Option Momentum*

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Abstract

This paper improves continuous-time variance swap formulas to derive exact returns on benchmark VIX option portfolios. In contrast to existing approximation formulas based on the continuous log-portfolio, the improved methodology calculates returns on a portfolio with discrete strike prices, rebalanced daily. This represents a feasible strategy on a model-free portfolio, with a model-free hedge that does not require estimating any parameters. The new formula preserves the variance swap interpretation; it decomposes returns into realized variance and option implied-variance.

We apply this new methodology to explore return momentum on option portfolios across different $S\&P$ 500 stocks. We find that stock options with high historical returns continue to outperform options with low returns. This predictability has a quarterly pattern, resembling the pattern of stock momentum found by Heston and Sadka (2008). In contrast to stock momentum, option momentum lasts for up to five years, and does not reverse.

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1 Introduction

Early tests of market efficiency examined autocorrelation of stock returns (Fama and French, 1988) as well as predictability of market variance (Canina and Figlewski (1993), Day and Lewis (1992), Lamoureux and Lastrapes (1993), Fleming (1998), and Christensen and Prabhala (1998)). While autocorrelation of aggregate stock market returns is weak, Jegadeesh (1990) and Jegadeesh and Titman (1993) document strong momentum in the cross-section of U.S. stock returns.[1] Moskowitz and Grinblatt (1999) and Grundy and Martin (2001) extended that cross-sectional predictability to stock industry returns, and Jostova et al (2013) extended it to bond returns.[2] Predictability in the cross-section implies that at least some assets have predictable returns. Despite the relevance and success of momentum strategies across asset classes, the literature has not yet investigated momentum in the cross-section of option returns across different stocks.

In order to investigate option momentum, we need to calculate returns on benchmark option portfolios. The standard published benchmarks for option volatility are the Chicago Board of Options Exchange (CBOE) VIX portfolio of $S\&P$ 500 index options, and the corresponding equity-VIX portfolios for options on individual stocks. Carr and Madan (1998) and Britten-Jones and Neuberger (2000) derived formulas that link VIX to the value of swaps on realized variance. But these formulas are only approximate, because they require a continuum of strike prices, and because they make additional

[1] Rouwenhorst (1998) and Griffin, Ji and Martin (2003) confirmed this cross-sectional effect in other countries.

[2] Asness et al (2013) and Jegadeesh and Titman (2011) also review evidence of momentum across countries, currencies, and commodity futures. Our focus is on the cross-section of U.S. stock options.

continuous-time diffusion approximations. For empirical work, it is difficult to verify the adequacy of these approximations across hundreds of different stocks.

This paper derives a new formula to calculate *exact* returns on tradable option strategies. These strategies employ equity-VIX portfolios of options on individual stocks, constructed by CBOE's standard "model-free" VIX weighting methodology. We calculate monthly returns on these portfolios, including daily dynamic hedges in the underlying stocks. The advantages of our approach are: 1) It provides *exact* returns on standard benchmark equity-VIX portfolios, 2) It uses a daily "model-free" hedge that does not require estimating any model parameters, and 3) It explains option returns with a simple "variance swap" decomposition into realized variance and option implied-variance. In other words, our methodology is the first to translate continuous-time variance swap intuition into exact predictions for discrete option data.

This paper explores predictability of monthly returns on equity-VIX portfolios of options across different $S\&P$ 500 stocks. It finds that positive returns (in the cross-section) strongly continue for 12 months. Unlike stock returns, option returns show no tendency to reverse the gains from momentum (DeBondt and Thaler, 1985, 1987). Instead, momentum continues periodically for up to 60 months. In particular, option momentum displays a quarterly pattern of continuation. This periodic pattern matches the quarterly pattern of stock momentum over the past year, documented by Heston and Sadka (2008).

The variance swap decomposition is useful for exploring the sources of momentum returns. The cross-section of realized variance is persistent, with a strong quarterly pattern. But the cross-section of option implied-variance is even more persistent than realized variance is. In other words, overpriced options tend to stay overpriced, and underpriced options tend to stay underpriced. The cross-section of option implied-variance has a smaller seasonal pattern than realized variance, suggesting that markets do not fully incorporate seasonality of market volatility.

The option momentum effect is correlated with previous anomalies. For example, it is well-known that option returns have a (negative) variance premium, and this variance premium extends to the cross-section. Specifically, Carr and Wu (2009) and Goyal and Saretto (2009) showed that stock options with high prices, relative to their historical volatility, have lower subsequent returns than options with low prices. In other words, there is a variance premium associated with option *value*, as measured by historical variance divided by current price. In contrast, option *momentum* is essentially a measure of historical variance divided by historical price. While returns to option momentum and option value are correlated, multivariate analysis shows that these two effects are distinct. In addition to being distinct from option value, the returns to historical option momentum also remain largely unexplained by risks and other option return predictors, and do not lie within the bid-ask spread.

Section 2 discusses the data used in our analysis. Section 3 explains how the theoretical link between variance swaps and option strategies inspires profitable momentum strategies. Section 4 controls for option value, risk, and a wide range of option return predictors. Section 5 examines the impact of option bid-ask spreads to the profitability of option momentum strategies, and a final section concludes.

2 Data and Methodologies

We begin by constructing option strategies across individual stocks, and later analyze the returns on these strategies. There are competing methodologies for accommodating options with different strike prices. Bakshi and Kapadia (2003) use delta-hedged returns on selected option series, and Jones, Khorram, and Mo (2020) use delta-hedged straddle returns. The gains of their delta-hedged option portfolio qualitatively represent a volatility risk premium that depends on the options being used. In contrast, the most pominent published benchmarks for option prices are the Chicago Board of Options Exchange *VIX* index for $S\&P$ 500 options (CBOE, 2019[3]) and the corresponding equity-VIX indices for options on individual stocks. These indices are based on portfolios of options, weighted by the squared reciprocals of their strike prices. Carr and Wu (2008) interpolated option prices to measure an idealized continuous VIX portfolio, and then used a continuous-time variance swap approximation to the returns on their portfolio. Although it is not literally a tradable option strategy, the variance swap approach has an intuitive advantage of decomposing returns into risk-neutral variance and realized variance. We construct returns on a discrete daily-hedged analog of the continuous variance swap option strategy. This method provides a tradable strategy, while preserving the intuition of the variance swap decomposition.

The CBOE (2019) VIX index is based on the (interpolated) market value of a portfolio at time t comprising options expiring at time T.

[3]CBOE White Paper used to construct the VIX index can be found at: https://www.cboe.com/micro/vix/vixwhite.pdf

$$V(t;T) = 2\sum_i \frac{O(K_i,t;T)\Delta_i}{K_i^2}, \tag{1}$$

where $O(K,t;T)$ represents time t price of an out-of-the-money call or put option with strike price K and expiration T, and Δ_i represents the gap between adjacent strike prices.[4] Importantly, VIX portfolios are "model-free" because their construction does not depend on any model parameters. Carr and Madan (1998) showed that we can approximate the VIX price with a continuous integral over strike prices.[5]

$$\hat{V}(t;T) = 2\int_0^\infty \frac{O(K,t;T)}{K^2}dK. \tag{2}$$

Given the spot price $S(T)$ at expiration, the option payoff $O(K,T;T)$ equals $Max(S(T)-K,0)$ for a call option and $Max(K-S(T),0)$ for a put option. In the absence of intermediate dividends, integrating these option payoffs over strike prices (2) shows the terminal payoff of the idealized VIX portfolio.

$$\hat{V}(T;T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1\right), \tag{3}$$

where r_f is the daily risk-free interest rate. The first term in the payoff (3) represents selling two units of the "log-portfolio". The second term represents a costless static hedge that leverages (the present value of) two dollars of stock at time t, and holds this hedge position constant until expiration at time T. The combined payoff is a U-shaped

[4]The sum uses out-of-the-money options with respect to the forward value of the strike price, $K(1+r_f)^{T-t}$.

