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Option Writing: *Using VIX to Improve Returns*

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The writing of put and call options has frequently been used as an adjunct to porfolio management. Selling options to buyers, who use them either for protection or to leverage a portfolio's return, has been analogized to the provision of casualty insurance: Just as the insurance companies that write home insurance benefit from selling fire insurance, so do the writers of options. They capture volatility risk premium, which reflects the compensation investors earn for providing insurance against market losses. Option prices reflect this volatility premium because of market participants' tendency to overestimate the probability of significant losses,[1] and an investor can capture this premium by selling options.

There are generally two option-writing or -selling strategies. The first is a buy-write, which entails writing call options against a long position in a stock or market index. The other is a put-write, in which the manager sells put options while holding a porfolio of US Treasury bills to ensure that the writer can fulfill contract obligations should the put buyer exercise the option. In both option-selling strategies, the upside potential is capped even when the underlying asset price rises considerably higher than the strike price; however, when the underlying asset price falls, option writing cushions the losses to the extent of the cash received through the sale of options. As a result, the returns of option-selling strategies tend to have lower volatility than those of the underlying asset.

Several studies have documented the attractive returns, especially risk-adjusted returns, of option-writing strategies. We contribute to the literature by demonstrating that investors can considerably improve their returns by deploying these strategies only during periods when anticipated volatility (as measured by VIX) is higher than usual. The economic intuition for our result stems from the observed differences in volatility risk premium in different market environments. We show that the difference between implied volatility and realized volatility varies across VIX regimes. Implied volatility is based on the market's forecasts of future volatilities extracted from the prices of options written on the asset of interest. The difference between the implied and realized volatility is particularly pronounced when the VIX index, which reflects the market's

[1] Investor behavioral bias toward overestimating downside risk has been documented by various studies. For example, Goetzmann, Kim, and Shiller (2016) discussed survey results that show that nearly two-thirds of retail and institutional investors consistently believe that there is a 10% chance of a catastrophic market crash within the next six months, when in reality the historical likelihood of such an event is about 1%. See also Ang et al. (2018).

implied volatility, is elevated. Thus, a strategy of selling options during high VIX regimes is expected to yield superior returns.

We find that a conditional option-writing strategy of staying fully invested in the market when the VIX is relatively low and writing calls or puts when VIX is high produces higher returns and lower volatility and downside risk (resulting in higher Sharpe and Sortino ratios[2]) than the market during the period of 1995 through June 2018. This conditional option-writing strategy also performs better—both on an absolute and a risk-adjusted basis—than the returns of unconditional option writing.

In the next section, we review the relevant literature. In the third section, we examine the time-varying characteristics of the volatility risk premium by analyzing the relationship between implied and realized volatility in different market environments. The findings in this section provide the motivation for exploring the risk and return characteristics of alternative option-writing strategies, including conditional optional writing; we undertake this examination in the fourth section of the article. The final sections contain areas for further research and concluding comments.

RELEVANT PRIOR LITERATURE

The literature relevant to our study can be segregated into two broad groups: one that pertains to measuring and forecasting volatility and another that deals with option-selling strategies. Although we begin our review with the first strand of the literature, we will focus mainly on the second because it is more directly relevant to our article.

There is a very rich body of studies on modeling volatility. Their roots lie in Engle's (1982) path-breaking autoregressive conditional heteroskedasticity paper, which sets out a model of forecasting volatility as a time-varying function of current information. Since then the generalized autoregressive conditional heteroskedasticity (GARCH) class of models, initially created by Bollerslev (1986) and with many subsequent variations, have been extensively used in volatility modeling. One aspect of this extensive body of literature that is particularly relevant for our study is the observation that the volatility of equity index returns respond asymmetrically to past negative and positive return shocks, with negative returns resulting in larger future volatilities. As a possible explanation for this asymmetry, researchers have posited a volatility feedback effect (i.e., heightened volatility requires an increase in the future expected returns to compensate for the increased risk, in turn necessitating a drop in the current price to go along with the initial increase in volatility).[3]

Turning to the second strand of literature, we note that although there are several studies on option writing, the vast majority have focused on buy-write rather than put-write strategies. This focus is in large part explained by the similarities in return characteristics of the two option-writing strategies.

In 2002, the Chicago Board Options Exchange (CBOE) introduced the Buy Write Index (BXM), which is designed to track the performance of a covered call strategy where the underlying is the S&P 500 Index. One of the earliest studies on the performance of this buy-write strategy was by Whaley (2002), who showed that from 1988 to 2001 the index provided nearly the same return as the S&P 500 while having a standard deviation of returns one-third lower than that of the S&P 500. Two subsequent studies by Feldman and Roy (2004) and by Callan Associates (2006) found essentially the same results.

