Option Momentum

STEVEN L. HESTON, CHRISTOPHER S. JONES, MEHDI KHORRAM,
SHUAIQI LI, and HAITAO MO*

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ABSTRACT

This paper investigates the performance of option investments across different stocks by computing monthly returns on at-the-money straddles on individual equities. It finds that options with high historical returns continue to significantly outperform options with low historical returns over horizons ranging from 6 to 36 months. This phenomenon is robust to including out-of-the-money options or delta-hedging the returns. Unlike stock momentum, option return continuation is not followed by long-run reversal. Significant returns remain after factor risk adjustment and after controlling for implied volatility and other characteristics. Across stocks, trading costs are unrelated to the magnitude of momentum profits.

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*Steven L. Heston is with the Smith School of Business at the University of Maryland. Christopher S. Jones is with the Marshall School of Business at the University of Southern California. Mehdi Khorram is with the Saunders College of Business at the Rochester Institute of Technology. Shuaiqi Li is at the Systemic Risk Centre in the London School of Economics. Haitao Mo is at the Ourso College of Business at Louisiana State University. This paper includes results that previously appeared in two working papers. We are grateful for comments from our discussants, Bjorn Eraker (AFA), Alexander Philipov (NFA), Zhiguang Wang (SWFA), Rohit Allena (FMA), and Xiaoyan Zhang (CICF), from seminar participants at the University of Maryland, Baruch College, NYU Tandon, ITAM, and the Virtual Derivatives Workshop, and from Peter Carr, Pedro Garcia-Ares, Juhani Linnainmaa, Dilip Madan, Aurelio Vasquez, and Liuren Wu. We thank two referees, an associate editor, and the editor, Stefan Nagel, for their many suggestions. All errors are our own. We have no conflicts of interest to report.

Momentum, the tendency for assets that have earned above-average returns in the past to continue to outperform in the future, is one of the most pervasive and widely studied financial market anomalies. While the original study of Jegadeesh and Titman (1993) focused solely on U.S. common stock returns, the phenomenon has been found in global stocks (Rouwenhorst (1998)), corporate bonds (Jostova et al. (2013)), commodities (Erb and Harvey (2006)), and currencies (Okunev and White (2003)). Momentum is also found in stock portfolios, including industries (Moskowitz and Grinblatt (1999)), countries (Richards (1997)), and long/short factors (Ehsani and Linnainmaa (2021); Gupta and Kelly (2019)). In this paper we ask whether or not momentum exists within the options market.

We focus on the returns of delta-neutral straddles on individual equities but also consider other strategies based on model-free VIX portfolios and dynamic hedging. Straddles, which combine approximately equal positions in a put and a call with the same maturity and strike price, are constructed to set each straddle's overall delta to zero. The result is a strategy whose returns are approximately invariant to the performance of the underlying stock, which implies that the performance of a straddle-based momentum portfolio will be essentially unrelated to any momentum in the underlying stocks.

We find that momentum is a far stronger phenomenon in options than it is in other asset classes, with a pre-cost Sharpe ratio at least three times higher than that of the standard cross-sectional momentum strategy for stocks. We also find, similar to stocks, that one-month returns tend to reverse over the following month, though this result is less robust to different methods for computing option returns. In contrast to stocks, there is no evidence of long-term reversal in option returns.

Momentum is stable over our sample, significant in every five-year subsample and in almost all subgroups formed on the basis of firm size, stock or option liquidity, analyst coverage, and credit rating. After controlling for other characteristics in Fama-MacBeth regressions, or after factor adjustment using the model of Horenstein, Vasquez, and Xiao (2019), momentum remains highly significant.

The momentum strategy based on the past year of returns, with an annualized Sharpe ratio of 1.53, offers strong risk-adjusted returns. Furthermore, momentum returns are positively skewed, with a relatively modest maximum drawdown relative to their mean returns or relative to the drawdowns of alternative option strategies. Thus, the large average returns we document do not appear to accompany the type of crash risk that Daniel and Moskowitz (2016) show exists for stock momentum portfolios.

Transactions costs lower the performance of the momentum and reversal strategies, but both remain profitable under reasonable assumptions if strategies are modified to reduce the effects of these costs. These modifications include forming portfolios from straddles with more extreme past returns (deciles rather than quintiles), discarding straddles constructed from options with large bid-ask spreads, and combining the momentum and reversal signals into a single composite strategy. Surprisingly, we find no relation between the strength of the momentum effect and the bid-ask spreads of the firm's options.

Following advances in the stock momentum literature, we also examine several other types of momentum. We find that the so-called "time series momentum" strategy of Moskowitz, Ooi, and Pedersen (2012) delivers returns that are very similar to the standard cross-sectional strategy. Options also display momentum at the industry level, similar to the findings of Moskowitz and Grinblatt (1999) for stocks, and in factor portfolios, echoing similar results by Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019). We demonstrate, however, that only the standard cross-sectional momentum strategy survives pairwise spanning tests. Industry momentum returns can be explained by the standard cross-sectional momentum factor, while the reverse is not true. While factor momentum appears to be distinct from the other forms of momentum we consider, its average return does not survive factor adjustment with respect to the Horenstein, Vasquez, and Xiao (2019) model or our extension of it.

Again borrowing from the stock momentum literature, we examine a number of potential explanations of our findings. The behavioral models proposed to explain stock momentum do so by producing underreaction (Barberis, Shleifer, and Vishny (1998), Grinblatt and Han (2005)), delayed overreaction (Daniel, Hirshleifer, and Subrahmanyam (1998)), or a mixture of both (Hong and Stein (1999)). Potential rational explanations include cross-sectional variation in unconditional expected returns (e.g., Conrad and Kaul (1998)), time-varying risk premia (e.g., Grundy and Martin (2001), Kelly, Moskowitz, and Pruitt (2020)), and compensation for crash risk (Daniel and Moskowitz (2016)).

Delayed overreaction can be ruled out given our finding that there is no tendency for options to exhibit long-run reversal. Because we find no evidence of crash risk or negative skewness in momentum returns, it is unlikely that momentum profits represent compensation for those types of risks. We can also rule out that momentum arises purely as a result of cross-sectional variation in unconditional expected returns.

The remaining two hypotheses, underreaction and time-varying risk premia, are impossible to distinguish. We can, however, ask whether momentum profits appear to be the result of time-varying factor risk exposure. Following Grundy and Martin (2001), we examine variation in loadings on market, volatility, and jump risk factors. We find only weak evidence of time-varying betas, and no evidence that risk premia and betas interact in the way necessary to produce the momentum effect.

Our paper is related to a number of studies documenting mispricing in the options market. Stein (1989) shows a tendency for long maturity options on the S&P 100 Index to overreact to changes in short-term volatility. Poteshman (2001) confirms the finding in S&P 500 Index options and also finds evidence of underreaction at shorter horizons. While some of our results are qualitatively similar, our analysis differs in its focus on the cross section of individual equity options. In addition, the momentum pattern we document operates at much longer horizons, ranging from months to years, rather than days, and we find no evidence of overreaction. Other evidence of behavioral effects in options includes Han (2008), who finds that index option prices are affected by sentiment, while Eisdorfer, Sadka, and Zhdanov (2020) find that options are underpriced when there are five weeks, rather than the usual four, between expiration dates. Boyer and Vorkink (2014) find evidence that skewness preferences drive the pricing of individual equity options.

In the broader empirical options literature, we contribute by proposing several new predictors of the returns of individual equity options. Notable contributions of this literature include the historical-implied volatility differential of Goyal and Saretto (2009) and the implied volatility slope of Vasquez (2017), which we find to be the two strongest predictors in our sample. Other papers in this area include Cao and Han (2013), who study idiosyncratic risk and option returns, and Bali and Murray (2013), who analyze the effects of risk-neutral skewness. Cao et al. (2021b) show that the existence of credit default swaps on a firm lowers expected option returns, while Christoffersen, Goyenko, Jacobs, and Karoui (2018) find a negative relation between option liquidity and returns.

Our finding of short-term reversal in option returns relates to the literature on order imbalances in options markets. Muravyev (2016) finds that positive imbalances strongly predict low future returns, and he also shows evidence of option return reversal at the daily frequency. It is possible that monthly option returns are correlated with order imbalances, which could explain the short-term reversal we document in monthly returns. Alternatively, high recent option returns may reduce the capital available to option sellers, leading to more negative (because the sellers are short) risk premia (e.g., He and Krishnamurthy (2013)).

We contribute to the larger literature on momentum by showing support for the idea that momentum and reversal are not as strongly linked as is often thought. Lee and Swaminathan (2000), for example, find that long-run reversal among momentum portfolios exists only for certain levels of formation-period trading volume. Conrad and Yavuz (2017) show that the stocks in the momentum portfolio that contribute to the profitability of the momentum trade are different from those that subsequently exhibit long-run reversal. In our sample of straddle returns, we find no evidence of long-run reversal. Rather, option momentum persists over the multi-year horizons at which stocks tend to reverse. This is likely related to the fact that options, as short-lived assets, cannot accumulate mispricing over time in the same way that stocks can.

In the following section we briefly describe the data used in our analysis. Section 3 shows our main results, which focus on the standard cross-sectional momentum and reversal strategies applied to options. Section 4 examines the performance of alternative momentum and reversal strategies, namely time series, industry, and factor-based strategies. In Section 5, we subject these strategies to risk adjustment, check their consistency in the time series and cross section, examine spanning relations between them, and evaluate the impact of transaction costs and margins. Section 6 concludes.

I. Data

We obtain call and put prices from the OptionMetrics database, which provides end-of-day bid-ask quotes for options traded on U.S. exchanges. We retain options on common equity only and discard any options with expiration dates that are outside the regular monthly cycle. Using the WRDS link table, we merge this data with CRSP, which we use as the source of stock prices, returns, trading volume, market capitalization, and adjustments for stock splits. The availability of options data restricts our sample period to the interval from January 1996 to June 2019.