[5]See also Demeterfi et al. (1999), Britten-Jones and Neuberger (2000), and Jiang and Tian (2005) for various continuous-time derivations. Breeden and Litzenberger (1978) first expressed the risk-neutral density in terms of the second derivative of the option price with respect to the strike price. Carr and Madan (1998) then derived the formula (2) using integration by parts twice.

function of the stock price, resembling a squared stock return. Therefore, the price of this portfolio represents the approximate (risk-neutral) variance of return. Since the *S&P 500 VIX* index and equity-VIX indices on individual stocks represent standard deviation, they are proportional to the square-root of the portfolio value $V(t;T)$.

We could further reduce risk of the idealized VIX portfolio by dynamic hedging instead of using a fixed static hedge. This replaces the second term of (3) with delta-hedging of the log-portfolio. The elasticity of option value with respect to the stock price generally depends on a model. But due to the log-payoff (3), the delta of the idealized VIX portfolio does not. Instead, the delta-hedge of the log-portfolio buys $1/S(t)$ shares of stock for a price of $S(t)$, and rebalances to maintains a constant hedge value of one dollar. So, not only is the value of the VIX portfolio model-free, but its delta-hedge is also model-free. The dynamically hedged payoff is

$$V_{hedged}(T;T) = -2\log(\frac{S(T)}{S(t)(1+r_f)^{T-t}}) + 2\sum_{u=t+1}^{T}(r_S(u) - r_f), \tag{4}$$

where $r_S(u)$ represents the stock return on day u. We can replace the stock price in equation (4) to express the $V_{hedged}(T;T)$ payoff in terms of a telescoping series of daily stock returns $r_S(u)$ at times u between t and T:

$$V_{hedged}(T;T) = -2\sum_{u=t+1}^{T}\log(\frac{1+r_S(u)}{1+r_f}) + 2\sum_{u=t+1}^{T}(r_S(u) - r_f). \tag{5}$$

When daily returns on the stock and risk-free rate are small, a second-order Taylor series expansion shows that the dynamically hedged option portfolio (5) approximates the payoff of variance swap contract in Carr and Wu (2009):

$$V_{hedged}(T;T) \approx \sum_{u=t+1}^{T} (r_S(u) - r_f)^2. \tag{6}$$

The return on the unhedged VIX portfolio from equation (1) is simply the proportional change in its value

$$r_{unhedged}(t;T) = \frac{V(T;T) - V(t;T)}{V(t;T)}. \tag{7}$$

The return on the dynamically hedged VIX portfolio is adjusted by the difference between the static hedge term in (3) and the dynamic risk term in (4).

$$r_{hedged}(t;T) = \frac{V(T;T) - V(t;T) - 2\left(\frac{S(T)}{S(t)(1+r_f)^{T-t}} - 1 - \sum_{u=t+1}^{T}(r_S(u) - r_f)\right)}{V(t;T)}. \tag{8}$$

A comparison of the hedged return (8) with the Taylor Series approximation (6) shows that the dynamically hedged return on the VIX portfolio is approximately the realized variance relative to the VIX portfolio price.

$$r_{hedged}(t;T) \approx \frac{\sum_{u=t+1}^{T}(r_S(u) - r_f)^2}{V(t;T)} - 1. \tag{9}$$

Carr and Wu (2009) used the variance swap approximation to analyze variance premiums in the cross-section of option returns, and Bollerslev, Tauchen, and Zhou (2009) used it implicitly when forecasting returns variance premium. Giglio and Kelly (2017) later applied it to multiple asset classes. In unreported diagnostics, we found that the exact return on the underlying $S\&P$ 500 index VIX portfolio is 99% correlated with the variance swap approximation (6). In other words, the dynamically hedged payoff on the index VIX portfolio is very close to the realized variance over the month. But with individual stocks, the correlations of options returns with realized variance can be lower. Using returns on hedged option portfolios (8) is consistent with previous research that measured delta-hedged returns, while preserving compatibility with the variance swap literature (9).

An additional advantage of our benchmark approach is that it measures option portfolios with all available strike prices. These portfolios maintain consistent sensitivity to volatility because they always include at-the-money options. In a certain sense, a VIX portfolio is always at-the-money. In contrast, Bakshi and Kapadia's (2003) approach of delta-hedging a single option will generally lose vega sensitivity when the option drifts away from the money.

This paper uses data from the OptionMetrics Ivy DB database from January 1996 to December 2017. These data provide daily closing bid and ask quotes for U.S. equity options. We use the T-bill rate of appropriate maturity (interpolated when necessary) from OptionMetrics as the risk-free rate.[6] Finally, we obtain information about stock returns, dividends, and firm characteristics from CRSP and COMPUSTAT.

We apply a series of filters on the option data. First, we use only options on S&P 500 constituent stocks within the sample period. This leaves us with a total of 995 firms. Following Driessen, Maenhout, and Vilkov (2009), we remove all observations for which

[6]Since average interest rates over this period were less than 2% per year, they had little effect on our calculations with monthly returns.

the option open interest is equal to zero, in order to eliminate options with no liquidity. We discard options with zero bid prices, and with missing implied volatility or delta (which occurs for options with nonstandard settlement or for options with intrinsic value above the current mid price). We delete all observations whose ask price is lower than the bid price, and eliminate options whose prices violate arbitrage bounds. We also require the mid-point bid-ask option quote to be at least \$0.125, and the underlying stock price to be at least \$5. We delete firm-month observations containing stock splits. Following Christoffersen, Fournier, and Jacobs (2017), we remove firm-month observations for which the present value of dividends before expiration is larger than 4% of the stock price. Following Conrad, Dittmar and Ghysels (2013), we use an equal number of calls and puts to construct VIX portfolios, using the midpoint of bid-ask quotes. Our final sample includes 79,845 firm-month observations with 535,722 option contracts. On average, each equity VIX portfolio consists of 6.71 option contracts.

The official CBOE VIX methodology combines options with different expiration dates to achieve a 30-day weighted-average maturity. Our analysis uncovers temporal periodicity in option prices and returns. To measure returns accurately, we must calculate portfolio values without interpolating option prices across different maturities. Therefore, we establish option position in equity-VIX portfolios on a Friday of each month, with exactly 28 days to expiration on the third Friday of the subsequent month.[7] This avoids interpolation by using exact option prices instead of 30-day weighted-averages used by the CBOE (2019) VIX methodology. We calculate returns

[7] We usually establish the option positions on the third Friday of a month. In months with five Fridays, we postpone the portfolio formation by one week to keep a holding period of exactly 28 days. This procedure had little effect on our empirical results.

to expiration on the underlying equity-VIX portfolio (1), hedged daily according to (8), without using any approximations nor interpolations. The resulting option portfolio *value* and its *returns* are model-free.

Table 1 compares equity-VIX returns (8) with variance swap returns. The gross variance swap return is defined as the realized monthly variance of a stock return divided by the equity-VIX price (9). Panel A compares net equity-VIX returns with net variance swap returns. Options have a negative variance premium, averaging a loss of 4.19% per month. While this seems large compared to average equity returns, equity-VIX portfolios are risky and highly levered. The standard deviation of return exceeds 85% per month. There is a particularly fat right tail, where returns exceed 115% on the upper 5% of observations.