Ungar and Moran (2009) reviewed the performance of writing put options compared with various other strategies over the period of 1986–2008 and found that writing put options outperforms a plain vanilla buy-write strategy. To help explain this outcome, they pointed to previous studies, such as those by Rubenstein (1994) and Jackwerth (2000), which established that out-of-the-money put options are systematically overpriced. Academics have provided

[2] The Sharpe ratio is a measurement of excess return per unit of risk, typically measured by the standard deviation of returns. The Sortino ratio is a measurement of excess return per unit of downside risk, typically measured as the standard deviation of returns falling below a target rate. See Sharpe (1994) and Sortino and Price (1994).

[3] See Andersen et al. (2006) for an excellent discussion of this issue. The most commonly used GARCH formulations for describing this type of asymmetry are the variants of GARCH models by Glosten, Jagannathan, and Runkle (1993) and Zakoïan (1994); the asymmetric GARCH model by Engle and Ng (1993); and the exponential GARCH model by Nelson (1991).

several explanations for the mispricing of put options. For example, Bakshi and Kapadia (2003) considered overpricing in the context of negative volatility risk premium, and Gârleanu, Pedersen, and Poteshman (2009) connected it to excess demand for downside protection. In addition to plain vanilla covered call or put-write strategies, numerous studies have documented how variations in the options selected for selling have the potential to improve returns. McIntyre and Jackson (2007) undertook an empirical evaluation of covered call writing for a variety of maturity dates, strike prices, and assets; they found that call-writing strategies provide attractive returns, particularly on a risk-adjusted basis. Figelman (2008) synthesized a formula for the expected return of the covered-call strategy. He observed that "the [covered call] strategy on the S&P500 Index has exhibited strong historical risk-adjusted performance relative to the stock index itself. In order for investors to find the … strategy attractive, they must be convinced that going forward, *implied volatility will be higher, on average, than the corresponding realized volatility*" (Figelman 2008, pp. 91–92). In fact, we demonstrate in our article that this has indeed been the case for the last three decades.

He, Hsu, and Rue (2014) examined various covered call strategies using different maturity dates and strike prices with the S&P 500 Index as the underlying asset. They showed that performance is maximized when writing at-the-money calls with three-month maturity dates. Although most prior studies have examined strategies with a buy-write ratio of one, Diaz and Kwon (2017) explored the optimization of the covered call strategies by using different combination of calls; they found that from a risk–return perspective it is often optimal to sell a mix of options with different strike prices.

In a similar vein, Hill et al. (2006) explored covered calls for which the strike prices are set according to the volatility of the underlying asset. They found superior performance of writing calls with less than a 30% probability of exercise or with a strike price at least 2% out of the money. Che and Fung (2011) performed a similar analysis with Hang Seng Index futures as the underlying. They concluded that the performance of the strategies depends greatly on market conditions. Whereas prior studies have focused on optimal option-writing strategies based on factors such as strike prices, expiration times, and buy-write ratios, we contribute to the literature by examining the returns of a strategy that writes options only in selective market environments characterized by elevated VIX.

RELATIONSHIP BETWEEN VIX AND VOLATILITY

The VIX is the most popular index purporting to measure the market's expectation of the next month's stock market volatility. The rules-based index is derived from the prices of a wide variety of put and call options on the S&P 500 stock index (henceforth S&P). Because of its tendency to rise during periods of unsettled declining stock prices, the VIX is often called the *fear index*. The CBOE has created an historical record of the index dating back to 1990.[4] In this section, we examine the characteristics of the index and some of its statistical properties.

Under the current methodology, the VIX is constructed using S&P 500 option prices for options expiring between 23 and 37 days in the future (CBOE 2018). As such, the VIX is intended to represent the 30-calendar-day (approximately 21 trading days) forward volatility of the S&P 500 as a proxy for market volatility.

We introduce the following notation. Let V_t represent the index value of the VIX on day *t*. Let R_t equal a measure of realized volatility of the S&P index over (approximately) the past month. R_t is calculated as the standard deviation of the S&P returns for the past 21 trading days, including the current day, denoted by $t = 0$. The S&P returns are the log returns derived from the closing values of the S&P 500 Total Return Index. This is shown formulaically in Equation 1.

$$\textbf{Realized volatility} \text{ on day } t\text{: } R_t = Std(r_{t=0} \ldots r_{t=-20}) \qquad (1)$$

[4] The CBOE changed the methodology of the VIX index in 2004. The methodology was further refined in 2014. CBOE provides data on the VIX going back to its inception, with the daily closing values of the index calculated using the most current (i.e., 2014) methodology. Throughout this article, we have used these back-filled data on VIX, which precludes the possibility that the VIX values are affected by changes in the methodology used to calculate the index.