Most of our analysis focuses on the performance of zero delta straddles, which combine a put and a call with the same strike price and expiration date. Our sample construction is designed to balance two competing priorities. The first is that the options in our sample are actively traded, so that the returns that we calculate are valid. The second priority is that our sample is large enough to deliver statistically meaningful results. Unfortunately, liquidity filters, such as a requirement that open interest be nonzero, tend to reduce the sample size, putting these two priorities in conflict.

We strike a balance between these two concerns by imposing the positive open interest filter only during the holding period. This is where it is most important that the returns we work with are accurate, as biases or errors here will contaminate the performance measures we focus on. By dropping the open interest filter in the formation period, which is in some cases several years long, we increase the sample size by up to 50%. While the returns used in the formation period will perhaps be less meaningful, any noise or bias in the returns used here should if anything bias our findings toward the null of no predictability.

On each expiration day[1], we select two matching call/put pairs for each stock, where all calls and puts expire in the following month. One is the pair whose call delta is closest to 0.5. The other uses the same criteria but requires that both the put and the call have positive open interest on the day they are selected. In either case, if the call delta is less than 0.25 or greater than 0.75, we discard the observation. Thus, the sample targets options that are at-the-money and does not include contracts that are deep in-the-money or out-of-the-money.

From each pair, we form a zero delta straddle. This entails holding the call and put with weights that are proportional to $-\Delta_P C$ and $\Delta_C P$, respectively, where C (P) is the bid-ask midpoint of the call (put) and Δ denotes the option's delta.[2] The constant of proportionality is chosen such

[1]Prior to 2015, stock option expiration dates were Saturdays. The de facto expiration date was the prior trading date, which is the date we use.

[2]We use the deltas provided by OptionMetrics, which are computed using a binomial tree. The method used should coincide with the Black-Scholes formula when early exercise is suboptimal.

that the weights sum to one. Note that both weights are always positive and are typically close to 50/50.

To ensure that the strategies we consider are reasonably liquid, we discard any straddle in which the weighted average bid/ask spread of the call and put is greater than 50% of midpoint prices. If this occurs, we attempt to replace the straddle with another that is further from at-the-money, as long as the call delta is within the range given above.

Straddle returns are simply the weighted average of the returns on the call and the put. Because we hold straddles to expiration, call and put returns are calculated based on the split-adjusted price of the underlying stock on the expiration date, where split adjustment uses data from CRSP. The initial price of each option is taken as its bid-ask midpoint. Calculating returns in this way ignores the possibility of early exercise, though we find that non-dividend paying stocks, which are unlikely to be exercised early, show almost identical patterns. This is expected given that our analysis focuses on near-the-money options, for which early exercise is rarely optimal.

Our empirical analysis focuses on Goyal and Saretto's (2009) simple strategy benchmark of one-month at-the-money straddles, held to expiration. An alternative benchmark uses the CBOE VIX methodology.[3] When applied to individual equities, the CBOE calls these benchmarks equity-VIX indices, currently published for Apple (ticker symbol: VXAPL), Amazon (ticker symbol: VXAZN), IBM (ticker symbol: VXIBM), Google (ticker symbol: VXGOG), and Goldman Sachs (ticker symbol: VXGS).[4]

In addition to using at-the-money options, the VIX methodology includes out-of-the-money call and put options. When weighted proportionally to the reciprocals of squared strike prices, these options form an equity-VIX benchmark portfolio. At expiration, this option portfolio has a

[3] https://cdn.cboe.com/resources/vix/vixwhite.pdf

[4] https://www.prnewswire.com/news-releases/cboe-to-apply-vix-methodology-to-individual-equity-options-112955759.html

U-shaped payoff, approximating the squared stock return (Carr and Madan (2001)). In this sense, the portfolio represents the discounted risk-neutral variance. It is approximately delta neutral, with a delta of zero exactly if a continuum of strikes are available.

To compute a VIX return, we require at least two out-of-the-money calls and two out-of-the-money puts to be observed. Again, the weighted average bid/ask spread of the VIX portfolio must be no greater than 50%, expressed as a percentage of bid-ask midpoints, and only options with positive open interest are included at the start of the holding period. As with straddles, we do include options with zero open interest when computing VIX returns during the formation period. While this does enlarge the sample size, the greater data requirements for VIX returns leads us to relax the requirement used elsewhere that the formation period have no missing observations. Instead, we require that at least two thirds of the months in the formation period (rounding up) have a non-missing VIX return, and we compute the formation period return by averaging those observations.

Following Bakshi and Kapadia (2003), we also consider daily delta-hedging of our option straddles and equity-VIX portfolios. These strategies hold the same portfolios of one-month options to expiration, but they also subtract a portion of excess daily return on the underlying stock using a Black-Scholes delta hedge for each option, where the hedge is rebalanced daily.[5] This dynamic hedging lowers the overall volatility of the strategies.

For all strategies, we compute excess returns by subtracting the one-month Treasury bill rate from data on Ken French's website. All results in the paper use excess returns, though for brevity we typically just refer to them as "returns."

Finally, we extract a number of implied volatilities from the OptionMetrics Volatility Surface

[5]In some cases, the Black-Scholes delta for an option that we are hedging is missing from the Optionmetrics data files. When this occurs, we estimate a delta using the current stock price and the most recent non-missing implied volatility for that option.

File. We compute a one-month at-the-money implied volatility by averaging the values for the 30-day call and put, each with absolute delta equal to 0.5. We follow Goyal and Saretto (2009) by subtracting the rolling one-year historical volatility computed from daily stock returns to obtain their volatility difference measure. A similar implied volatility from 60-day options is used to compute the implied volatility slope of Vasquez (2017). We measure the slope of the implied volatility curve (the "smirk") from one-month options as the difference between the implied volatility of a 30-day call with delta of 0.3 and the implied volatility of a 30-day put with a delta of -0.3.

TABLE I ABOUT HERE

Our primary dataset is described in Panel A of Table I. The dataset contains about 385,000 observations of straddle returns with positive open interest. Given that our sample has 282 months, this translates to 1,369 straddles per month on average. Straddle returns have negative means (-5.3% monthly), large standard deviations (81% monthly), and substantial positive skewness, as indicated by the low median.

The table further shows that the historical and implied volatilities of the firms in our sample are similar to those reported in prior studies (e.g., Vasquez, 2017). With an average market cap of around $10.6 billion, the table also shows that optionable firms tend to be larger than average, and analyst coverage is similarly higher than average. The table also reports stock illiquidity, proxied by the average Amihud (2002) illiquidity measure over the past 12 months, and option illiquidity, measured by the weighted average percentage bid-ask spread of the puts and calls in the straddles we examine, also averaged over the past 12 months. Analyst coverage is the number of analysts covering each stock, updated monthly.[6]

To compare the properties of straddle returns and VIX returns, Panel B examines data for which straddle returns and VIX returns are both available. This leads to a smaller sample but

[6] The analyst coverage and forecast data are from the I/B/E/S Unadjusted Summary file.

makes the comparison between straddle and VIX returns cleaner. We compute these returns both with and without dynamic delta hedging.

The table shows that VIX returns are generally more negative, with higher standard deviation and a longer right tail. For both straddle and VIX returns, dynamic hedging has relatively modest effects on average returns and results in larger reductions, as expected, in standard deviations. The decrease is particularly large for VIX returns, whose U-shaped payoff results in a larger gamma, making dynamic hedging more beneficial. After hedging, straddle and VIX returns are almost identical in terms of standard deviation.

II. Results

In this section we present our main findings documenting momentum and reversal in straddle returns. We begin with univariate sorts and Fama-MacBeth regression and then add controls for other option return predictors. Next, we examine alternative option return methodologies and longer-horizon return dependence. Finally, we examine the dependence structure more closely, showing the declining importance of returns at longer lags.

A. Momentum and reversal in the cross section of straddles

Some of our primary results are summarized in Figure 1, which shows slope coefficients from the Fama-MacBeth regression

$$R_{i,t} = a_{n,t} + b_{n,t} R_{i,t-n} + \epsilon_{i,t},$$

where $R_{i,t}$ is the return on a straddle on stock i in month t. Following Fama (1976), we can interpret $b_{n,t}$ as the excess return on a diversified portfolio of stock straddles with a historical portfolio return of 100% at lag n. In the figure, n determines the placement on the horizontal axis, and the top and bottom panels differ only with respect to the range of lags displayed.

FIGURE 1 ABOUT HERE

The figure shows that straddle returns in the previous month are likely to be reversed in the following one. While the return at lag two is not predictive of future returns, at lags three and higher the slope coefficient turns positive, indicating momentum rather than reversal. Impressively, the slope coefficients on lags three through 12 are all positive and all statistically significant.

Beyond lag 12, statistical significance wanes, but the slope coefficients remain clearly positive on average. This positive mean continues even beyond lag 100, as shown in the lower panel. While the sample used to estimate coefficients with such long lags is small, both in the time series and the cross section, these results indicate a complete lack of long-term reversal in straddle returns.

As is standard in momentum studies, our primary measure of momentum is based on multiple returns over a formation period that is months to years long. In the momentum literature, these returns are aggregated using standard compounding or simple averaging. We find that the latter approach is preferable due to the extreme volatility of straddle returns, which frequently take values close to -100%. With just one of these values in the formation period, the cumulative return will be close to -100% as well. The result is a large number of cumulative returns clustered around this value, making portfolio sorts less meaningful. Simple averaging reduces the impact of return outliers and makes the momentum signal somewhat more symmetric. Results based on cumulative returns are nevertheless very strong.[7]

TABLE II ABOUT HERE

Table II examines the relation between past and future straddle returns using a variety of different formation periods. We sort firms into quintile portfolios based on average returns in the

[7] A "2 to 12" momentum strategy based on cumulative returns delivers a high-minus-low return of 4.4% per month (t=5.94), which is comparable to the values reported in Table II.

formation period and report the mean and t-statistic of each quintile's equally weighted portfolio returns.[8] We also report the long/short high-minus-low portfolio. The holding period remains a single month in all cases.