Panel A of Table 1 shows that the variance swap return averages a loss of 2.64% per month. The discrepancy with average equity-VIX return of -4.19% per month comes from a convexity bias in the variance swap approximation formula. Overall, the two measures of return have similar distributions, but the average equity-VIX return is more negative than the average variance swap return.

Panel A measures the discrepancy between equity-VIX returns and variance swap returns at the individual firm level. Alternatively, Panel B shows the difference between cross-sectional average equity-VIX returns and variance swap returns in an equally weighted portfolio across all firms. This is effectively a portfolio of option portfolios. By exploiting the benefit of a large cross section, this approach diversifies the approximation error between equity-VIX returns and variance swap returns. The average difference between equally weighted variance swap returns and equally weighted equity-VIX returns is only 0.23% per month.

To reliably calculate correlations and risk-exposures, Panel C of Table 1 restricts the sample to 650 stocks which had data available to calculate equity-VIX prices for at least 30 monthly observations. Panel C shows that across these 650 stocks, the average within-firm correlation between equity-VIX return and variance swap return is 75%, and the median correlation is 87%. An equally weighted portfolio of all equity-VIX's gives an even higher correlation of 92%. By comparison, the $S\&P$ 500 Index VIX produced a 99% correlation between the variance swap return and the exact dynamically hedged VIX return. While variance swap return is a less accurate proxy for returns on equity-VIX option portfolios than it is for index-VIX option returns, much of this discrepancy gets diversified away in large portfolios. It is reassuring to know that the two measures are similar enough to support comparison of our new results with previous research.

The last row of Table 1 Panel A shows the Black-Scholes deltas, i.e., elasticities with respect to the stock price. The deltas of the idealized continuous VIX portfolios (3) are exactly zero, and Table 1 shows that the deltas of the equity-VIX portfolios are nearly zero. Under the Black-Scholes assumptions, the equity-VIX portfolios should be uncorrelated with stock returns. Panel C shows this is not the case. Equity-VIX returns have strong negative betas with respect to the stock return and even stronger negative betas with respect to $S\&P$ 500 returns. This is because of negative correlation between stock returns and innovations in variance. The final row of Panel C shows that equity-VIX returns have an average positive beta of 0.4 with respect to returns on $S\&P$ 500 index-VIX returns. In other words, equity-VIX returns share exposure to systematic market variance.

Options on individual equities have an additional American early exercise feature. While there are many numerical methods and approximations to the optimal exercise policy, a simple approximation is to exercise options early when their exercise value exceeds a certain threshold of the ask prices of options. Table A1 in the Appendix performs sensitivity analysis to show that the early exercise premium (0.36%) is small relative to the variance premiums in Table 1 and the returns of our momentum strategies.[8] Therefore, we ignore early exercise when computing returns in subsequent tables.

3 Option Portfolio Strategies

The previous section described construction of returns on our monthly equity-VIX portfolios. We use returns to expiration on these discrete model-free option portfolios. In the rest of this paper, when we form momentum strategies each month, we only consider firms that were included in the S&P 500 Index at that month, so that our strategy does not have forward-looking bias. Bakshi, Kapadia, and Madan (2003) used 31 individual stocks, and Carr and Wu (2009) used 35 individual stocks. Our substantially larger cross-section allows exploration of many different investment strategies.

Jegadeesh and Titman (1993) developed the simplest benchmark for stock momentum strategies. Their "relative strength" strategies sort stocks based on historical return over 3-, 6-, 9-, or 12-month periods, and then hold the equally weighted top decile of winner stocks and short the bottom decile of loser stocks for subsequent 3-, 6-, 9, or

[8]By using a binomial tree method, Driessen, Maenhout, and Vilkov (2009) find that the early exercise premium is between 0.3% and 1.1% for the 1-month option price. Our result lies in this range.

12-month periods. We measure the corresponding option strategy that buys the equally weighted top decile of equity-VIX option portfolios and shorts the equally weighted bottom decile of losers every month. Following Jegadeesh and Titman, we rebalance these portfolio each month to maintain equal weights.

Table 2 shows the results of simple decile spread strategies based on all combinations of 3-, 6-, 9-, and 12-month formation periods and 3-, 6-, 9-, or 12-month holding periods. The results are consistently profitable. Across all formation periods and all holding periods up to one year, the top decile of winners outperformed the bottom decile of losers. For example, with the 3-month-formation/3-month-hold strategies, the top decile of winners earned an average of 2.74% per month, while the bottom decile of losers lost 7.88% per month. This difference exceeds 10% per month. Across all strategies, the option decile spreads are economically large and statistically significant.

The strategies in Table 2 were not optimized for options. Table 2 merely represents an out-of-sample test of Jegadeesh and Titman's original strategies on an entirely new asset class. To understand why these strategies might be profitable, we decompose the option portfolio returns according to the variance swap approximation of the previous section.

Equation (9) shows that the gross return on an equity-VIX portfolio for the i^{th} stock over month t is approximately the realized variance, $RV_i(t)$, divided by the cost of the equity-VIX portfolio $VIX_i^2(t-1)$. In logarithms, this relationship is

$$log(1 + r_i(t)) \;\approx\; log(RV_i(t)) - log(VIX_i^2(t-1)). \tag{10}$$

This return decomposition shows that predictability in equity-VIX returns reflects predictability in realized variance relative to equity-VIX prices. To diagnose the sources of momentum profits, we run the cross-sectional regression

$$log(RV_i(t)) = \gamma_{0,t} + \gamma_{k,t} \cdot log(RV_i(t-k)) + \epsilon_i(t). \tag{11}$$

The coefficient estimate $\gamma_{k,t}$ shows the extent to which the cross-section of realized variance in one month is predicted by the previous cross-section lagged by k-months. The average of $\gamma_{k,t}$ over all months t shows the average relationship. Figure 1 (a) shows that the cross-section of realized variance is persistent, with coefficients exceeding 0.6 for short monthly lags, and declining as lags grow to five years. Figure 1 (a) also displays the corresponding average coefficients for the analogous regression of the cross-section of logarithms of equity-VIX prices $log(VIX_i^2(t))$ on their own lags. Option prices are even more persistent than realized variance, with average coefficients exceeding 0.8 for short monthly lags, and remaining above 0.5 even for lags of five years. Across different lags, both the realized variance and VIX^2 coefficients exhibit a striking quarterly periodicity. It appears that variance has a quarterly seasonal pattern across stocks, and to a large extent, option prices anticipate the pattern in future variance.

To ascertain whether option prices properly anticipate the persistence and seasonality of realized variance, we run the cross-section regression using continuously compounded variance swap returns,

$$log(1 + \tilde{r}_i(t)) = \gamma_{0,t} + \gamma_{k,t} \cdot log(1 + \tilde{r}_i(t-k)) + \epsilon_i(t), \tag{12}$$

where $\tilde{r}_i(t)$ denotes the variance swap return. While compounded variance swap returns are not exactly equal to returns, they are a good approximation. Figure 1 (b) shows that the resulting pattern of average γ coefficients across different lags remains positive and visibly seasonal for at least five years. Figure 1 (b) suggests that option prices fail to properly anticipate the persistence and periodicity of realized variance.

Table 3 shows the coefficients of first year lags from Figure 1 (b). The univariate columns shows that coefficient estimates are all highly significant at all lags, with t-statistics ranging from 6 to 11. To measure the incremental statistical significance of individual lags, the multivariate column of Table 3 reports average (of time-series) coefficients from multivariate cross-sectional regression that includes a full year of monthly lags. The multivariate t-statistics are at least 3 at the quarterly lags of 3-, 6-, 9-, and 12-months. But they are mostly statistically insignificant at other lags. This indicates that persistence in the cross-section of option returns is primarily a quarterly seasonal phenomenon.