We define forward volatility (F_t) as the standard deviation of market returns over the next 21 trading days (starting with day $t+1$). This is shown formulaically in Equation 2.

$$\textbf{Forward volatility} \text{ on day } t\text{: } F_t = Std(r_{t=+1} \ldots r_{t=+21}) \quad (2)$$

For ease of comparison to the VIX throughout this article, we show both realized and forward volatility as daily volatility annualized and multiplied by 100.

In Exhibit 1, we examine how VIX has been related to past volatility and how well it predicts future volatility. Our analysis uses the daily closing values for the index for the nearly 30-year period of January 1990 through June 2018. These three decades allow us to look at the relationship between the VIX and actual volatility in a variety of market conditions.

Panel A of Exhibit 1 contains the results of regressing the VIX on realized volatility. We note that VIX is highly correlated with past (realized) volatility as demonstrated by an adjusted R^2 of 0.78. Panel B shows that there is also statistically significant persistence in volatility but that the R^2 between past and future volatility is only 0.55. Finally, Panel C shows that VIX does a better job than past volatility alone in explaining future volatility (R^2 of 0.61), but the relationship leaves nearly 40% of the variance of forward volatility unexplained. That said, it is worth noting that VIX, which is based on option prices, does provide at least some additional information concerning the future path of volatility when compared with realized volatility alone.

As previously discussed, it is well known that VIX tends to overstate both realized and forward volatility.[5] Exhibit 2 summarizes this relationship between VIX and the two measures of volatility using data from January 1990 through June 2018. In Panel A, we show the difference between VIX and both realized volatility and forward volatility by VIX quartile. We find that VIX levels are higher than both realized past volatility and forward volatility over the next 21 trading days with an average overestimation of approximately four points.

As discussed earlier, this systematic overstatement is commonly attributed to the buy–sell dynamics of the underlying options on which VIX is based. Because VIX has a negative correlation with stock prices, equity investors find that the purchase of volatility-sensitive derivatives offers important insurance benefits. Investors who are long VIX realize gains when the market falls, thereby offsetting negative equity returns. Such buying of volatility derivatives increases their prices and leads to a systematically larger prediction of future volatility than is actually realized. What is particularly interesting

EXHIBIT 1

Regression Analysis of VIX and Volatility, January 1990 to June 2018

Explanatory Variable	Coefficient	*t*-Stat
Panel A: Explained Variable—VIX		
Realized Volatility	0.7595	161.28
Intercept	7.7673	92.99
Adjusted R^2	0.7841	
Panel B: Explained Variable—Forward Volatility		
Realized Volatility	0.7435	93.84
Intercept	3.8822	27.60
Adjusted R^2	0.5522	
Panel C: Explained Variable—Forward Volatility		
VIX	0.9134	106.57
Intercept	–2.4652	–13.79
Adjusted R^2	0.6133	

EXHIBIT 2

VIX and Volatility, January 1990 to June 2018

Panel A: Difference Between VIX and:

VIX Quartile	Intraquartile Range	Mid-point of VIX Quartile	Realized Volatility	Forward Volatility
1	9.14–13.65	11.40	3.48	2.88
2	13.66–17.44	15.55	4.00	3.90
3	17.45–22.73	20.09	4.71	4.50
4	22.74–80.86	51.80	4.26	5.27
Overall			**4.11**	**4.14**

Panel B: Deviation From Average Difference:

VIX Quartile	Realized Volatility	Forward Volatility
1	–0.63**	–1.26**
2	–0.11	–0.23*
3	0.60**	0.36*
4	0.15	1.13**

*Notes: * denotes the difference is statistically significant at the 95% level. ** denotes the difference is statistically significant at the 99% level.*

[5] For example, see Figelman (2008).

is that the difference between VIX and observed volatility is larger at higher levels of volatility. For example, as shown in the last column of Panel A, in the lowest quartile of VIX values, VIX overstates forward volatility by 2.88 points; in the highest quartile, it overstates by 5.27 points.

Panel B of Exhibit 2 further examines the deviations by quartile. Here, we look at the average deviation in each quartile compared with the overall average deviation. The last column contains these values for the comparison between VIX and forward volatility. The values show a clear pattern: VIX understates forward volatility in the lower quartiles and overstates in the upper quartiles. These differences between VIX and forward volatility in each of these quartiles are statistically significant, as noted in the exhibit. These findings provide the motivation for the strategies discussed in the next section.

PERFORMANCE OF CONDITIONAL STRATEGIES

Because expected volatility—which is the most important determinant of option prices—is generally perceived to tend to overstate realized volatility, it has been argued that strategies involving option writing may produce better risk–reward outcomes than simple long-only equity strategies. Some investors buy put options to protect the money value of their portfolios from capital losses in the event of a market decline. These are called *protective puts*. However, investors may be overpaying for that protection if the implied volatility in the prices of put options is systematically higher than realized volatility.