Given the results from Figure 1, the results are not surprising. We see significant evidence of cross-sectional reversal at lag one and strong momentum for longer formation periods. It is notable that the "classic" momentum strategy, based on lags two to 12, is the strongest, both in terms of average return spread and statistical significance. Nevertheless, it is clear that lags 13 to 24 also offer highly significant predictive information. Even returns at lags 25 to 36 are positively related to current returns, though statistical significance declines somewhat, in part due to the smaller sample of firms with option returns available over those formation periods.[9]

Panel B of Table II shows the results of quintile sorts on variables that have already appeared in the empirical options literature. One is the difference between implied and historical volatilities, shown by Goyal and Saretto (2009) to forecast future option returns. Another is the amount of idiosyncratic volatility in the underlying stock, as defined by Cao and Han (2013). Sorting by market cap of the underling firm also generates a spread in straddle returns, as demonstrated first by Cao et al. (2021a). From Vasquez (2017), the slope of the term structure of at-the-money implied volatilities is the fourth measure. The final measure is the slope of the implied volatility curve (the "smirk") from one-month options. This is related to the skewness variable examined by Bali and Murray (2013).

Comparing the two panels of the table, it is clear that momentum offers performance that is close to that of the best predictors from the existing literature, which are the spread between

[8]We use quintile sorts rather than decile sorts because of the somewhat smaller sample of optionable stocks. Results using deciles are nevertheless very similar, as are terciles.

[9]Momentum and reversal are both qualitatively consistent and always significant if we instead weight by market capitalization or the dollar value of the open interest in the put and the call used to construct the straddle.

implied volatility and historical volatility (IV-HV) and the term spread in implied volatilities (IV term spread). The reversal strategy, while highly significant statistically, offers returns that are more in line with the strategies with lower return spreads (idiosyncratic volatility and size).

Although the results presented in this table suggest that momentum patterns in straddles roughly mimic those in stocks, it is worth pointing out a critical difference between stock reversal and momentum and the findings reported here. In stocks, a natural interpretation of the reversal strategy is that a period-t price that is "too low" leads to negative returns in period t and positive returns in period $t+1$. The same interpretation does not apply here because the options used to compute the period-t return are different from those used to construct the return in period $t+1$, as the former set expires at the start of period $t+1$. Thus, the momentum patterns we document in this paper may more accurately be described as cross-serial correlations, in that all forms of reversal and momentum reflect the returns on some set of options predicting the future returns on a completely different set.

Digging in a little deeper, the straddle return over period t only depends on option prices at the end of period $t-1$. This is because the final payoff on options held to expiration depends only on the underlying stock price at time t. Thus, if option prices became distorted at the end of period t, this would only impact straddle returns in period $t+1$, because period-t returns do not depend on period-t option prices. Thus, short-term reversal is a counter-intuitive finding in our option setting, and it cannot arise from simple bid-ask bounce, as studied by Roll (1984). To explain reversal, we would need microstructural biases in options prices that are correlated with past returns on expiring options.

B. Controlling for other predictors

We next ask whether the predictive ability of past returns remains after controlling for other characteristics. We assess this using Fama-MacBeth regressions, where the controls are the same variables used in Panel B of Table II.[10]

TABLE III ABOUT HERE

From the regression results in Table III, we see that controlling for these characteristics has a relatively minor effect when we focus on the one-month formation period. For longer formation periods, including controls has almost no effect on the coefficient estimates or t-statistics for past returns. Similarly, adding a past return measure to the set of controls has little effect on the coefficient estimates of the controls, though in some cases their statistical significance is reduced. The overall impression given by the table is that past straddle return provides a signal that is fairly unrelated to other predictors.[11]

C. Alternatives to the static straddle

To assess the robustness of our option returns, Table IV compares monthly quintile spreads on at-the-money straddles to quintile spreads on equity-VIX benchmarks, constructed according to the CBOE VIX methodology. Table IV also compares these static return-to-expiration strategies with delta-hedged versions, which dynamically hedge by trading the underlying stocks using the

[10]We use Fama-MacBeth (1973) cross-sectional regressions, instead of panel regression, because cross-sectional regressions avoid hindsight bias by computing the slope coefficients using information available before time t.

[11]In corresponding results based on panel regressions, the short-run reversal phenomenon disappears, and the control variables mostly lose their statistical significance. The standard "2 to 12" momentum effect remains very strong, however, with slightly smaller coefficient estimates. This contrasts strongly with results from the stock momentum literature. Kelly, Moskowitz, and Pruitt (2020), for example, estimate a coefficient on past returns that is essentially zero when using the panel regression framework.

Black-Scholes delta. This reduces risk by maintaining a zero delta each day, instead of letting the portfolio sensitivity drift during the month.

TABLE IV ABOUT HERE

Table IV shows that all the momentum strategies are profitable for horizons ranging from 6 to 36 months. The dynamically hedged strategies are usually more profitable and more statistically significant than their static counterparts. For example, the 1-12 month static straddle quintile spread earned 3.64% per month, whereas its daily-hedged counterpart earned 5.59% per month.

The dynamically hedged VIX returns show a pattern of profitable return continuation at all horizons. Dynamically hedged straddles show neither reversal nor continuation with short-term formation periods of 1 or 1-2 months. Both static strategies show reversal with these short formation periods, a pattern that is reminiscent of Lehmann (1990)'s short-term stock return reversal.

Mechanically, the difference between hedged and unhedged returns is due only to a stock trading strategy. To understand this strategy, consider a long straddle position whose delta hedge is rebalanced daily. The positive gamma of the position means that the delta hedge must sell stock following a positive return, which is itself a type of reversal strategy. Since high-frequency stock reversal strategies tend to be profitable (Lehmann (1990)), delta hedging increases the average return of a long options strategy. Conversely, delta hedging reduces the returns of a short options strategy, but by a lesser amount. The difference between the returns on these delta hedges explains the qualitatively different performance of the hedged and unhedged short-term reversal strategies.

Overall, Table IV shows that option momentum strategies are robustly profitable for all benchmarks when using formation horizons of at least 6 months. The remainder of our paper focuses on the simplest benchmark of static at-the-money straddles.[12]

[12] Understanding the reversal properties of high-frequency option and stock returns remains an interesting topic for market microstructure research.

D. Signal decay

One important difference between stock and option momentum and reversal patterns appears to be in the long-term persistence of option returns. In stocks, it has been well known since De Bondt and Thaler (1985) that stock returns experience reversal at horizons of 3-5 years. In contrast, Figure 1 suggests that the relation between current and lagged returns remains positive even at lags as long as 10 years.

This finding raises the possibility that momentum arises due to cross-sectional variation in unconditional expected returns, a hypothesis considered for stocks by Lo and MacKinlay (1990), Jegadeesh and Titman (1993), and Conrad and Kaul (1998). While the stock evidence in Jegadeesh and Titman (2001) and Lewellen (2002) appears to undermine this explanation, the possibility remains that it does explain option momentum. As Jegadeesh and Titman (2001) emphasize, if momentum is caused by variation in unconditional return expectations, then current and lagged returns should be similarly related regardless of the length of the lag. In stocks, this implication is contradicted by the presence of long-horizon reversal.

In this section we reexamine long-run persistence and reversal in returns to augment the evidence already presented in Figure 1. We present regressions in which current returns are regressed on past returns at lags one to 60. As opposed to Figure 1, similar lags are grouped together, which will reduce the number of predictors and also make them less noisy, and which should help reduce the large standard errors apparent in the figure. The regressions will also include multiple predictors, so that we can assess the incremental predictive power of longer-lagged returns relative to shorter lags.

TABLE V ABOUT HERE

The regression results, shown in Table V, provide a number of take-aways. First, by comparing regression (1) with the other five regressions in the table, the short-run reversal effect (the coefficient on the lag 1 return) is generally strengthened by the inclusion of past returns at longer lags. Second, the slope coefficients on past returns at longer lags are positive, with only one exception. In most cases these coefficients are at least significant at the 5% level. Including these longer lags also leads to an improvement in fit, as evidenced by higher average adjusted R-squares. Third, the slope coefficients are always most positive for the "2 to 12" past return and generally decline as the lag lengthens. While some individual results are statistically weak, it is most likely because the size of the sample decreases markedly for long lags because we require additional years of past straddle returns to be available. Overall, the table paints a clear picture of momentum profits persisting for up to five years.

We test the declining pattern of slope coefficients formally by reporting p-values from the Patton and Timmermann (2010) test of monotonicity. This is a test of the null hypothesis that the coefficients on different return lags (excluding lag 1) are constant or increasing, the alternative hypothesis being that the coefficients are decreasing. We find strong rejections for several regressions, indicating that longer lags are less important than shorter ones. We fail to reject in regressions that include very long lags (beyond 36 months), which we once again believe is most likely due to a lack of power resulting from too many explanatory variables, a shorter sample, and fewer firms.

