns are in percent per month.

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
$\lambda+$	2.30	1.73	0.97	0.60	6.00	32.27	70.88
$\lambda-$	3.67	3.73	3.80	4.24	8.50	25.10	52.22
μ_z+	4.19	4.53	5.14	7.22	16.36	39.99	68.28
μ_z-	1.65	0.85	-0.42	-2.05	-1.47	15.85	53.09
σ_z+	2.31	2.02	1.68	1.89	6.30	18.01	33.02
σ_z-	3.61	3.21	2.44	1.30	2.41	28.08	134.23
BCJ	3.84	3.62	3.39	3.44	4.70	9.72	24.49
CFLL	-3.38	-7.09	-12.39	-13.03	30.04	88.74	149.39
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
$\lambda+$	-43.08	-36.74	-30.25	-23.82	-17.57	-12.31	-8.47
$\lambda-$	-40.67	-34.46	-27.89	-21.72	-16.22	-11.62	-8.33
μ_z+	-37.66	-31.69	-25.70	-20.07	-14.86	-10.68	-7.64
μ_z-	-45.11	-38.68	-32.23	-25.18	-18.90	-13.25	-9.09
σ_z+	-42.19	-35.78	-29.19	-22.72	-16.85	-11.90	-8.23
σ_z-	-40.51	-34.77	-29.15	-23.19	-17.39	-12.47	-8.78
BCJ	-65.98	-56.51	-44.42	-31.82	-21.33	-14.04	-9.50
CFLL	-74.62	-68.54	-60.51	-49.96	-35.84	-19.98	-10.34
Panel C: Option Portfolio							
	ATMS	PSP	CNS	CSP	STRN		
Baseline	-7.21	-9.30	-2.45	1.46	-25.35		
$\lambda+$	-8.25	-9.18	-3.14	-0.09	-25.73		
$\lambda-$	-6.17	-9.60	-1.79	3.16	-25.27		
μ_z+	-4.80	-9.10	-0.84	3.23	-17.68		
μ_z-	-9.53	-9.27	-3.93	-0.38	-30.89		
σ_z+	-7.52	-7.79	-2.10	0.46	-23.82		
σ_z-	-7.40	-11.59	-3.48	2.44	-27.42		
BCJ	-8.97	-11.64	-3.22	2.97	-39.38		
CFLL	-24.18	-13.87	-12.93	-16.38	-51.82		

Table A5: Sensitivity Analysis: Risk Aversion

This table reports expected option returns for the SVJ+ model using different values of risk aversion (γ) ranging from 0 to 20 while keeping other parameters same. Returns are in percent per month.

Panel A: Call Option

$\gamma \backslash K/S$	0.96	0.98	1	1.02	1.04	1.06	1.08
0	7.32	9.45	12.80	18.10	22.14	21.35	19.62
2	6.90	8.82	11.89	17.12	23.64	27.79	31.35
4	6.29	7.85	10.39	15.04	22.94	32.59	43.22
6	5.47	6.56	8.33	11.82	20.06	35.25	54.13
8	4.37	4.85	5.65	7.56	14.77	34.00	60.78
10	2.96	2.70	2.32	2.34	7.31	29.39	64.09
12	1.14	-0.03	-1.77	-3.92	-2.31	18.92	60.66
14	-1.32	-3.68	-7.18	-11.93	-13.73	6.81	53.06
16	-4.34	-7.97	-13.22	-20.32	-26.33	-14.43	31.02
18	-8.12	-13.20	-20.29	-29.61	-38.64	-35.29	1.54
20	-12.88	-19.58	-28.58	-39.84	-50.99	-55.13	-34.67

Panel B: Put Option

$\gamma \backslash K/S$	0.92	0.94	0.96	0.98	1	1.02	1.04
0	-9.65	-9.41	-9.16	-8.85	-8.44	-7.84	-6.88
2	-15.30	-13.59	-12.03	-10.65	-9.41	-8.25	-7.00
4	-21.59	-18.44	-15.51	-12.89	-10.66	-8.79	-7.15
6	-28.30	-23.84	-19.56	-15.65	-12.28	-9.55	-7.42
8	-34.79	-29.33	-23.90	-18.76	-14.22	-10.51	-7.76
10	-41.93	-35.61	-29.10	-22.71	-16.85	-11.95	-8.38
12	-48.66	-41.82	-34.53	-27.10	-19.99	-13.81	-9.22
14	-57.34	-50.10	-42.06	-33.45	-24.74	-16.75	-10.61
16	-63.55	-56.38	-48.17	-39.06	-29.42	-20.08	-12.46
18	-69.35	-62.56	-54.55	-45.30	-35.03	-24.43	-15.11
20	-75.42	-69.16	-61.55	-52.43	-41.82	-30.19	-19.08