Option writing is then recommended as an optional strategy to take advantage of the possibility that people overpay for protection. Insurance companies that write fire-insurance policies profit from setting rates that are far higher than would be required on the basis of the actual probability that the insured houses will burn down. By analogy, the argument is that the writers (i.e., sellers) of put options will find that providers of volatility insurance would profit under most market corrections.

Option-Writing Strategies

Two kinds of writing strategies are commonly employed. The first is to go long an individual stock, or an exchange-traded fund (ETF) representing a market index, while simultaneously selling (writing) call options on the security or index. The sale is often made at the money (i.e., at the same price at which the security or ETF is trading) or slightly in the money (i.e., slightly above the market price). Writing puts typically involves selling put options at the money while depositing margin in the form of safe US Treasury bills with a maturity equal to the duration of the option.

Exhibit 3 represents the payoffs from both strategies. The graph assumes that the index (or stock) sells at $40 and that the call and put options sell at $4 per share. The solid line represents the payoffs from buying the index or stock if the price rises or falls. The buyer of 100 shares benefits or loses in exact proportion to his or her investment as the price rises or falls. The investor who is long on the index and writes a $4 call gains 10% at any price above $40. While the call buyer exercises the call at any price above $40, the investor receives both the sale proceeds and the $4 option premium. If the price falls below $40, the option is not exercised, and the investor is left holding a depressed stock. The investor's loss is reduced by the receipt of the option premium, and he or she suffers a net loss only if the price goes below 36. The dotted line illustrates the payoff. The writer of the 100 puts is in exactly the same position. Neither calculations take into account any dividends from the long holding or interest on the margin deposited by the put seller.

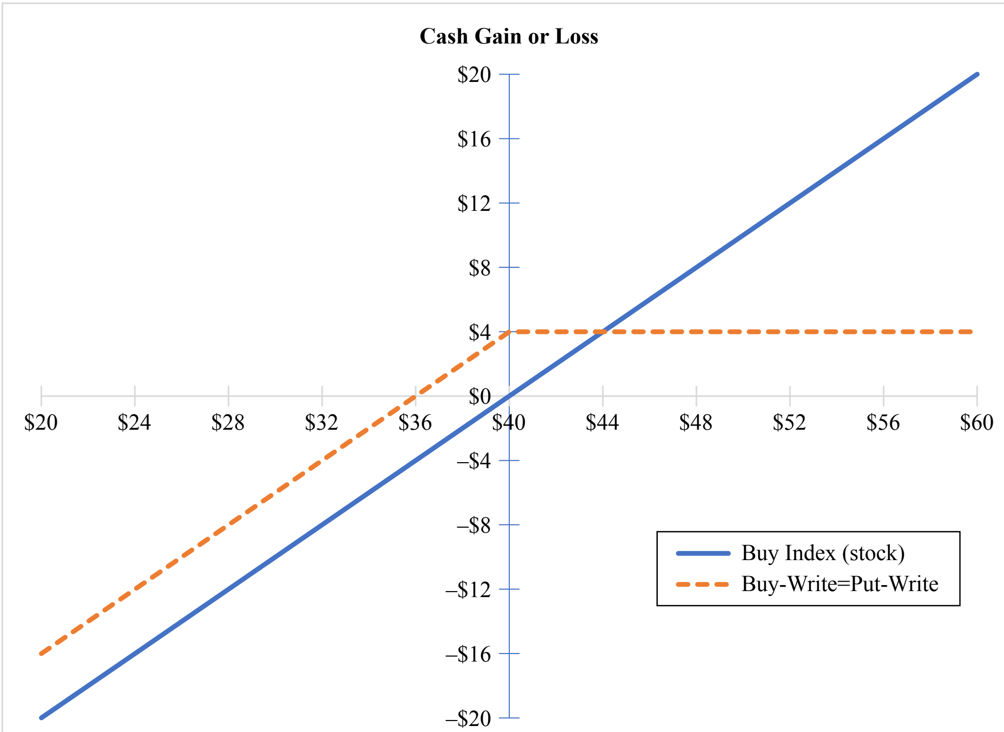
As noted earlier, several studies have documented the advantages of these strategies, which broadly result in returns similar to those of the overall market with lower volatility that translates into higher risk-adjusted return than the market. A few key features make this possible: (1) when the underlying falls, the losses are partially offset by the premium received; (2) the Treasuries (in case of put-write) provide yield or the underlying securities (in the case of buy-write) provide dividends, thereby augmenting returns; and (3) the capped upside reduces the volatility of returns.

Data on Option-Writing Strategies

The CBOE provides indexes that represent the historic returns of both buy-write (BXM) and put-write (PUT) strategies. The CBOE provides historical data for

EXHIBIT 3

Illustration of Payoffs (call and put strike $40, premium $4)



these two indexes using a consistent methodology going back to June 1986.