To recap, Table 2 provides simple and robust evidence that momentum strategies are profitable across options on different stocks. Figure 1 and Table 3 indicate this predictability has a quarterly pattern that lasts for up to five years. This suggests that we investigate strategies that exploit momentum and specifically quarterly momentum for various horizons up to five years.

Inspired by Table 3 and Figure 1, Table 4 reports returns on one-month equally weighted decile portfolios of equity-VIX option strategies ranked according to different historical measures of variance swap momentum. The Year 1 "All" deciles are sorted based on the geometric average of all 12 monthly variance swap returns over the past year; the Year 2 "All" deciles are sorted based on monthly lags 12-24, and so forth. The Year 1 quarterly decile portfolios are sorted only based on monthly lags 3, 6, 9, and 12. The Year 2 quarterly portfolio uses lags 15, 18, 21, and 24, and similarly for Years 3, 4, and 5. The nonquarterly decile portfolios are sorted on the monthly lags of a given year that are *not* quarterly, e.g., lags 1, 2, 4, 5, 7, 8, 10, and 11 for Year 1.

Table 4 shows that average monthly returns are nearly monotonic across momentum deciles sorted based on the past year of returns. Using all months in the past year, the lowest decile lost 13.47% per month, while the highest decile gained 2.65% per month. The difference exceeds 16% per month, and is highly statistically significant. Sorting deciles using only four lags of 3-, 6-, 9-, and 12-months is nearly as profitable, with a decile spread of 14.77%. The quarterly effect must be quite strong for a noisy momentum strategy using only 4 lagged months to be nearly as profitable as a strategy using all 12 lagged months within the past year. In fact, the t-statistic for this quarterly winner-loser strategy exceeds the t-statistic for the full-year strategy. The Year 1 Non-Quarterly strategy is also profitable; the corresponding 10-1 decile spread exceeds 11%. The Year 1 Quarterly decile spread outperforms the Non-Quarterly decile spread by 3.42% per month.

To examine the source of profits of momentum strategies, we report the risk-adjusted returns for the short- and long-leg in the portfolio Year 1 "All", controlling for the VIX returns of $S\&P$ 500 Index, five Fama and French (2015) factors, and stock momentum factor. Results are reported in Table 5. In terms of raw returns, the short leg (13.47%) contributes most to total profit (16.13%), as shown in the first row of Table 4. After adjusting for the risk exposure to index VIX returns, which is largely negative, the winner portfolio contributes 70.4% to total risk-adjusted profits (11.9% out of 16.9%). This resembles the pattern of stock market momentum in Jegadeesh and Titman (1993).

The pattern of quarterly continuation in Table 4 relates to previous patterns of momentum in stock returns. Heston and Sadka (2008) found a quarterly pattern of continuation when using lagged stock returns less than one year. But beyond one year, this quarterly pattern disappeared. Instead, long-term stock returns exhibit long-term reversal (DeBondt and Thaler, 1985, 1987), with continuation at annual lags. The cross-section of option returns shares the quarterly pattern of continuation. While the quarterly pattern of options gets weaker and statistically less significant as the horizon recedes, it definitely does not turn into reversal within five years.

In unreported diagnostic tests, we have explored variables that might be related to the quarterly seasonality in option returns. These include firm earnings months, dividend months, and option expiration cycles. None of these variables alone explain the seasonal pattern in realized volatility or in option returns. Jones, Khorram, and Mo (2020) find similar seasonal momentum effects in straddle returns, and conclude that these effects remain strong after controlling for characteristics and factor risk. A behavioral explanation is that markets fail to fully anticipate seasonality in volatility. This resembles the behavioral bias across expiration dates documented by Eisdorfer, Sadka, and Zhdanov (2017). Alternatively, there might be a risk premium associated with quarterly seasonal volatility. Similar patterns remain unexplained in the stock momentum literature, and present questions for future research.

4 Control for Risk and Option Return Predictors

If markets are efficient, then excess returns of options strategies should be compensation for systematic risk. While our equity-VIX portfolios are hedged to be insensitive to stock risk, they are constructed to be very sensitive to variance risk. Systematic market variance has a well-known negative risk premium (Bakshi and Kapadia, 2003). The existence of a variance premium makes it plausible that past returns are correlated with exposure to variance. For example, stocks with high past variance swap returns might have high future comovement with systematic market variance.

Table 4 controls for risk by regressing the long-short momentum strategy returns on five Fama and French (2015) factors and the momentum factor of Carhart (1997). It also includes the VIX returns of $S\&P$ 500 Index as an additional risk factor. The intercept "alpha" from this regression represent risk-adjusted average returns. These risk-adjusted means are generally close to the average decile spreads, and do not alter their statistical significance. There is little indication that momentum returns in the cross-section of options are related to stock factors (including momentum) or to covariance with systematic market volatility.

Given the profitability of momentum strategies in options, a concern is whether the momentum return effect is truly new, or just a disguised manifestation of existing anomalies. In particular, Goyal and Saretto (2009) and Carr and Wu (2009) documented a significant negative return premium on options with high implied variance, relative to their historical variances. We define option value as rolling 1-year historical variance divided by *current* equity-VIX price. Option momentum is similar to option *value*, because option momentum is historical realized variance divided by historical equity-VIX price.

Table 6 distinguishes option momentum from option value using a double-sort. The rows first sort stocks into equally weighted quintiles by 12-month option value. Then, the columns sorts by option momentum. The value effect is quite strong, and returns are almost monotonic in every column. But they are also almost monotonic in every row. The average excess return on the quintile spread of high momentum minus low momentum across all stocks exceeds 12% per month, and is largely unchanged when adjusted for risk factors. It appears that the effect of option momentum is distinct from previously documented profitability of option value.

While option momentum is not subsumed by option value, it may capture some effects overlapped with previously documented option return predictors. To control for these variables, we put them along with option momentum into a vector $Z_i(t-1)$, which is known at month $t-1$. We then run a cross-section regression

$$r_i(t) = \gamma_{0,t} + \gamma'_{k,t} Z_i(t-1) + \epsilon_i(t), \tag{13}$$

where: $r_i(t)$ is the excess return of equity-VIX portfolio over risk-free rate; the vector $\gamma'_{k,t}$ represents coefficients for the option return predictors. The controlled variables include HV-IV (volatility deviation in Goyal and Saretto (2009)), IVOL (idiosyncratic volatility in Cao and Han (2013)), Slope_VTS (slope of implied volatility term structures in Vasquez (2017)), VOV (volatility of volatility constructed using option implied volatilities in Cao et al. (2019)), RN_Skew (risk-neutral skewness in Bakshi et al.

(2003)), Option Demand (option demand pressure calculated as the ratio of the average option open interest times $|\Delta|$ of option contracts over the past week to the total stock trading volume over the past week), Amihud (Amihud illiquidity measure (Amihud (2002))), and stock characteristics including firm size, book-to-market ratio, past one month stock return, stock return momentum, analyst forecast dispersion, cash holding, profitability, and stock issues constructed as Cao et al. (2020). To check the robustness of results, we also use delta-hedged at-the-money (ATM) call and put returns (calculated as Bakshi and Kapadia (2003)) as the dependent variable, respectively.

Table 7 shows that controlling for all of these option return predictors only moderately reduces the option momentum coefficient from 0.152 to 0.115. Results using delta-hedged call and put returns display very similar pattern. Option momentum remains highly profitable and statistically significant. We conclude that returns to option momentum are substantially independent of the option return predictors documented in previous literature.