In the stock literature, the finding of both momentum and long-term reversal has resulted in some behavioral explanations centered around the idea of delayed overreaction (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998)). The pairing of momentum and long-term reversal is also present in corporate bonds, as shown by Bali, Subrahmanyam, and Wen (2021). In contrast, the complete lack of any evidence of long-term reversal in option returns appears to be inconsistent with this mechanism. Rather, our results are more consistent with an explanation based on underreaction, which may result from behavioral biases, such as conservatism (Barberis, Shleifer, and Vishny

(1998)), or from market frictions, such as gradual information diffusion (Hong and Stein (1999)).[13] At this point we also cannot rule out the hypothesis that momentum is driven by time-varying risk premia.

If the explanation is in fact underreaction, then it is unlikely to be the result of the disposition effect, which Grinblatt and Han (2005) suggest as a potential cause of stock momentum. The disposition effect implies that investors will tend to hold onto poorly performing position, but it is impossible to do so in our setting given that the short-term nature of the options we analyze forces portfolio turnover via expiration.

Table V also implies that variation in unconditional expected returns is not a complete explanation, as more recent returns are clearly more predictive than returns at longer lags. Thus, option momentum must be driven by some form of serial dependence.

III. Related strategies

In this section we analyze different alternatives to the standard momentum strategy of Jegadeesh and Titman (1993). These include the "time series momentum" strategy of Moskowitz, Ooi, and Pedersen (2012), the industry momentum strategy of Moskowitz and Grinblatt (1999), and the factor momentum strategy of Gupta and Kelly (2019) and Ehsani and Linnainmaa (2021).

One alternative that we do not consider in detail is stock momentum. The contemporaneous correlation between our primary momentum portfolio and the UMD factor from Ken French's website is just -0.061. If we form an equally-weighted momentum strategy, consistent with our straddle portfolios, the correlation is nearly unchanged, at -0.064. When we use the VIX portfolio returns with daily rebalanced deltas, the correlation with equally weighed stock momentum is

[13]The Barberis, Shleifer, and Vishny (1998) model also features overreaction, but this is not the mechanism that generates momentum. The full model of Hong and Stein (1999) features overreaction and underreaction, though the "newswatchers only" model only generates underreaction.

-0.075. These results confirm that stock and option momentum are distinct findings.

A. *Time series momentum*

Using the framework of Lo and MacKinlay (1990), Lewellen (2002) decomposes the classical momentum strategy of Jegadeesh and Titman (1993) and shows that its profitability has three potential sources. One is autocorrelation in a stock's own returns. Another is cross-sectional variation in unconditional means, which we believe is ruled out by results in the prior section. The last is negative cross-serial correlation in firm returns. That is, a winner can remain a winner because its own high return forecasts low returns by other firms in the future.

In futures markets, Moskowitz, Ooi, and Pedersen (2012) find that a more successful "time series momentum" strategy is obtained from an alternative portfolio construction that reduces or eliminates the latter two sources. By holding assets based on their past absolute return rather than relative return, we may form a strategy that isolates the own autocorrelation effect. This is useful when autocorrelations and cross-serial correlations are both positive, as the former will contribute to momentum profits while the latter will detract.

Our implementation of time series momentum (TS) follows Goyal and Jegadeesh's (2018) analysis of U.S. stocks. We buy all straddles whose past average excess returns (over some formation period) are positive and short all straddles with negative past average excess returns. We size each position in the strategy at $\$2/N$, where N is the total number of straddles held long or short. Individual positions of $\$2/N$ ensure a total active position (total long plus total short positions) of \$2. As in Goyal and Jegadeesh (2018), we compare this strategy to the cross-sectional strategy (CS) in which winners and losers are determined based on whether past returns are higher or lower than contemporaneous cross-sectional means and in which we long an equal-weighted portfolio of winners and short an equal-weighted portfolio of losers, again resulting in a total active position of

\$2. Finally, also following Goyal and Jegadeesh (2018), we omit the scaling by lagged volatility that Moskowitz, Ooi, and Pedersen (2012) use. Scaling has little effect given that we are not dealing with heterogeneous asset classes and the options that are held long and short have approximately the same volatilities.

TABLE VI ABOUT HERE

Table VI reports average returns on these two strategies for a variety of formation periods. First focusing on the cross-sectional strategies, we see that short-term reversal return is somewhat smaller when the long and short sides of the trade each include roughly half the sample (rather than just the extreme quintiles), though statistical significance is relatively unchanged. The high-low spreads for momentum-type strategies (e.g. lags 2 to 12) are also smaller here than in Table II, which is again to be expected given the inclusion of stocks with less extreme past returns. Again, however, t-statistics do not change much. This confirms that momentum is pervasive across all options, not just those in the extremes of the distribution of past returns.

Turning next to the time series strategies, we see high-low spreads that are larger than the corresponding spreads from cross-sectional strategies for all formation periods, with out-performance that is statistically significant for half. In addition, the two types of strategies are not closely correlated, with correlations ranging from 0.21 to 0.50. The dominance of time series momentum echoes similar findings in international asset classes and in equity markets (Moskowitz, Ooi, and Pedersen (2012) and Goyal and Jegadeesh (2018)). However, Goyal and Jegadeesh (2018) argue that time series momentum in equity markets embeds an additional risk premium due to a time-varying net long position in the equally weighted portfolio of all stocks. Goyal and Jegadeesh (2018) show that the seemingly strong dominance of time series momentum in equity markets is attributed to that embedded position, which is on average long the market.

Applying Goyal and Jegadeesh's insight, time series straddle momentum is subject to the same critique, embedding an imbalance between the exposures of the long and short sides, which differs from the balanced net zero exposure of the cross-sectional strategy. In options, however, the imbalance now results in a strategy that is on average net short straddles, which is the result of their negative average returns.

To control for the embedded exposure imbalance and compare the two types of momentum strategies on a common footing, we follow Goyal and Jegadeesh (2018) and construct a modified cross-sectional strategy (CSTVM) that is the sum of CS and a time-varying investment in the equally weighted portfolio of all straddles (TVM). The size of the TVM position is chosen to replicate the time-varying imbalanced exposure in the time series strategy.

The last two columns of Table VI confirm the prediction that the TS strategy is on average overweighted in short option positions. When we compare the TS strategy to CSTVM, which is similarly imbalanced, performance differences become insignificant both economically and statistically irrespective of the formation periods. In addition, the correlation of two strategies is high, ranging from 0.93 to 0.99. Hence, consistent with Goyal and Jegadeesh (2018), the embedded exposure imbalance fully explains the seeming success of TS relative to CS. We conclude that there is no obvious distinction between cross-sectional and time series strategies in straddles. For the remainder of the paper, we therefore limit our attention to the more common cross-sectional strategies.

B. Industry momentum

In a highly influential paper, Moskowitz and Grinblatt (1999) show that industry portfolios also display momentum. They further argue that industry momentum subsumes most if not all of the profitability of the stock-level momentum strategy. While subsequent work (e.g. Grundy and Martin (2001)) has shown that industry momentum and stock momentum are distinct, the power of industry momentum remains striking.

In this section we construct the industry momentum strategy of Moskowitz and Grinblatt (1999), replacing stock returns with straddle returns. As in that paper, we classify firms into 20 different industries, calculate industry portfolio returns, rank industries by their performance over some formation period, and then form a long and a short momentum portfolio from the top and bottom three industries, respectively.[14] The results are shown in Panel A of Table VII.

TABLE VII ABOUT HERE

In the short run, we find neither reversal nor momentum in industry portfolios using short formation periods. This is in contrast to Grinblatt and Moskowitz, who show that industry stock portfolios display momentum even with a one-month formation period.

The profitability of the standard "2 to 12" momentum strategy is similar to that based on individual straddles, but formation periods that exclude the first 12 lags are ineffective for industry portfolios, whereas for individual straddles even the "25 to 36" strategy delivered statistically significant average returns. These results imply that cross-sectional variation in unconditional expected returns is a poor explanation of momentum at the industry level.

C. Factor momentum

Early evidence of momentum in "factor" portfolios was provided by Lewellen (2002), who showed the existence of momentum in portfolios formed on the basis of firm size and the book-to-market ratio. More recently, both Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019) have examined larger numbers of long/short factors proposed in the finance literature and conclude that the factor momentum strategy is superior to individual stock momentum and in fact may explain

[14] We differ from Moskowitz and Grinblatt (1999) by examining average past returns rather than compounded returns.

it completely. We follow this work by analyzing factor momentum in the options setting.

The literature on option factors is nascent, and the factor structure of options is relatively unstudied. One exception is the recent paper of Horenstein et al. (2019, HVX), which finds evidence that a four factor model performs well in explaining option returns. These factors include the excess returns on short delta-hedged SPX options as well as high-minus low portfolios formed on the basis of firm size, idiosyncratic volatility, and the difference between implied and historical volatilities. We implement their model with minor differences. We use straddles rather than delta-hedged calls and use quintile rather than decile sorts, which we find to result in additional noise and no increase in signal. Neither one of these differences should have much of an effect.

In the interest of expanding the factor universe somewhat, we augment the HVX model with three other factors. These include high-minus-low factors based on the implied volatility term spread and the slope of the implied volatility smirk, as well as the excess return on an equally weighted portfolio of short equity straddles. This gives us seven factors in total.

Our implementation of factor momentum follows that of Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019), which is a time series momentum strategy on factor portfolios. That is, we go long factors whose past average excess returns (over some formation period) are positive and short factors whose past returns are negative.

Panel B of Table VII shows that factors display momentum using all formation periods considered. Similar to the stock-based results of Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019), momentum is found even at the shortest formation periods. More surprisingly, highly delayed formation periods are also profitable. The standard "2 to 12" strategy is actually less profitable than one based on returns from 13 to 36 months ago.