Both the BXM and PUT indexes use a monthly roll. In the case of the BXM, this means that the index is constructed as if the investor held the S&P 500, and each month on the date of expiration of the prior monthly option contract, the investor sells the relevant option at a weighted average price. Dividends paid on the component stocks underlying the S&P 500 Index and the dollar value of option premium deemed as received from the sold call options are functionally reinvested in the covered S&P 500 Index portfolio. The PUT index follows a similar monthly roll process, but holding risk-free assets instead of the S&P 500 Index. Given this monthly roll feature of the BXM and PUT indexes, in this section we use monthly performance data to evaluate these strategies.[6]

Exhibit 4 shows summary performance statistics for the S&P 500 Total Return index and the BXM and PUT indexes from January 1990 through June 2018.[7] The results are broadly consistent with prior studies.[8] Over this time period, all three have similar returns, with the BXM and PUT indexes experiencing lower volatility and therefore higher risk-adjusted returns than S&P 500, as demonstrated in higher Sharpe and Sortino ratios.[9]

Conditional Strategy Construction

As discussed earlier, we observe that the difference between VIX (as a measure of implied volatility) and future volatility increases at higher levels of VIX. We therefore expect the returns of the BXM and PUT

[6] A detailed write up of methodology is provided by the CBOE (2010, 2014).

[7] In Exhibits 4–7, the average return is defined as the annualized average monthly logarithmic returns.

[8] See, for example, Whaley (2002) and Ungar and Moran (2009).

[9] As discussed earlier, the BXM and PUT represent a similar theoretical payoff. Despite this theoretical consistency, the rationale for the excess returns earned by PUT over BXM are discussed here: http://www.cboe.com/micro/bxm/bxm-put-conundrum.pdf.

Exhibit 4

Performance Statistics of Different Strategies, January 1990 to June 2018

	S&P 500	Buy-Write	Put-Write
Average Return	9.29%	8.20%	9.28%
St. Deviation	14.25%	10.13%	9.79%
Sharpe	0.46	0.54	0.67
Sortino	0.67	0.75	0.90

Exhibit 5

Excess Return by VIX Quartile, January 1995 to June 2018

Excess Return Over S&P		
VIX Quartile	**Buy-Write**	**Put-Write**
1	–4.1%	–4.3%
2	–6.4%	–4.8%
3	0.4%	3.3%
4	1.6%	2.4%

indexes, which reflect the gains from selling options, to be higher at higher levels of the VIX. Exhibit 5 shows the excess performance of the BXM and PUT indexes over the S&P Total Returns by VIX quartiles.

The VIX quartiles are constructed such that they are free from hindsight bias. In particular, we determined the quartile cutoffs for the VIX based only on historical data (i.e., VIX levels in the period prior to the current month). Therefore, as one moves forward in time, the strategies add one month of additional data to determine the VIX cutoff. To ensure a sufficient sample on which to base these cutoffs, we start in 1995, which provides us with a minimum of five years of history. We then use the median VIX level of the prior month to categorize the excess returns of BXM and PUT indexes into VIX quartiles. The results are consistent with our findings in Panel B of Exhibit 2: The two option-selling strategies provide positive excess returns in both the third and fourth VIX quartiles and underperform the market in the first two quartiles.

We use these results to construct two conditional option-writing strategies that seek to capitalize on this pattern. The conditional strategies are based on a simple rule: Invest in S&P 500 if VIX is below its historical median and engage in option writing if VIX is above the historical median. For example, starting in January 1995, we determine the median historical VIX level, using data for the period of January 1990 through December 1994. At the beginning of January 1995, if the median VIX level in the prior month (i.e., December 1994) is higher than the historical median VIX value (i.e., using data between 1990 and 1994) then we enter the option-selling strategy. If the median VIX is lower than the median value, we stay in the S&P 500. We make this same evaluation in each subsequent month by looking at the full VIX history up through the prior month to compute the historical VIX median and compare the median VIX level of the prior month to the historical median.[10] In each month, options are written if the VIX level of the prior month is above the historical median. By using only historical data in deciding whether to engage in option selling, we avoid any hindsight bias.

Conditional Strategy Performance

Exhibit 6 compares the performance of these conditional strategies to the performance of the original strategies and the market. The conditional strategies are shown in the final two columns.

The results are clear. The conditional BXM and conditional PUT have higher returns than either the S&P Total Return or the respective unconditional option-selling strategies. Importantly, the conditional strategies offer meaningful improvements in both Sharpe and Sortino ratios over the market and over the unconditional returns of option selling.