Panel C: Option Portfolio

$\gamma \backslash$ Portfolio	ATMS	PSP	CNS	CSP	STRN
0	2.24	-8.08	3.74	11.59	-0.54
2	1.30	-8.21	3.20	10.46	-3.27
4	-0.07	-8.37	2.34	8.84	-7.21
6	-1.91	-8.59	1.15	6.82	-12.26
8	-4.23	-8.82	-0.40	4.36	-18.41
10	-7.21	-9.30	-2.45	1.46	-25.35
12	-10.83	-9.88	-5.02	-1.96	-33.14
14	-15.92	-11.24	-8.77	-6.48	-41.18
16	-21.28	-12.53	-12.95	-11.12	-49.61
18	-27.63	-14.62	-18.23	-16.31	-57.63
20	-35.17	-17.89	-24.87	-22.01	-65.50

Table A6: Robustness: Alternative Measures of the Volatility Risk Premium

This table reports results of the following monthly predictive regression:

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

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

	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%

Table A7: Robustness: Controlling for Other Variables

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

	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%

Table A8: Robustness: Controlling for Option Betas

This table examines the relationship between the volatility risk premium (VRP) and future option returns controlling for option betas. $Beta_S$ is computed as index price times delta (O_S) divided by option price: $\frac{SO_S}{O}$. $Beta_V$ is computed as vega (O_V) divided by option price: $\frac{O_V}{O}$. $Beta_J$ is computed as the squared index price times gamma (O_{SS}) divided by option price: $\frac{S^2 O_{SS}}{O}$. 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.

	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%

Table A9: Robustness: Holding-Period Option Returns

This table reports results of the following monthly predictive regression:

$$\text{OPTION\_RET}^i_{t,\,t+15} = \alpha^i + \beta^i \text{VRP}_t + \epsilon, \quad i \in \{call, put, straddle\}$$

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

	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%

Table A10: Robustness: Measuring Option Returns

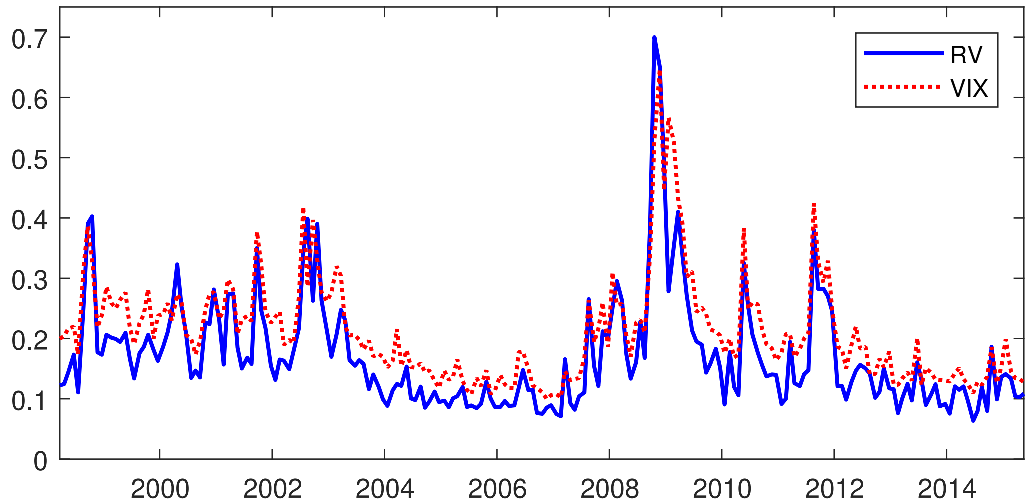
This table reports average option returns by using different ratios of the effective bid-ask spread to the quoted bid-ask spread (25%, 50%, and 100%). The average option returns from the paper, which are computed based on the assumption that options are transacted at the mid-point of the bid-ask spread, are also included for comparison (denoted by "Mid-point").

Panel A: Call Option							
K/S	0.96	0.98	1.00	1.02	1.04	1.06	1.08
Mid-point	6.36	6.89	6.50	1.89	-1.47	-18.12	-25.05
25%	5.84	6.19	5.59	0.49	-3.86	-22.84	-31.11
50%	5.32	5.49	4.69	-0.87	-6.12	-26.90	-38.22
100%	4.31	4.14	2.95	-3.45	-10.25	-33.58	-48.19
Panel B: Put Option							
K/S	0.92	0.94	0.96	0.98	1.00	1.02	1.04
Mid-point	-52.07	-45.02	-37.86	-27.76	-22.36	-15.76	-13.15
25%	-53.13	-45.97	-38.80	-28.65	-23.05	-16.37	-13.61
50%	-54.14	-46.89	-39.70	-29.51	-23.72	-16.96	-14.06
100%	-56.03	-48.63	-41.43	-31.18	-25.04	-18.14	-14.95
Panel C: Option Portfolio							
	ATMS	PSP	CNS	CSP	STRN		
Mid-point	-8.47	-18.54	-3.93	13.56	-38.64		
25%	-9.26	-20.06	-5.16	12.08	-39.86		
50%	-10.04	-21.51	-6.34	10.65	-41.04		
100%	-11.56	-24.24	-8.63	7.91	-43.26		

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

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

Panel A: Realized Volatility and the VIX



Panel B: Volatility Risk Premium