Conrad and Kaul (1998) and Lewellen (2002) decompose momentum returns into a temporary component due to autocorrelation and a permanent component due to cross-sectional variation in expected returns. The surprising profitability of 1-month factor momentum strategies indicates autocorrelation as a source of profits. The profitability of strategies based on formation periods 2- to 3-years old suggests that factor momentum may also be the result of variation in the unconditional returns of the factors, which is captured by any sort based on past returns. Because of our comparatively short option sample, we lack the power to distinguish between persistent and permanent variation across means. Nevertheless, the results suggest the possibility that factor momentum is driven both by autocorrelation and differences in unconditional means.

IV. Risk and robustness

In this section we ask whether the profitability of option momentum and reversal is accompanied by undesirable levels of risk, or whether the returns on the strategies presented can be explained by exposure to other priced factors. We also examine whether there is any redundancy between strategies that are most closely related. Finally, we investigate the consistency of these strategies, both over time and in the cross section, and evaluate the impact of transactions costs and margin.

A. Risk and consistency of performance

We next examine the risk and time consistency of the different strategies considered. Our primary focus is on the degree of tail risk and on whether the returns on the primary strategies we investigate are stable over our sample period.

Table VIII shows some basic performance statistics on 13 different portfolios. Panel A includes the cross-sectional momentum and reversal strategies, as well as the related strategies based on industry and factor portfolios. Panel B shows results for the seven factors based on prior research, as described in Section III.C.

TABLE VIII ABOUT HERE

In this section, long/short portfolios formed based on past returns are constructed to have positive mean returns. This allows for a more meaningful interpretation of sign-dependent risk measures such as skewness and maximum drawdown.[15] For portfolios based on the standard momentum formation period, this results in going long the winners and short the losers for individual straddles, industries, and factors. For portfolios based solely on a single month of past returns, the nature of the strategy differs between individual straddles or industries and factors. This is because individual straddles display short-term reversal, while factors display short-term momentum. Industries display neither, really, but have a small and insignificant tendency for reversal. We therefore examine the low-minus-high portfolio for individual straddles and industries when sorting on the one month lag and the high-minus-low portfolio for factors.

Overall, the results in Table VIII show that the reversal and momentum strategies based on individual straddles have relatively low risk, at least compared with other option strategies. For example, the individual straddle momentum strategy has an average return that is slightly larger than that of an equally weighted portfolio of short straddles, but its standard deviation is only half as large. Furthermore, the momentum portfolio shows positive skewness and a maximum drawdown of 56%, while the equally weighted short portfolio is highly negatively skewed and suffers from a maximum drawdown greater than 100%.[16]

The momentum strategy on individual straddles has a Sharpe ratio of 0.441 on a monthly basis, which is an impressive 1.53 annualized. This lags behind only the best two performing factors, namely the implied-minus-historical volatility factor of Goyal and Saretto (2009) and the implied

[15]The maximum drawdown is the largest fraction by which the cumulative value of a portfolio has fallen below its prior maximum.

[16]The maximum drawdown is poorly defined in any sample in which there is a single return lower than -100%, which is the case for six of the factors in the table. For these values we simply report the maximum drawdown as being greater than one.

volatility term spread factor of Vasquez (2017).

Momentum strategies based on industries or factors are much more volatile than those based on individual straddles, and each has a maximum drawdown above 100%. Industry and factor momentum are also negatively skewed. Thus, both of these strategies may be less attractive than their average returns would suggest.

Turning next to strategies based on just the first return lag, we see similar patterns. Short-term reversal in individual straddles has a monthly Sharpe ratio of 0.330, or 1.14 annualized. Furthermore, its return distribution is positively skewed, though greater kurtosis and larger drawdowns relative to momentum make the strategy less attractive. Industry- and factor-based strategies continue to suffer from greater volatility, and maximum drawdowns are large in both cases, above 100%.

A surprising result from the table is that the majority of long/short factors based on individual straddles display a clear positive skew. In contrast, factor- and industry-based portfolios tend to show lower or negative skews, though even these are modest relative to the pronounced left skews of the short SPX straddle and the short equally weighted stock straddle portfolio. The relative lack of outliers and the positive skewness appear to rule out the possibility that the mean returns on momentum or short-term reversal represent compensation for return asymmetry. Thus, while skewness may be an important determinant of option prices, it is a poor explanation of relative cross-sectional returns.

In the stock market, Daniel and Moskowitz (2016) document that momentum portfolios "experience infrequent and persistent strings of negative returns," or "momentum crashes." While skewness may be an adequate measure of tail risk in serially independent returns, the possibility of serial correlation motivates us to also consider maximum drawdown as a measure of the importance of momentum crashes. Our results show that if there are any option momentum crashes, then they must be regarded as mild, at least relative to the strategy's average return. Investment practitioners often compute the so-called "Calmar ratio" by dividing annualized returns by the maximum drawdown. The value obtained for the cross-sectional momentum portfolio is 1.34. In contrast, the Fama-French UMD factor has a Calmar ratio that is around 0.1 over its entire history, which is the result of a drawdown exceeding 75% in the early 1930s. Examining UMD over our own sample period lowers its Calmar ratio to just 0.08. Option momentum therefore has a lower maximum drawdown but an average excess return that is perhaps ten times higher. While the tail risk in cross-sectional short-term reversal is somewhat greater, the Calmar ratio is still 0.67. Thus, while we cannot rule out the possibility that a "Peso problem" hides some unrealized tail event, there is simply no evidence that the returns on momentum or reversal – at least when implemented with individual straddles – are justified on the basis of their exposure to crash risk.

FIGURE 2 ABOUT HERE

In order to assess the stability of momentum and reversal, we examine five-year moving averages of the returns to each of these portfolios, focusing on cross-sectional strategies formed using individual straddles. The results, in Figure 2, show that these moving averages are positive for both strategies at all times. The included 95% confidence intervals further indicate that the momentum return has been significantly positive in every five-year interval in our sample.

B. Factor adjustment

We now address the issue of whether the profitability of momentum and reversal strategies is subsumed by other factors that are already in the literature. Though the literature gives little guidance on what factors to include, a notable exception is Horenstein, Vasquez, and Xiao (2019), who propose a four-factor model. This model includes the excess return on short delta-hedged SPX options as well as high-minus low portfolios formed on the basis of firm size, idiosyncratic volatility, and the difference between implied and historical volatilities.

In the interest of subjecting reversal and momentum to a somewhat stronger test, we also augment the HVX model with the same additional three factors used earlier, namely long/short factors based on the implied volatility term spread and the slope of the implied volatility smirk in addition to the equally weighted short equity straddles return. While HVX find that the term spread factor is redundant, they draw this conclusion from analysis that does not include momentum or reversal as test assets. We believe that including this factor, which has the second highest Sharpe ratio, is conservative given our purposes.

Table IX reports the results of these regressions. We report results for cross-sectional strategies based on individual options and for strategies formed from industry and factor portfolios.

TABLE IX ABOUT HERE

To summarize, for strategies based on individual straddles, momentum survives factor adjustment while reversal does not. In particular, reversal is mostly explained by the loadings on the volatility difference variable of Goyal and Saretto (2009) and the implied volatility term spread of Vasquez (2017), which have much larger premia than most other factors. This suggests that reversal profits are related to the tendency of options with high implied volatility, either relative to actual or longer-term implied volatility, to underperform. It is possible that volatility differences reflect behavioral overreaction, in that high straddle returns in the recent past cause short-term implied volatilities to increase too much. This hypothesis may be indistinguishable from one in which high past option returns are correlated with order imbalances (Muravyev (2016)) or intermediary capital (He and Krishnamurthy (2013)), either of which may produce higher implied volatilities and lower future returns. In any case, while the findings in Table IX do not negate our finding of short-term reversal, they imply that it is not a distinct source of expected return.

In contrast, the momentum alpha is large and highly significant in both regressions based on individual straddles. Other factors do explain some of the variation in momentum returns, and the alpha is either moderately smaller or slightly higher than the unconditional mean in Table VIII, but it is clear that momentum profits are not simply an expression of sensitivity to the other factors.

Industry-based strategies lead to similar results under factor adjustment. The alpha of the short-term strategy is more positive but still insignificant. Using the longer formation period, we find that factor adjustment explains little of the return on industry momentum. The alpha of the strategy is positive and significant for both models.

The strong short-term momentum of factor portfolios is completely explained by factor exposure. The positive return on the "2 to 12" momentum strategy becomes negative after factor adjustment and marginally significant, which is mostly due to its strong exposure to Goyal and Saretto's (2009) implied minus historical volatility factor.

To sum up, momentum in individual straddle returns and industry portfolio returns are the only two strategies whose average returns are significant, with the same sign, both with and without factor adjustment, for both models.

C. Dynamic betas

Similar to Grundy and Martin (2001), firms in the winner portfolio are likely those whose straddles are more positively exposed to risk factors, such as aggregate volatility, when those risk factors exhibited positive surprises over the formation period. When past aggregate volatility shocks were on average negative, then the winners will tend to be those with low volatility betas. This induces time variation in the momentum strategy's factor loadings, which will depend on the realization of factors over the formation period. If risk premia are also time varying, it is possible that the interaction of betas and risk premia could explain the momentum strategy's profitability.

To investigate this issue, we first test whether winner and loser portfolios exhibit differences in factor sensitivities that are positively related to the factor performance over the formation period. For risk factors, we choose those likely relevant for the options market and with clear economic interpretations. Specifically, we examine factors that are designed to capture market return, volatility, and jump risks.