Exhibit 7 compares the returns of the conditional strategies to the S&P Total Return on an annual basis. The first column shows the annual returns of the S&P 500, the second column the conditional buy-write strategy, and the third column the conditional put-write strategy. This exhibit highlights the three different regimes for the strategy: years in which the strategy stays in the S&P index, years in which the strategy shifts to option writing and outperforms the S&P 500 index, and years in which the strategy shifts to option writing and underperforms the S&P 500.

[10] Thus, each month, as we move forward in time from January 1995 onward, we have one additional month's data on VIX to compute its historical median.

EXHIBIT 6

Performance Statistics of Different Strategies, January 1995 to June 2018

	S&P 500	Unconditional Buy-Write	Unconditional Put-Write	Conditional Buy-Write	Conditional Put-Write
Average Return	9.49%	7.64%	8.67%	10.09%	10.88%
St. Deviation	14.63%	10.59%	10.40%	11.58%	11.36%
Sharpe	0.49	0.50	0.61	0.67	0.75
Sortino	0.71	0.69	0.81	0.95	1.05

EXHIBIT 7

Annualized Return of S&P and the Conditional Write Strategies

Year	S&P Total Return	Conditional Buy-Write	Conditional Put-Write	Option Writing Months
1995	31.90%	31.90%	31.90%	0
1996	20.67%	18.07%	18.40%	10
1997	28.79%	23.62%	24.44%	12
1998	25.14%	17.35%	17.01%	12
1999	19.10%	19.20%	19.07%	12
2000	–9.55%	7.14%	12.28%	12
2001	–12.65%	–11.57%	–11.24%	12
2002	–24.98%	–7.95%	–8.97%	12
2003	25.22%	21.68%	22.93%	7
2004	10.33%	10.33%	10.33%	0
2005	4.80%	4.80%	4.80%	0
2006	14.66%	14.66%	14.66%	0
2007	5.35%	8.78%	9.64%	4
2008	–46.20%	–33.76%	–31.15%	12
2009	23.48%	23.04%	27.39%	12
2010	14.03%	5.51%	10.41%	10
2011	2.09%	6.90%	5.74%	6
2012	14.84%	8.88%	9.12%	4
2013	28.06%	28.06%	28.06%	0
2014	12.83%	12.83%	12.83%	0
2015	1.37%	–5.39%	–5.23%	2
2016	11.30%	8.47%	8.38%	2
2017	19.75%	19.75%	19.75%	0
2018	2.61%	4.73%	5.07%	3
Average	9.49%	10.09%	10.88%	

Notes: Shaded rows denote the strategies that remained invested in the S&P. Outlined rows denote strategies that outperformed the S&P.

The shaded rows show the years in which the strategies remain invested in the S&P all year long. This occurs in 7 of the 23.5 years in Exhibit 7 (approximately one-third of the time). These years directly correspond with positive S&P 500 returns and low-volatility environments.

The boxed areas show the years in which the strategies outperformed the S&P. Again, this occurred in seven years. These years generally coincide with periods of negative (or low) returns and higher volatility. On average the outperformance during these seven years is approximately 9.7%. This more than compensates for the nine years in which the strategies underperform because the average annual underperformance in those years is approximately 3.8%. These years of underperformance generally correspond with bull runs, wherein the option premiums are insufficient to offset the capped upside of option selling.

Exhibit 8 shows the cumulative returns of the two conditional strategies and of the market. The exhibit highlights the performance of the strategies over time. After an initial period of underperformance, both strategies consistently outperform the S&P following its first sustained decline and then continue to outperform over the remainder of the period.

Exhibit 9 provides further insight into how the conditional strategies perform in market downturns. Based on monthly returns from 1995 through 2018, there were five periods in which the S&P 500 dropped by more than 5% below its prior peak. The exhibit shows those periods and the associated drawdowns for the S&P 500 and for the conditional strategies. In all cases, the conditional strategies have smaller losses than the S&P 500 alone. In fact, during the two longer drawdown periods in 2000 and 2007, the conditional strategies peak later than the S&P 500, resulting in a drawdown that is not only shallower in severity but also shorter in duration. These smaller losses in down markets largely explain the higher risk-adjusted returns of the conditional strategies.