5 Transaction Cost Analysis

Equity options have large trading costs. The median percentage bid-ask spread of our equity-VIX portfolios, defined as absolute bid-ask spread divided by the mid-point price of equity-VIX portfolio, is 14%. Such large trading costs might eliminate the profits on option strategies if mispricing lies entirely within the bid-ask spread. Margin requirements are another type of friction. Santa-Clara and Saretto (2009) show that margin requirements limit the notional amount of capital that can be invested in option strategies. Therefore, Table 8 evaluates the effect of these two trading frictions.

Table 8 uses the decile spread strategies from the first row of Table 4, forming monthly momentum portfolio based on "All" returns within the last year. The "0%" in the first column of Table 8 measures option prices at the mid-point of bid-ask quotes, just as in Table 4. The last column uses the full quoted bid-ask spreads. The intermediate columns use 50% and 75% of the quoted bid-ask spread around the mid-point prices.

Table 8, Panel A shows that the "All", "Quarterly", and "Non-Quarterly" strategies remain profitable for trading costs equal to 50% of the quoted bid-ask spread. When costs exceed 75% of the bid-ask spread, the "All" and "Quarterly" strategies earn insignificant profits, and the "Non-Quarterly" strategy loses insignificant money. When paying full bid-ask spreads, all the strategies lose money. Muravyev and Pearson (2019) show that the average effective bid-ask spread ratio for trades taking into account of high frequency trade timing ability is around 50%.

In the presence of bid-ask spreads, one could just trade the cheaper options. A simple strategy is to restrict trades to equity-VIX portfolio with percentage bid-ask spreads below the sample median of 14%. Panel B shows that this restriction hardly changes average profits when trading at the mid-point of the bid-ask spread. Indeed, this restriction insubstantially improves the mid-point profits from momentum based on "All" months from 16.1% to 17.0%. Using mid-point returns, restricting the sample increases the volatility and lowers the t-statistic due to a smaller sample of available firms. But it substantially improves profits when paying transactions costs. Even when paying the full bid-ask spread, the "All" strategy earns 9.1% per month, and the "Quarterly" strategy earns 7.1% per month. These post-trading-cost profits are positive at the 1% level of statistical significance. We conclude that with appropriate trade execution, the post-transactions cost momentum strategies preserve about half the mid-point trading profits.

Since our option momentum strategy sells options in loser portfolios, we investigate the impact of margin requirements. We compute margins of the option positions in loser portfolios following the CME margin system, which is applied to institutional investors' margin accounts. Specifically, we implement the scenario analysis algorithm used in Goyal and Saretto (2009). Each day, we use ±15% as the range for stock price movement, with progressive increments of 3%, and ±10% as the range for level of volatility. We then calculate option positions using the Black and Scholes (1973) model under each scenario, and determine the margin by the largest loss among those scenarios.

The initial margin haircut ratio is defined as $\frac{M_0 - V_0}{V_0}$, where M_0 is the initial margin of option positions in the firm's VIX portfolio when the trade is implemented, and V_0 equals the sum of option prices when the position is opened. Since additional margin calls may occur after the position is established, we also report the maximum haircut ratio during the holding month. Since the loser portfolio is equally weighted, we calculate the portfolio-level margin haircut by taking an equal-weighted average of the haircuts for individual firms.

Panel C reports the margin haircut ratio of shorting the loser portfolio in our "All" strategy. The initial haircut ratio has an average of 3.18 and maximum value of 6.64.[9]

[9] As a benchmark, Santa-Clara and Saretto (2009) find that the initial margin of writing an ATM

For each dollar of written options, investors need to borrow \$3.18, on average, to satisfy the initial margin requirement, which limits investors' option exposure to 31% of their capital. During the holding period after portfolio formation, the maximum haircut ratio has an average of 4.77 and maximum value of 8.94. To further explore the impact of margins on option momentum returns, we check the correlation between initial haircut and the momentum strategy return during the subsequent holding period. The two have a correlation of -0.27, which means initial haircuts tend to be high when the subsequent strategy returns are low. In this sense, the initial margins actually lower investors' exposure to potential negative momentum returns.

To measure the joint impact of bid-ask spreads and margin requirements faced by institutional investors, we compute monthly returns from investing the inverse initial margin ratio, $\frac{V_0}{M_0 - V_0}$, in our 12-month option momentum strategy, and allocating the remainder to the risk-free asset. We also assume investors face 50% effective bid-ask spread. Panel C reports the results in the "Return (%)" column. The average monthly return equals 4.53% with a t-statistic of 4.59. The minimum return is -31.17%. The annual Sharpe Ratio is 1.00. Therefore, option momentum strategies are profitable after considering both margins and reasonable bid-ask spreads.

6 Conclusions

This paper finds that a variety of momentum strategies are profitable across options on individual stocks. Option momentum is a measure of historical option returns, i.e.,

index put has an average of 2.6 and maximum value of 11.6.

realized variance relative to historical option prices. A related measure of option value is realized variance relative to current option prices. Returns to option momentum are distinct from returns to option value, and are not explained by standard risk factors, stock characteristics, or bid-ask spreads.

Option momentum has intriguing commonalities and contrasts with stock momentum. Momentum in options across S&P 500 firms displays a strong quarterly periodicity that matches the Heston and Sadka (2008) pattern of momentum within one year, but does not match the Heston and Sadka annual pattern for long-term momentum. Unlike stocks, options do not show long-term reversal of momentum profits. Instead, option momentum, particularly quarterly momentum, remains profitable for up to five years. It is tempting to speculate about risk factors or behavioral biases that might explain returns to option momentum. A successful theory would explain the quarterly pattern in options, and why the patterns of momentum profits are different in stocks and options.

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Table 1: Summary Statistics of Equity-VIX Returns

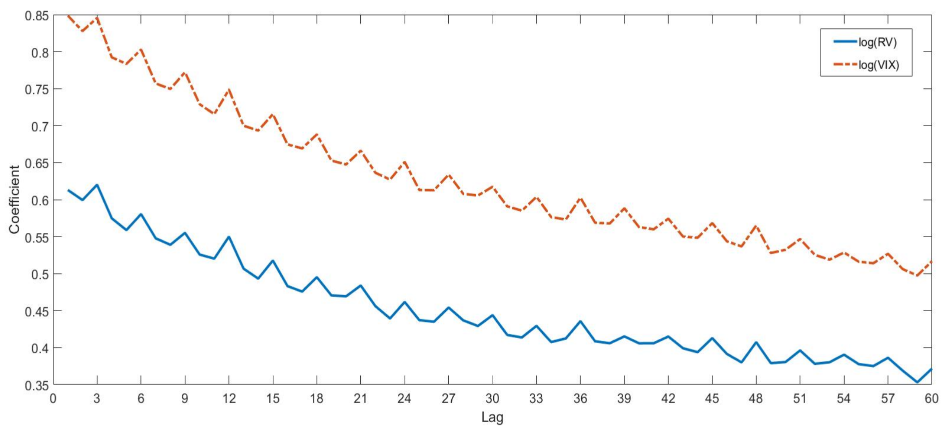
The sample data are from January 1996 to December 2017. We select firms that were included in the $S\&P$ 500 index during that period. There are 263 months of returns and 79,854 firm-month observations in total. Equity-VIX Return is the actual realized return of underlying equity-VIX portfolio, constructed as a static position in a basket of options plus a daily rebalanced position in the underlying stock. Variance Swap Return (VSR) is defined as the realized variance of the stock return divided by the price of the equity-VIX portfolio minus 1. Equity-VIX Return - VSR is the difference between the equity-VIX return and variance swap return. EW Equity-VIX Return is the cross sectional average of equity-VIX returns each month. EW Variance Swap Return is the cross sectional average of firms' variance swap returns each month. Black-Scholes Delta Elasticity is the elasticity of equity-VIX portfolio with respect to the underlying stock price at the formation date. β_{Stock} is the exposure of the firm equity VIX return to its stock return; β_{SP500} is the exposure of firms' equity-VIX returns to the $S\&P$ 500 index return; $\beta_{MKT\ VIX}$ is the exposure of firm equity-VIX returns to the $S\&P$ 500 index VIX return. Correlation(Equity VIX Return,VSR) is the firm level time-series correlation between equity-VIX returns and variance swap returns. When calculating β_{Stock}, β_{SP500}, $\beta_{Mkt\ VIX}$ and Correlation(Equity-VIX Return, VSR), we require firms to have at least 30 observations. There are 650 firms meeting this requirement.