The market return factor is motivated by CAPM and measured by the return on the S&P 500 Index. The latter two risk factors have been extensively motivated and documented in the option pricing literature (e.g., Heston (1993) and Bakshi, Cao, and Chen (1997)), though they can be measured in a number of different ways. In our first and main specification, our proxy for aggregate volatility risk is the return on the one-month at-the-money S&P 500 Index straddle, and our jump factor is the return on a one-month S&P 500 put option with Black-Scholes delta closest to -0.25. We pick the delta of -0.25 for several reasons. First, it is desirable that factor returns are based on options with reasonable liquidity, and deeper out-of-the-money options tend to have wide spreads. Choosing -0.25 is therefore a balance in fulfilling requirements of reasonable liquidity and being sufficiently out of the money. More importantly, deeper out-of-the-money option returns do not display enough return variation for us to accurately estimate factor loadings.[17]

In our second specification, we follow Cremers, Halling, and Weinbaum (2015) by using S&P 500 Index straddles of different maturities to construct a portfolio with nonzero vega but zero gamma, which is interpreted as a pure volatility factor. Similarly, a portfolio with zero vega but nonzero gamma is interpreted as a jump factor. The third factor model we consider uses the CBOE's VIX and SKEW indexes to construct volatility and jump factors. All factors are in excess of the risk-free return.

[17]Because we hold options until expiration, options that expire out of the money will have returns of -100%. If we had chosen a much deeper out-of-the-money put, then this -100% return would have occured for the vast majority of the observations we have. As a result, if this return had been used to construct a factor, it would have been difficult to estimate betas with respect to it, much less betas that are allowed to change over time.

Because results turn out to depend little on the model chosen, we focus only on the first one. Implementation details and results for the Cremers et al. (2015) vega/gamma model and the model based on VIX and SKEW factors are available in the internet appendix.

We follow Grundy and Martin (2001) and characterize the formation period factor realizations as either "down," "flat," or "up." Down realizations are at least one standard deviation below the factor's mean, up realizations are at least one standard deviation above the mean, and flat realizations are in between. We then run the following regression of the returns of the winner-minus-loser spread portfolio ($r_{HL,t}$) for the holding period t:

$$
\begin{aligned}
r_{HL,t} = a &+ [\; m_{down}\; D_t^{down,mkt} + m_{flat}\; D_t^{flat,mkt} + m_{up}\; D_t^{up,mkt} \;]\; r_{mkt,t} \\
&+ [\; v_{down}\; D_t^{down,vol} + v_{flat}\; D_t^{flat,vol} + v_{up}\; D_t^{up,vol} \;]\; r_{vol,t} \\
&+ [\; j_{down}\; D_t^{down,jmp} + j_{flat}\; D_t^{flat,jmp} + j_{up}\; D_t^{up,jmp} \;]\; r_{jmp,t} + \epsilon_t,
\end{aligned}
$$

where $r_{mkt,t}$, $r_{vol,t}$, and $r_{jmp,t}$ are three risk factor returns, and dummy variable $D^{\delta,k}$ is equal to 1 if the cumulative performance of factor k over the formation period was of type $\delta = \{down, flat, up\}$ and 0 otherwise. m_δ, v_δ, and j_δ represent the corresponding factor betas, which are conditional on the factor's performance over the formation period being of type δ. If the mechanism in Grundy and Martin (2001) for time-varying factor loadings is at work, then they should be higher for $\delta = up$ than for $\delta = down$.

TABLE X ABOUT HERE

Table X reports the results of estimating this regression model when we examine the benchmark momentum strategy on individual straddles with the 2 to 12-month formation period. In addition to the full model, we also examine restricted cases in which only one or two factors are included. Columns (1)-(3) report the models when only one factor is used. From column (1), the winner minus loser spread portfolio does not load on the market factor following any type of market factor performance over the formation period, as indicated by the insignificant estimates for m_{down}, m_{flat}, and m_{up}. In column (2), we observe that the spread portfolio depends positively on the volatility factor following a high realization of that factor ($v_{up} > 0$). While the difference between v_{up} and v_{down} is not statistically significant, it is nevertheless consistent with the Grundy and Martin (2001) mechanism. In column (3), we see that the spread does not load significantly on the jump factor following high or low realizations of that factor.

Columns (4) to (7) examine multifactor specifications. Except in one case following "flat" realizations. we see that the momentum strategy does not load significantly on market returns, which is not surprising given that the straddles are constructed to be delta-neutral. Loadings on the volatility factor are significant in some cases following "up" realizations of the volatility factor, once again weakly signaling that the Grundy and Martin (2001) mechanism may be at work. Loadings on the jump factor are generally insignificant. The one exception, in column (7), shows a negative loading on the jump factor following a high jump factor realization, which is not the expected sign. Overall, the evidence is therefore limited that the straddle momentum strategy exhibits time-varying risk factor sensitivities that depend on the factor performance over the formation period.

Although weak, the evidence nevertheless raises the possibility that time-varying factor loadings may explain a portion of the profit of the straddle momentum strategy if factor risk premia are also time-varying. To test this possibility, we estimate and hedge out the time-varying factor exposures of the momentum strategy and evaluate the profit of the hedged strategy returns. For example, for a three-factor model, the hedged return of the winner minus loser spread portfolio is $r_{HL,t} - (m_t\, r_{mkt,t} + v_t\, r_{vol,t} + j_t\, r_{jmp,t})$, where m_t, v_t, and j_t are time-varying factor exposures. Following Grundy and Martin (2001), we estimate the risk factor model using a rolling window of the most recent 60 months (with a minimum of 36 months).

The bottom rows of Table X report the hedged returns of the momentum spread portfolio when we use each risk factor model. In all cases, hedging using time-varying betas has almost no effect on average returns, which are all very close to the unhedged average return of 0.0603 (with a t-statistic of 6.87).[18] This appears mainly to be the result of the long and short legs of the momentum strategy having similar average factor loadings and the time-variation in those loadings being small. Overall, the evidence suggests that time-varying factor loadings are not an explanation for straddle return momentum.

The minor effects of risk adjustment is likely related to the fact that systematic risk in straddles is less important than it is in stocks. For example, regressing stock returns on the market factor yields an average R-square of 0.2 to 0.3, depending on the sample period. Regressing straddle returns on the SPX straddle return results in an average R-square of around 0.1. The greater importance of idiosyncratic returns means that momentum rankings will have little to do with systematic risk, and the resulting momentum strategy will have less of a tendency to have time-varying betas.

D. Spanning tests

In this section we ask whether any of the three momentum strategies we have analyzed are redundant, meaning that they offer no risk-adjusted return other than that implied by their exposure to another strategy. Given the relative weakness after factor adjustment of strategies formed on a single month of past returns, we focus solely on the standard "2 to 12" formation period.

The form of these tests is simple. The returns on one long/short momentum portfolio is taken

[18]Because of the slightly shortened sample period resulting from the need to estimate factor loadings, we report average unhedged returns corresponding to the period in which hedged returns are available. This results in slight differences relative to the values reported in Table II.

as the dependent variable, while a different long/short momentum portfolio is the independent variable.[19] We also examine regressions in which the additional seven non-momentum factors are used as additional controls. The results are reported in Table XI.

TABLE XI ABOUT HERE

Panel A shows that individual straddle momentum is not spanned by industry or factor momentum, whether or not the additional controls are included. While industry momentum explains a portion of individual momentum, the amount is fairly small. Factor momentum explains almost none of the returns on individual straddle momentum.

Panel B asks whether the returns on industry momentum can be explained. The results here are clear: there is no industry momentum alpha after controlling for individual straddle momentum. Factor momentum again appears relatively unimportant, and results are fairly insensitive to the inclusion of other factors as controls.

Finally, Panel C tries to explain factor momentum returns. The table shows that the other two long/short momentum portfolios are nearly unrelated to factor momentum, explaining less than 2% of the variation in the realized returns on factor momentum.

In stocks, the results of Moskowitz and Grinblatt (1999) suggest the primacy of industry momentum. Grundy and Martin (2001) dispute this conclusion, while Novy-Marx (2012) shows that industry momentum is largely explained by its exposure to the Fama-French Up-Minus-Down (UMD) factor. Our own results in straddles are analogous, but even stronger, as industry momentum is fully explained by individual straddle momentum and itself explains little variation in the other two momentum strategies.

[19]We have also run regressions with two long/short momentum portfolios as independent variables. The results we present suggest that one of these variables will be generally be irrelevant, which is in fact what we find when including both.

As Novy-Marx (2012) notes, the one variety of industry momentum in stocks that is not spanned by UMD is at very short horizons, with the formation period including only the most recent month. In contrast, Table VII shows that there is no short-term industry momentum for straddles.

Given the relatively nascent literature on factors in option returns, it is possible that the factors we consider are an incomplete representation of the true factor structure. Keeping this in mind, our results nevertheless contrast sharply with Ehsani and Linnainmaa (2021) and Gupta and Kelly (2019), who find that factor momentum explains most or all of the performance of both individual stock and industry momentum. For straddles, factor momentum explains almost none of the variation in other momentum strategy returns.

To summarize, Table XI suggests that there are two distinct sources of priced momentum, individual and factor. As shown in Table IX, however, only the former survives risk adjustment. Our remaining analysis therefore focuses on the standard cross-sectional momentum strategy constructed from individual straddles.

E. Consistency in the cross section

In this section, we investigate how pervasive momentum and reversal are by examining different subgroups of the cross section of straddles. There are several motivations for doing this. First, if these straddle return anomalies are confined to small and illiquid stocks, which make up a small portion of the overall market, they may be regarded as less important economically and less relevant to investors (Fama and French (2008) and Hou, Xue, and Zhang (2020)). Second, a confirmation of those anomalies in most or all of the subgroups would mitigate the concern that they are the outcome of data snooping. Third, if they are more prominent in the subgroups in which traders face greater limits to arbitrage (Shleifer and Vishny (1997)), then mispricing would receive more credibility as their underlying source.

We first investigate short-term reversal in Panel A of Table XII. To generate each column, we perform 3-by-3 sequential double sorts of straddles every third Friday, first on the conditioning variable shown in the column header, and then on the straddle return at the 1-month lag. Within each tercile of the conditioning variable, we compute equal-weighted portfolio returns and report the profitability of the strategy that buys the highest tercile of formation period straddle returns and shorts the lowest. The bottom rows show the differences in spread between the lowest and highest terciles of the conditioning variable.