EXHIBIT 8

S&P 500 and the Conditional Write Strategies, January 1995 to June 2018

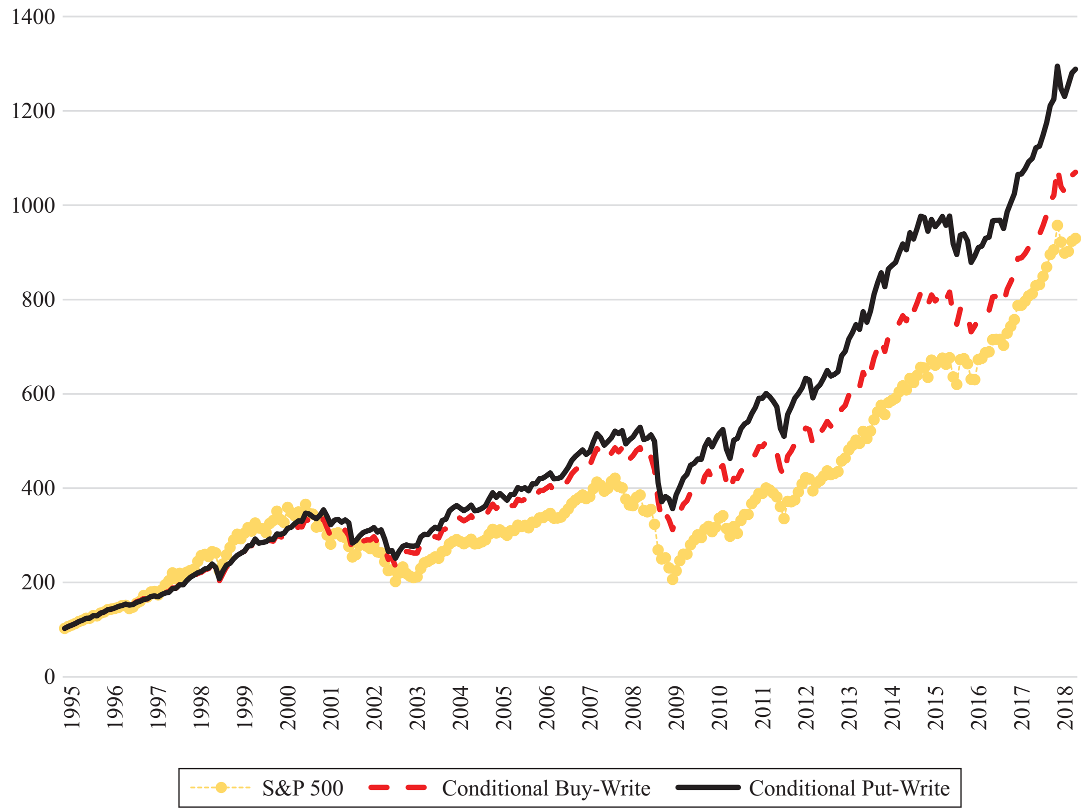


EXHIBIT 9

Performance of S&P and Conditional Write Strategies During >5% Drawdowns

		Drawdown Duration					
S&P Peak	**S&P Trough**	**S&P 500**	**BXM**	**PUT**	**S&P Total Return**	**Conditional Buy-Write**	**Conditional Put-Write**
Jun-98	Aug-98	2	2	2	−23.93%	−14.50%	−12.95%
Aug-00	Sep-02	25	25	20	−44.73%	−30.19%	−29.00%
Oct-07	Feb-09	17	9	9	−50.95%	−35.81%	−32.66%
Apr-11	Sep-11	5	5	5	−16.26%	−13.59%	−13.72%
Jul-15	Sep-15	2	2	2	−8.36%	−7.59%	−7.65%
				Average	−28.85%	−20.34%	−19.20%

Note: PUT peaked in January 2001, and BXM and PUT peaked in May 2008.

Robustness of the Conditional Strategies

In the preceding analysis, we focused on BXM and PUT indexes compared with the S&P 500 over the period of January 1995 through June 2018. We now consider the robustness of these strategies in two ways: (1) how the conditional BXM and PUT strategies perform over randomly selected periods of time, and (2) whether other variations of the BXM strategies can benefit from conditional deployment.

Although the conditional strategies clearly outperform the S&P from 1995 through June 2018, the

EXHIBIT 10

Monte Carlo Analysis of Conditional Strategies

	Conditional Strategy Outperforms	
Conditional BXM	**S&P 500**	**BXM (unconditional)**
Annual Return	82.9%	94.6%
Sharpe	92.4%	87.5%
Sortino	91.5%	88.5%
Conditional PUT	**S&P 500**	**PUT (unconditional)**
Annual Return	86.7%	93.4%
Sharpe	93.5%	75.6%
Sortino	92.2%	83.7%

annual performance presented earlier in Exhibit 7 also shows that in approximately one third of the years the conditional strategies underperform the S&P. This raises the question of whether the observed outperformance is simply an artifact of the particular time period we have analyzed. To examine this question, we use a Monte Carlo analysis in which we evaluate the performance of the conditional strategies over different time periods. We undertake this analysis by selecting 10,000 different periods with random start dates and random lengths of at least 12 months. Exhibit 10 shows the results. In this exhibit, we compare the percentage of random time periods when the conditional strategies outperform the market and the unconditional variant of the respective option-selling strategy.