	Mean	Std	5%	25%	50%	75%	95%
Panel A							
Number of Firms Each Month	304	111	147	203	293	411	468
Number of Strikes	6.71	4.90	4.00	4.00	6.00	8.00	14.00
Index-VIX Return(%)	-23.29	72.66	-73.10	-56.43	-37.18	-15.49	65.52
Index Variance Swap Return(%)	-24.39	74.18	-74.72	-58.32	-38.75	-13.41	60.02
Equity-VIX Return (%)	-4.19	85.52	-69.18	-42.78	-19.49	14.73	115.1
Variance Swap Return (%)	-2.64	101.93	-71.66	-48.74	-24.73	11.73	126.3
Equity-VIX Return - VSR (%)	-1.55	78.48	-37.83	1.45	5.84	12.82	25.82
Black-Scholes Delta Elasticity	-0.05	0.09	-0.17	-0.07	-0.04	-0.02	0.00
Panel B							
EW Equity-VIX Return (%)	-3.46	32.85	-38.03	-22.88	-9.87	6.64	56.13
EW Variance Swap Return (%)	-3.23	44.19	-39.80	-26.13	-12.02	5.66	67.08
EW Equity-VIX Return - VSR (%)	-0.23	18.84	-19.89	-2.77	2.67	7.28	11.87
Panel C							
Correlation(Equity-VIX Return, VSR)	0.75	0.31	0.13	0.69	0.87	0.95	0.99
β_{Stock}	-2.24	2.55	-6.37	-3.36	-2.07	-0.98	1.06
β_{SP500}	-4.02	3.50	-9.75	-5.98	-3.82	-1.96	1.18
$\beta_{Mkt\ VIX}$	0.40	0.31	-0.06	0.24	0.38	0.55	0.85

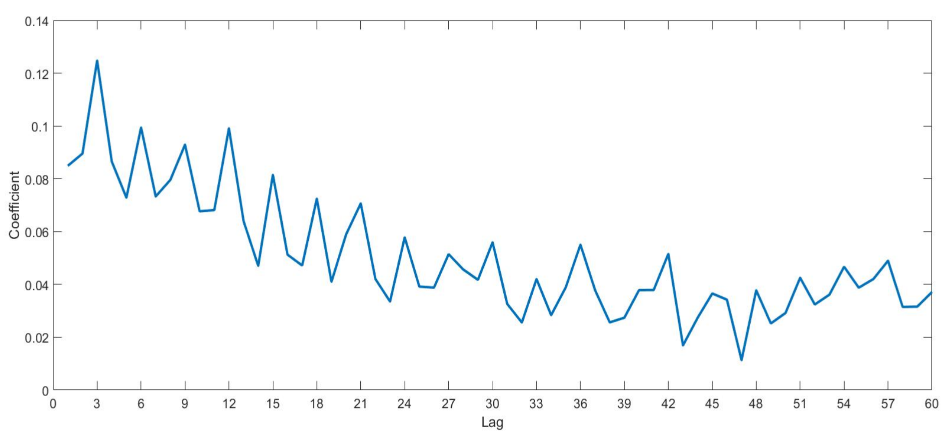
Table 2: Option Momentum Strategy Returns

The momentum portfolios are formed based on J-month lagged equity-VIX returns and held for K months as in Jegadeesh and Titman (1993). In addition, we require the firms to have non-missing equity-VIX returns for at least $\frac{2}{3}J$ past months. The values of J and K for the different strategies are indicated in the first column and row, respectively. To avoid forward-looking bias, we only include firms that are included in the $S\&P$ 500 index when we form the portfolio. The portfolios are equally weighted. The average monthly returns of these portfolios are presented in this table. The t-statistics are reported in parentheses. Portfolio returns are expressed in percent. The sample period is from January 1996 to December 2017.

J	K=	3	6	9	12
3 Loser		-7.88	-6.81	-6.41	-6.42
		(-3.53)	(-3.09)	(-2.95)	(-2.94)
3 Winner		2.74	0.52	-0.93	-1.46
		(1.00)	(0.21)	(-0.39)	(-0.62)
3 Winner-Loser		10.63	7.32	5.49	4.96
		(5.90)	(5.44)	(4.67)	(4.43)
6 Loser		-8.15	-7.69	-7.03	-7.10
		(-3.48)	(-3.36)	(-3.08)	(-3.15)
6 Winner		1.93	0.37	-0.74	-1.02
		(0.69)	(0.14)	(-0.30)	(-0.41)
6 Winner-Loser		10.08	8.05	6.29	6.08
		(5.09)	(4.93)	(4.06)	(4.22)
9 Loser		-7.89	-7.61	-7.65	-7.17
		(-3.07)	(-3.16)	(-3.27)	(-3.09)
9 Winner		1.63	1.05	-0.01	-0.31
		(0.60)	(0.40)	(-0.00)	(-0.12)
9 Winner-Loser		9.52	8.67	7.64	6.86
		(4.67)	(4.82)	(4.34)	(4.19)
12 Loser		-5.60	-7.18	-6.91	-7.15
		(-2.22)	(-2.91)	(-2.83)	(-3.02)
12 Winner		1.21	0.40	-0.17	-0.91
		(0.43)	(0.15)	(-0.07)	(-0.36)
12 Winner-Loser		7.21	7.58	6.74	6.24
		(3.27)	(3.95)	(3.68)	(3.57)



(a) Coefficients of $log(RV_{i,t-k})$ and $log(VIX^2_{i,t-k})$



(b) Coefficients of $log(VSR_{i,t-k})$

Figure 1. Monthly univariate cross-sectional regression of the form $x_{i,t} = \alpha_{k,t} + \gamma_{k,t} \cdot x_{i,t-k} + \varepsilon_{i,t}$, are calculated for each month t and lag k, where $x_{i,t}$ is either the logarithm of realized variance (RV), logarithm of the price of equity-VIX portfolio, or the logarithm of the variance swap return (VSR) of firm i in month t. The regression is calculated for every month t from January 1996 through December 2017 and for lag k values of 1 through 60. Figures (a) and (b) plot the time-series averages of $\gamma_{k,t}$.

Table 3: Univariate and Multivariate Cross-sectional Regressions of Variance Swap Returns

Monthly univariate cross-sectional regression of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} \cdot r_{i,t-k} + \varepsilon_{i,t}$, are calculated for each month t and lag k, where $r_{i,t}$ is the continuously compounded variance swap return of firm i in month t. The regression is calculated for every month t from January 1996 through December 2017 and for lag k values 1 through 12. Monthly multivariate cross-sectional regression takes the form: $r_{i,t} = \alpha_{k,t} + \sum_{k=1}^{12} \gamma_{k,t} \cdot r_{i,t-k} + \varepsilon_{i,t}$. To avoid forward-looking bias, we only include firms that are included in the *S&P 500* index when we form the portfolio. The time-series averages of $\gamma_{k,t}$ along with their t-statistics, are reported in the table.