TABLE XII ABOUT HERE

We consider the following five conditioning variables: firm size, measured by the stock's most recent market equity capitalization; stock illiquidity, proxied by the average Amihud (2002) illiquidity measure over the last year; option illiquidity, measured by the average percentage bid-ask spread of the puts and calls in each straddle, also averaged over the past 12 months; analyst coverage; and, finally, the most recent credit rating.[20]

The first four variables proxy for impediments to arbitrage in the options market. While firm size and stock illiquidity are typically used as proxies of the costs of trading stocks, options on the stocks with small size and high illiquidity also tend to be less liquid and more costly to trade. As such, they can be seen as indirect measures of the costs of trading options faced by arbitrageurs. On the other hand, high option illiquidity provides a direct indicator of the high costs of trading options.

Analyst coverage may proxy for either the diffusion rate of public information flow or information uncertainty (Hong, Lim, and Stein (2000) and Zhang (2006)). Options on the stocks with lower

[20]Following Avramov, Chordia, Jostova, and Philipov (2007), we use S&P Long-Term Domestic Issuer Credit Ratings, which is available from the Compustat S&P Ratings database. These data are not available after February 2017.

analyst coverage are likely slower in incorporating public information. They may also experience more speculative activities from irrational investors as a result of their high information uncertainty. This poses a convergence risk that could deter option arbitrage activity. In stocks, studies such as Hong, Lim, and Stein (2000) and Zhang (2006) show that momentum profits are greater for firms with lower analyst coverage.

Finally, Avramov et al. (2007) find that stock momentum exists only among stocks with low credit ratings, and Avramov et al. (2013) find that the profitability of stock momentum derives exclusively from periods of credit rating downgrades. As such, we add credit rating as the last conditioning variable and ask whether credit ratings remain important in signaling the profitability of momentum and reversal in straddle returns.

Panel A indicates that the tendency of straddles to reverse their most recent monthly return permeates the entire cross section. It is evident among small and large firms and among companies with low and high stock or option liquidity. It is present whether analyst coverage is high or low, for all credit ratings, and does not depend on whether the firm experienced a downgrade in the 12 months prior to the holding period.[21] The table shows that reversal is more pronounced for stocks with higher levels of stock and option liquidity, which makes microstructure-based explanations of short-run reversal less plausible. In addition, reversal is more pronounced for stocks with low impediments to arbitrage (large size, high analyst coverage, and more liquidity), suggesting that mispricing from an overreaction to past shocks may not be the main explanation. Finally, we see that credit rating does not exhibit any relation to the profitability of reversal. Overall, the results

[21]For the analyses that exclude or include downgraded firms, we do not exactly follow the exclusion choice of Avramov et al. (2013), which discards observations from six months before to six months after a downgrade. This is because this approach suffers from a potential look-ahead bias. Instead, our exclusion and inclusion choices can be feasibly implemented in real-time trading strategies. However, our findings are robust if we adopt their exclusion design.

leave few clues about the origins of short-run reversal.

Panel B reports the same analyses for straddle momentum. Like reversal, momentum is pervasive in the cross section. Unlike reversal, however, momentum is more prominent in stocks facing high impediments to arbitrage. This is consistent with the hypothesis that underreaction to past shocks is a significant driver of the momentum phenomenon. Further, momentum is stronger for low-grade stocks and becomes statistically insignificant for high-grade stocks, which is similar to the results of Avramov et al. (2007), who find that stock momentum is absent for high-grade stocks. It is different from Avramov et al. (2013), however, in that straddle momentum remains significant for stocks that have not downgraded recently, while stock momentum loses efficacy in this case.

In light of existing research (Gebhardt, Hvidkjaer, and Swaminathan (2005), Jostova et al. (2013)) showing that stock momentum has a spillover effect on other asset classes, it is natural to ask whether option momentum would be affected by controlling for past stock returns. While a straightforward mechanical link between stock and option momentum can be ruled out by the fact that option momentum remains profitable even when dynamically delta-hedged. It is conceivable that past stock returns are correlated with future changes in volatility, perhaps due to market underreaction to common information.

Empirically, Cao and Han (2013) find that past stock returns predict option returns positively at horizons of 1-36 months, though the relation is not particularly strong or robust. In our own sample of straddle returns, we find a relation that is slightly negative but insignificant. More importantly, the profitability of option momentum is equally strong among firms with low and high past stock returns, suggesting no appreciable link between stock and option momentum.

F. Transactions costs and margin

A natural question to ask is whether the profitability of the strategies we investigate are robust to transactions costs. Accounting for transactions costs is difficult for a number of reasons, however.

One is that option traders commonly use limit orders, so they tend not to be liquidity takers in the traditional sense, and orders are often filled inside the quotes set by option market making firms. When trading straddles and other option combinations, option exchanges offer trader additional avenues for price improvement using the so-called complex order book. This allows a trader to post limit orders for multi-leg strategies, like a straddle, at prices that would be better than those obtained by taking the bids or the asks of each leg separately. Interestingly, posting an order to the complex book is something that is only available to end users and not market makers. The market maker's role is only to choose whether or not to fill these orders. In some ways it is a reversal of taker/maker roles relative to other markets. Market makers still earn an implicit spread, but it may be much less than that implied by the quotes on individual legs.

Further, as Muravyev and Pearson (2020) show, even liquidity-taking strategies face costs that are much less than those implied by end-of-day quoted spreads. They argue that this is because the fair value is often closer to one side of the bid-ask quotes. When fair value is closer to the ask, for example, we tend to see traders buying. Quotes overstate the cost of trading because the actual difference between fair value and price paid is much less than half the spread. It is also the case that option bid-ask spreads are constantly widening and contracting (possibly the result of orders placed by non-market makers). This gives another way for the opportunistic trader to reduce costs relative to end-of-day quotes.

Another natural strategy for controlling transactions costs would be to only trade securities for which the expected return exceeds the transactions cost estimate. In our setting, this can be accomplished by trading straddles that have a more extreme buy or sell signal and that have relatively low bid-ask spreads. We believe that such transactions cost-optimized strategies are standard in practice.

Finally, the after-cost performance of a strategy only tells us whether the signal on which the strategy is based is useful when that signal is traded in isolation. It is quite possible that any single signal would not be strong enough to generate positive after-cost returns. But at the same time, a multi-signal strategy, which we believe would be more likely in practice, might be highly profitable even after costs are accounted for.

TABLE XIII ABOUT HERE

With these considerations in mind, Table XIII reports returns on transactions cost-adjusted average returns for the momentum and reversal strategies. Following the results in Table 5 of Muravyev and Pearson (2020), we consider one-way costs that are a fixed fraction of the quoted half spread. "Algo" traders, for example, pay 20% of the half spread, a value that follows from Muravyev and Pearson's finding that algorithmic traders pay an effective half-spread of \$0.026 on average when trading at-the-money options, when the average quoted half-spread is \$0.128. "Adjusted" and "effective" half-spreads are 51% and 76%, respectively, of the quoted values on average. We also consider cases with and without a cost to exit the stock position that would result from the exercise of options that expire in the money. The assumption of no cost would follow if those positions are exited in the closing auction. When we impose a cost on liquidating stock, we assume that cost is equal to half of the closing bid-ask spread.

In addition to the baseline strategies examined above, we consider strategies that are optimized for transactions costs in two ways. First, we examine strategies based on extreme deciles rather than quintiles, given that the higher average returns of decile-based strategies are more likely to survive trading costs. Second, we consider strategies that avoid options with bid-ask spreads above 10% of option midpoints, as these are clearly the costliest to trade.

Panels A and B show that the main momentum and reversal strategies are not profitable if one assumes that the entire quoted spread must be paid. However, portfolios that are formed to account for transactions costs are quite profitable for both strategies under a number of reasonable assumptions about transactions costs paid. Most notably, both strategies would be highly profitable if one were able to achieve the level of transactions costs that Muravyev and Pearson document of their "algo" traders, regardless of whether transactions costs must be paid on stock liquidation.

Transactions costs weigh somewhat more on reversal than they do on momentum for baseline strategies, but for transactions cost-optimized strategies the reduction in average returns is similar. This is consistent with results from Table XII that showed that reversal was actually more profitable, even without accounting for transactions costs, among more liquid stocks. As a result, it is clearly more profitable to choose high-liquidity options when it comes to trading reversal.

As we argued above, examining each strategy in isolation likely leads to an overstatement of the importance of transactions costs. Panel C therefore shows the results of a composite strategy formed by sorting stocks based on the average values of their reversal and momentum z-scores. We find that mean returns after transactions costs are positive for the decile/low spread portfolio even if the full effective spread is paid, though when stock liquidation costs are taken into account the significance of this positive mean is lost. Nevertheless, the composite strategy survives relatively large transactions costs, indicating that our results are highly relevant, both for liquidity takers and market makers.

Since our option momentum and reversal strategies involve written option positions, we investigate the impact of margin requirements. Following Goyal and Saretto (2009) and Santa-Clara and Saretto (2009), we compute margin requirements for the option positions in the short portfolios by implementing the Standard Portfolio Analysis of Risk (SPAN) system, which is a widely used scenario analysis algorithm. Two key factors are necessary in SPAN, the range of the underlying stock price movement and the range of the underlying volatility movement. Every expiration Friday of the month, we follow Goyal and Saretto and use ± 15% of the underlying price on that day for the former factor, with progressive increments of 3%, and ± 10% of the level of implied volatility on that day for the latter one. We then calculate the price of each option using the Black and Scholes (1973) model under each scenario and determine the margin of that option by the largest loss among those scenarios.