As Exhibit 10 shows, the conditional strategies have greater returns compared with the S&P 500 and the unconditional option writing strategies over 80% of the time. This percentage is higher than the outperformance percentage shown in Exhibit 7 because the Monte Carlo simulation considers random periods of time greater than or equal to 12 months. As Exhibit 7 makes clear, one must have a long holding period to provide sufficient time for the strategy to outperform. The strategies also perform better in terms of downside risk as shown by better Sortino ratios in more than 80% of the outcomes. The Monte Carlo results provide compelling evidence of the robustness of our findings regarding the superior performance of the conditional option-selling strategies.

Throughout this article, we have focused our analyses on the BXM and PUT indexes. As noted earlier, numerous academic researchers have documented variations of the buy-write strategy with the goal of improving returns, such as writing 2% out-of-the-money calls. The CBOE provides historical data for four variations of the BXM, including

EXHIBIT 11

Performance of Buy-Write Variations, January 1995 to June 2018

	Average Return	Standard Deviation	Sharpe Ratio	Sortino Ratio
S&P 500	9.49%	14.63%	0.49	0.71
BXY (unconditional)	9.17%	12.33%	0.56	0.79
Conditional BXY	10.45%	12.79%	0.64	0.92
BXMD (unconditional)	9.45%	12.70%	0.56	0.81
Conditional BXMD	10.71%	13.27%	0.63	0.92
BXMC (unconditional)	9.05%	11.24%	0.60	0.84
Conditional BXMC	10.29%	11.87%	0.67	0.96

1. BXY—2% out of the money calls
2. BXMD—sells call option with delta closest to 30
3. BXMC—sells 0.5 unit if VIX below 20, 1 unit if VIX above 20
4. BXMW—using weekly options over the next four weeks.[11]

Exhibit 11 shows the results of implementing the conditional strategy on each of these covered call variations. In each case, we find a similar outcome: The conditional strategy improves both the absolute and risk-adjusted performance when compared with the underlying index or the S&P 500 alone.

FURTHER RESEARCH

We have focused on S&P 500–based option selling strategies in this article based on a straightforward VIX-based rule. There are three main areas for further research. First, as highlighted in Exhibit 7, the strategy can underperform during long bull runs with elevated volatility, as occurred in the late 1990s. This suggests that the strategy might be improved by consideration of market conditions beyond volatility alone. The second

[11] CBOE only provides data for this index back to July 2012 because of the availability of weekly S&P 500 options. Although this index is not included in Exhibit 11 because of the limited data period available, over the period July 2012 to June 2018, the conditional strategy does improve absolute and risk-adjusted performance similar to the other indexes.

main area concerns variations on the plain vanilla covered call strategy. In Exhibit 11, we saw that several variations of plain vanilla call writing also benefit from a conditional writing strategy. That said, as noted earlier, various studies[12] have looked at a wide range of methods to improve the covered call strategy, and one might wish to consider whether these variations might also benefit from a conditional strategy based upon market conditions.

One final area for further research is to examine whether the strategies might yield attractive returns when applied to more volatile emerging markets. Using daily data on the ETF EEM to represent emerging markets and SPY to represent the US equity markets, we find that emerging markets are considerably more volatile than US equity markets. For example, over the past 15 years, emerging market volatility was nearly 10 points higher than the volatility in US markets. This difference grows during periods of market turmoil and exceeded 22 points in 2008. This suggests that one might be able to generate even higher returns by using a conditional buy-write strategy in emerging markets.[13]

CONCLUDING COMMENTS

In this article, we examined how buy-write and put-write strategies can be improved though a simple conditional strategy that sells options only when the VIX index is elevated. We started with an examination of market volatility. Consistent with prior studies, we found that implied volatility is consistently higher than future volatility. We extended this research by showing that this overestimation grows at higher levels of the VIX index. After observing that this extends to option-writing indexes that exhibit excess returns during periods of elevated VIX, we developed conditional option writing strategies that only write options when the VIX is elevated above its historical median.

We document that these conditional strategies outperform both the S&P 500 Total Return Index and the continuous option-writing strategies. Monte Carlo analysis shows that our results are robust across various time periods. These findings suggest that portfolio managers who are using option-writing strategies should consider selectively deploying this strategy only in market conditions that are characterized by higher than normal levels of volatility.

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[12] For example, see Hill et al. (2006); McIntyre and Jackson (2007); Figelman (2008); He, Hsu, and Rue (2014); and Diaz and Kwon (2017).

[13] The authors are aware of at least one fund (managed by a firm named WaveFront) that has actually implemented an emerging market buy-write strategy. That fund has found that the actual returns from implementing this strategy, even after accounting for transaction costs and other implementation charges, have often exceeded returns of the emerging market ETF and yielded superior Sharpe and Sortino ratios.

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