	Univariate		Multivariate	
Lag	Coefficient	t-statistic	Coefficient	t-statistic
1	0.085	7.85	0.043	2.24
2	0.089	9.65	0.026	1.93
3	0.125	11.26	0.053	3.10
4	0.087	8.74	0.049	2.34
5	0.073	6.93	0.030	2.21
6	0.099	9.83	0.046	2.95
7	0.073	9.24	0.013	0.51
8	0.080	9.35	0.023	1.05
9	0.092	10.46	0.078	3.93
10	0.068	6.93	0.027	1.42
11	0.068	7.51	0.019	1.49
12	0.099	11.30	0.050	3.73

Table 4: Returns of Strategies Based on Past Variance Swap Returns

Every month firms are grouped into ten portfolios according to various categories based on the geometric average of past variance swap returns. To avoid forward-looking bias, we only include firms that are included in the $S\&P$ 500 index when we form the portfolio. For example, the trading strategy that is formed based on past quarterly returns during Year 2 ranks firms according to their average log variance swap returns over historical monthly lags 15, 18, 21, and 24. The trading strategy "All" in a given year is formed based on each firm's average log variance swap return over that lagged year. The equity-VIX's in each portfolio are equally weighted across firms, and portfolios are rebalanced monthly. To calculate alpha, we control for the VIX return of the $S\&P$ 500 index, five Fama and French (2015) risk factors, and the Carhart (1997) stock momentum factor. The average monthly returns of these portfolios are presented in percent, with t-statistics reported in parentheses. The sample period is from January 1996 through December 2017.

	Strategy	1	2	3	4	5	6	7	8	9	10	10-1	Alpha
Year 1	All	-13.47	-7.82	-4.82	-3.56	-4.86	-1.58	-1.77	0.00	1.44	2.65	16.13	16.92
												(8.42)	(8.21)
	Quarterly	-12.56	-6.97	-5.62	-2.26	-3.23	-2.47	0.72	-0.10	-0.67	2.21	14.77	15.39
												(8.75)	(8.71)
	Non-Quarterly	-11.51	-6.57	-5.56	-2.73	-2.61	-1.31	-2.17	-0.84	0.71	0.13	11.64	11.52
												(6.49)	(5.99)
Year 2	All	-9.10	-4.24	-5.13	-3.45	-2.32	-3.78	-3.97	-2.96	-1.75	-1.20	7.90	5.75
												(3.98)	(2.74)
	Quarterly	-7.26	-6.95	-2.98	-4.23	-4.62	-2.94	-1.23	-1.09	-3.85	0.54	7.80	8.27
												(4.21)	(4.15)
	Non-Quarterly	-5.92	-5.09	-6.36	-2.31	-3.52	-3.25	-1.17	-3.51	-3.50	-2.63	3.29	1.34
												(1.48)	(0.57)
Year 3	All	-7.72	-5.87	-5.67	-3.70	-6.22	-4.87	-2.65	-5.45	-3.66	-3.63	4.09	2.01
												(2.03)	(0.94)
	Quarterly	-7.05	-7.91	-6.08	-6.67	-5.44	-4.10	-2.16	-2.38	-2.56	-3.84	3.21	2.88
												(1.83)	(1.52)
	Non-Quarterly	-6.95	-4.60	-4.26	-4.58	-4.37	-5.44	-4.30	-3.79	-4.47	-5.21	1.73	0.06
												(0.97)	(0.03)
Year 4	All	-7.15	-5.63	-5.42	-4.95	-4.61	-4.76	-5.33	-4.81	-6.36	-4.21	2.94	3.11
												(1.68)	(1.65)
	Quarterly	-7.12	-5.41	-4.02	-5.71	-4.85	-5.78	-7.31	-5.47	-3.75	-1.81	5.31	4.85
												(2.96)	(2.50)
	Non-Quarterly	-6.11	-6.13	-4.35	-4.85	-4.46	-7.06	-4.64	-4.56	-5.45	-5.84	0.26	-0.67
												(0.15)	(-0.34)
Year 5	All	-6.54	-7.66	-8.57	-8.07	-5.62	-7.73	-6.14	-6.84	-5.25	-3.55	2.99	0.18
												(1.26)	(0.07)
	Quarterly	-9.89	-8.51	-6.82	-5.93	-7.63	-5.58	-7.55	-5.78	-5.99	-3.89	6.00	5.39
												(3.46)	(2.86)
	Non-Quarterly	-6.24	-6.42	-6.60	-10.19	-8.13	-6.51	-7.45	-5.39	-3.91	-4.90	1.34	-0.94
												(0.65)	(-0.343)

Table 5: Risk-adjusted Option Momentum Returns

Option momentum portfolios are formed by sorting firms' geometric average of all 12 monthly variance swap returns over the past year, the same as the first row in Table 4. The table presents results from the following time-series regression: $r_{p,t} = \alpha_p + \beta_p \cdot F_t + \varepsilon_{p,t}$, where $r_{p,t}$ is the monthly excess return of loser, winner, and long-short portfolio, respectively. F_t is a vector of risk factors including: the return of S&P 500 Index VIX portfolio in excess of the risk-free rate, the Fama and French (2015) five factors (MKT-Rf, SMB, HML, RMW, and CMA), and the Carhart (1997) momentum factor (Stock MOM). Coefficient estimates are reported with the associated t-statistics in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Loser	Winner	W-L
Alpha	-0.051***	0.119***	0.169***
	(-3.63)	(5.99)	(8.21)
Index VIX Ret-Rf	0.345***	0.395***	0.050
	(15.85)	(12.81)	(1.56)
MKT-Rf	-0.397	-0.002	0.395
	(-1.05)	(-0.00)	(0.71)
SMB	-0.962*	-1.237	-0.275
	(-1.82)	(-1.65)	(-0.35)
HML	-0.653	0.141	0.794
	(-1.34)	(0.20)	(1.10)
RMW	-0.096	0.543	0.639
	(-0.15)	(0.61)	(0.69)
CMA	-0.049	-1.231	-1.182
	(-0.06)	(-1.04)	(-0.95)
Stock MOM	0.022	-0.047	-0.069
	(0.11)	(-0.17)	(-0.24)
Adj. R^2	0.637	0.517	-0.004

Table 6: Average Monthly Returns on Equity-VIX Portfolios Sorted on Value and then Momentum

Each month, we first sort firms into quintiles based on option value, defined as $log(\frac{RV_{i,t-12,t}}{VIX^2_{i,t}})$, where $log(RV_{i,t-12,t})$ is the geometric average of firm i's realized variance over the past 12 months. Then, within each quintile, we sort firms based on option momentum, which is the compound variance swap return over the past 12 months. The "All" row shows statistics for portfolios sorted by momentum only, without controlling for value. Portfolios are equally weighted. Portfolio 1 has the lowest value or momentum. To avoid forward-looking bias, we only include firms in the $S\&P$ 500 index when we form the portfolio. To compute the alpha of portfolio returns, we control for the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the VIX return of the $S\&P$ 500 index. Returns are expressed in percent, with t-statistics in parentheses.

	Momentum						
Value	1 (Low)	2	3	4	5 (High)	5-1	Alpha
1 (Low)	-19.98	-13.66	-12.55	-9.63	-5.84	14.13	15.46
						(5.21)	(5.48)
2	-9.50	-8.14	-4.14	-5.83	-2.85	6.64	10.15
						(2.95)	(4.35)
3	-4.41	-4.40	-5.58	-2.90	1.07	5.48	2.99
						(2.18)	(1.13)
4	-3.23	0.19	0.89	-0.19	2.70	5.93	7.56
						(2.04)	(2.42)
5 (High)	-1.07	5.23	5.39	3.03	7.42	8.49	9.56
						(3.00)	(3.11)
All	-10.62	-4.20	-3.22	-0.87	2.04	12.67	12.69
						(8.48)	(7.93)

Table 7: Option Momentum Controlling for Option Return Predictors

We estimate the cross-sectional regression: $r_{i,t} = \alpha_t + \gamma_t \cdot Z_{i,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the monthly equity-VIX returns in excess of risk-free rate, and $Z's$ are option return predictors including Option MOM (continuously compounded variance swap return over the past 12 months), HV-IV (volatility deviation in Goyal and Saretto (2009)), IVOL (idiosyncratic volatility in Cao and Han (2013)), Slope_VTS (slope of implied volatility term structures in Vasquez (2017)), VOV (volatility of volatility in Cao et al. (2019)), RN_Skew (risk-neutral skewness in Bakshi et al. (2003)), Option Demand (option demand pressure), Amihud (Amihud illiquidity measure (Amihud (2002))), and stock characteristics in Cao et al. (2020). Results using delta-hedged ATM call and put returns (Bakshi and Kapadia (2003)) as dependent variables are also reported. The associated t-statistics in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from Jan. 1997 to Dec. 2017.

	Equity-VIX Return		Delta-hedged Call		Delta-hedged Put	
	(1)	(2)	(3)	(4)	(5)	(6)
Option MOM	0.152***	0.115***	0.007***	0.005***	0.007***	0.005***
	(8.30)	(6.05)	(7.25)	(6.71)	(8.27)	(6.13)
HV-IV		0.113***		0.009***		0.009***
		(2.72)		(4.57)		(4.79)
IVOL		-2.629***		-0.171***		-0.120***
		(-2.82)		(-4.48)		(-3.18)
Slope_VTS		0.640***		0.046***		0.048***
		(4.40)		(6.76)		(7.44)
VOV		-0.664***		-0.012		-0.028***
		(-3.00)		(-1.23)		(-3.08)
RN_Skew		0.017		-0.001***		0.002***
		(1.24)		(-2.72)		(3.61)
Option Demand		-0.005***		-0.000***		-0.000**
		(-3.67)		(-3.11)		(-2.05)
Amihud		88.835		1.960		3.350
		(1.34)		(0.85)		(1.38)
Size		0.003		-0.000		-0.000
		(0.37)		(-0.25)		(-0.21)
Book-to-Market		0.001		0.000		-0.000
		(0.19)		(0.72)		(-0.80)
$RET_{t-1,t}$		-0.171**		-0.009***		-0.012***
		(-2.25)		(-2.60)		(-3.76)
$RET_{t-12,t-1}$		0.019		-0.002**		-0.001
		(0.79)		(-2.15)		(-1.41)
Analyst Dispersion		-0.052		0.002		0.002
		(-0.91)		(0.70)		(0.81)
Cash Holding		0.029		-0.000		0.002*
		(1.04)		(-0.26)		(1.91)
Profitability		-0.016		0.001		0.001
		(-0.81)		(1.63)		(0.62)
Issue		0.082		0.005**		0.005**
		(1.60)		(2.15)		(2.55)
Intercept	-0.003	0.012	0.001	0.004	-0.003***	0.000
	(-0.14)	(0.08)	(0.75)	(0.85)	(-3.62)	(0.08)
R^2	0.016	0.160	0.017	0.194	0.019	0.190

Table 8: Impact of Transaction Costs

Option momentum portfolios are formed as in Table 4. The portfolio returns are computed from the mid-point price and from the effective bid-ask spread, estimated to be equal to 50%, 75%, and 100% of the quoted spread. In panel B, if the percentage bid-ask spread of VIX portfolio price of a firm is larger than the sample median, we don't trade the firm that month. All returns are expressed in percent, with t-statistics in parentheses. Panel C reports the margin haircut ratio of shorting loser portfolios. The initial margin haircut is defined as $(M_0 - V_0)/V_0$, where M_0 is the initial margin of option positions in equity-VIX portfolios when the trade is implemented, and V_0 equals the sum of option prices when the position is opened. Max haircut is the maximum haircut ratio during the month. Correlation between initial haircut ratio and the subsequent option momentum strategy return of the month is also reported. The column "Return (%)" in Panel C reports the monthly return of momentum strategy "All" with 50% effective spreads combined with initial margin requirements. The t-statistic is reported in parenthesis.

Panel A: Option momentum returns

	Percentage of Quoted Bid-Ask Spread			
	0%	50%	75%	100%
All	16.13	6.74	1.86	-3.22
	(8.42)	(3.62)	(1.00)	(-1.69)
Quarterly	14.77	5.85	1.24	-3.53
	(8.75)	(3.55)	(0.75)	(-2.08)
Non-Quarterly	11.64	2.52	-2.31	-7.46
	(6.49)	(1.44)	(-1.30)	(-4.08)

Panel B: Percentage bid-ask spread lower than median.

All	17.05	13.25	11.17	9.08
	(5.66)	(4.48)	(3.78)	(3.08)
Quarterly	13.91	11.53	9.35	7.17
	(5.52)	(4.08)	(3.31)	(2.53)
Non-Quarterly	11.95	8.13	6.03	3.93
	(4.90)	(3.43)	(2.54)	(1.65)

Panel C: Margin haircut ratio of loser portfolio.

	Initial haircut	Max haircut	Correlation	Return (%)
Mean	3.18	4.77	-0.27	4.53 (4.59)
Std	1.29	1.59		15.64
Min	0.68	1.23		-31.17
Max	6.64	8.94		

7 Appendix

Table A1: Early Exercise Premium

This table examines the difference between the European option return-to-expiration and the American early exercise return of our equity-VIX portfolios. We consider approximate policies that exercise options at end of each day if the exercise value is higher than 95%, 96%, 97%, 98% and 99% of the ask price of the option. Using these policies, there are up to 17,000 firm-month observations with early exercise. To calculate the early-exercise payoff of a call option, we borrow the strike price at risk-free rate and hold the stock position to option maturity; to calculate the early exercised payoff of a put option, we short-sell the stock and reinvest the payoff to maturity at risk-free rate. All dividends are reinvested to maturity at the risk-free rate.

The Mean calculates the monthly average error between the European return and the American return. All returns are expressed in percent. The standard error (Std) calculates the standard deviation of the error. The mean absolute error (MAE) calculates the monthly average absolute error. Correlation reports the correlation between European return and American return. Panel B shows that the maximum American exercise premium of .355% is achieved with an early-exercise threshold of 96%. This is smaller, by an order of magnitude, than the average European return-to-expiration of -4.19% in the first row of Table 1 Panel A. We conclude that early exercise is not quantitatively important to our analysis.

Panel A: Summary Statistics of European Return and American Return

	Mean	Std	5%	25%	50%	75%	95%
European	-4.195	85.52	-69.18	-42.78	-19.49	14.73	115.10
American 99%	-3.970	85.59	-69.06	-42.56	-19.22	15.01	115.45
American 98%	-3.895	85.58	-69.01	-42.49	-19.12	15.11	115.53
American 97%	-3.849	85.51	-69.02	-42.42	-19.04	15.19	115.47
American 96%	-3.839	85.47	-69.00	-42.38	-19.02	15.20	115.38
American 95%	-3.854	85.43	-69.02	-42.38	-19.02	15.19	115.43

Panel B: Early Exercise Premium

	Mean	Std	MAE	t-statistic	Correlation
99%	0.225	4.35	0.627	14.59	0.999
98%	0.299	5.00	0.782	16.91	0.998
97%	0.346	5.77	0.959	16.93	0.998
96%	0.355	6.40	1.099	15.68	0.997
95%	0.341	6.89	1.237	13.98	0.997