We define the initial margin ratio as M0/V0, where M0 is the initial margin when opening a short option position and V0 equals the option price when the short position is opened. Since the short portfolios are equally weighted, we calculate the portfolio-level margin ratio by taking an equal-weighted average of the ratios for individual firms in the short portfolio. This measures how much additional capital an investor needs to set aside, for every $1 bet on the zero-cost option momentum or reversal spread strategies, in an account holding approximately risk-free assets. As such, the return to the momentum or reversal spread strategy that accounts for margin is equal to the inverse initial margin ratio (V0/M0) times the return to the strategy when margin is not considered.[22]

The last column of Table XIII reports the impact of margins. After accounting for margins, the returns shrink by 50%-55% for momentum, reversal, and composite strategies, suggesting an average initial margin ratio slightly above 2 for those strategies. But all the margin-adjusted returns

[22]Suppose an investor shorts a straddle with a total value of $1, which requires that the investor post $\$M$ in margin. To implement a zero-cost long-short option strategy betting an equal dollar amount on both long and short legs, this investor would then buy a straddle with a $1 value using the proceeds from the short position. The additional capital needed from this investor and deposited in the margin account for maintaining the long-short option positions is therefore still $\$M$, which is invested in a risk-free asset. Hence, the corresponding portfolio return in excess of risk-free rate should be $(1/M)r_{long} - (1/M)r_{short} + (M/M)r_f - r_f = (1/M)(r_{long} - r_{short})$, where r_{long}, r_{short}, and r_f are returns on the long and short straddles and risk-free rate, respectively.

remain highly significant, albeit with a slight drop in statistical significance. In sum, momentum and reversal strategies remain highly profitable after accounting for margin.

V. Summary

This paper has documented continuation and reversal patterns in the cross-section of option returns on individual stocks. These patterns are highly significant, robust, and pervasive.

Most significantly, option returns display momentum, meaning that firms whose options performed well in the previous 6 to 36 months are likely to see high option returns in the next month as well. Momentum is present whether we measure past performance on a relative basis ("cross-sectional momentum") or an absolute basis ("time series momentum"). It is profitable in every five-year subsample and is far less risky than short straddle positions on the S&P 500 Index or individual stocks. Further, returns to these strategies show no evidence of the momentum crashes that periodically affect stocks, though it is possible that our sample is too short to detect such phenomena.

Because we work with delta-hedged option positions, our results are unexplained by stock momentum. The profitability of the strategy is also unaffected by controlling for other option characteristics, such as the difference between implied and historical volatilities, and is also robust to adjustment using factors constructed from these characteristics.

While momentum is also present in industry and factor portfolios, neither of these versions of the momentum strategy delivers positive alphas after controlling for other returns. Industry momentum is subsumed by individual firm momentum, while the reverse is not true. Factor momentum is almost completely distinct from individual firm momentum, but its positive mean turns into a negative alpha after adjustment using the model of Horenstein, Vasquez, and Xiao (2019) or an extension of it.

Though less robust to controls and methodology, we also find evidence of short-term cross-sectional reversal in option returns, in that firms with options that perform relatively well in one month tend to have options that perform relatively poorly in the next month. While the effect is highly stable over time, its average return can be explained by exposure to other option factors, most importantly the long/short factors formed on the basis of the difference between short-term implied volatility and either historical (Goyal and Saretto (2009)) or long-term implied (Vasquez (2017)) volatility. A high option return in one month tends to raise implied volatility more than it raises future realized volatility, which leads to lower future returns. Reversal is also absent when we implement daily dynamic delta hedging.

We find no evidence of long-run reversal in option returns, which is in stark contrast to the behavior of stocks. Moreover, at the 2- to 3-year horizons at which stocks start showing a tendency to reverse, option returns continue to show momentum. These result supports the view, advocated by Conrad and Yavuz (2017), that momentum and long-run reversal are distinct phenomena, with different root causes.

We address the question of whether risk exposures explain the returns to momentum in several ways. First, in an approach based on option theory, we neutralize the momentum strategy's returns to delta and/or vega risk, the former by daily delta hedging and the latter by examining returns on VIX portfolios. Though neutralized strategies are less volatile and presumably less dependent on systematic risk, we find that they are if anything more profitable than our baseline strategies. Secondly, we analyze exposures to economically motivated factors, finding that momentum has no significant exposure to factor risk, either unconditionally or conditional on past factor realizations. Lastly, we show that momentum has little apparent crash risk and a standard deviation that is lower than those of many other option strategies. Thus, if risk premia are the main driver of momentum profits, then the risks priced in equity options must be subtle and substantially different from those that are commonly thought to drive option risk premia.

We can also eliminate several other potential explanations for momentum. First, we can rule out that momentum arises purely as the result of cross-sectional variation in unconditional expected returns. The lack of long-run reversal suggests that an explanation involving delayed overreaction, which features in the models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999), is unlikely. And while our results may be consistent with underreaction, the cause of that underreaction cannot be the disposition effect (Grinblatt and Han (2005)), as the options we analyze expire in just one month. An investor who is reluctant to exit a poorly performing option trade simply does not have that choice given the short lives of these contracts.

We leave a number of questions for future research. Is momentum behavioral, or does it suggest new sources of risk premia that are as yet undetected? Does long-horizon momentum reflect variation in permanent or transitory (but persistent) expected returns? What is responsible for short-run reversal, which is surprisingly more pronounced in liquid options? It would be interesting to relate these puzzles to momentum phenomena in stock and bond markets.

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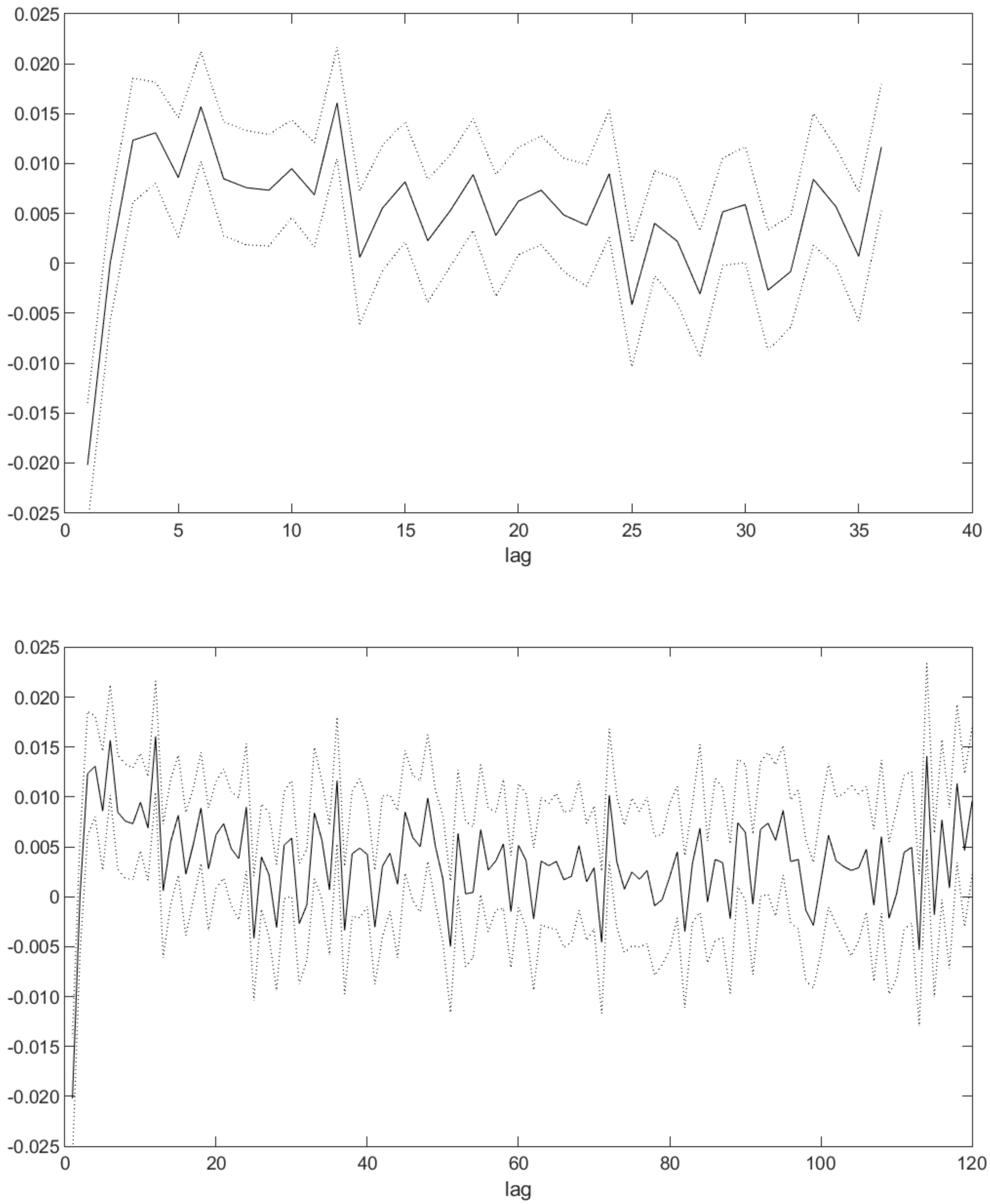

Figure 1. Straddle returns regressed on lagged values from the same firms. This figure shows the slope coefficients and 95% confidence intervals from Fama-MacBeth regressions in which monthly straddle returns are regressed on a single lagged monthly straddle return for the same firm. The length of the lag is shown on the horizontal axis. The top and bottom panels are identical except for the range of lags considered. Confidence intervals are computed using Newey-West standard errors with three lags.

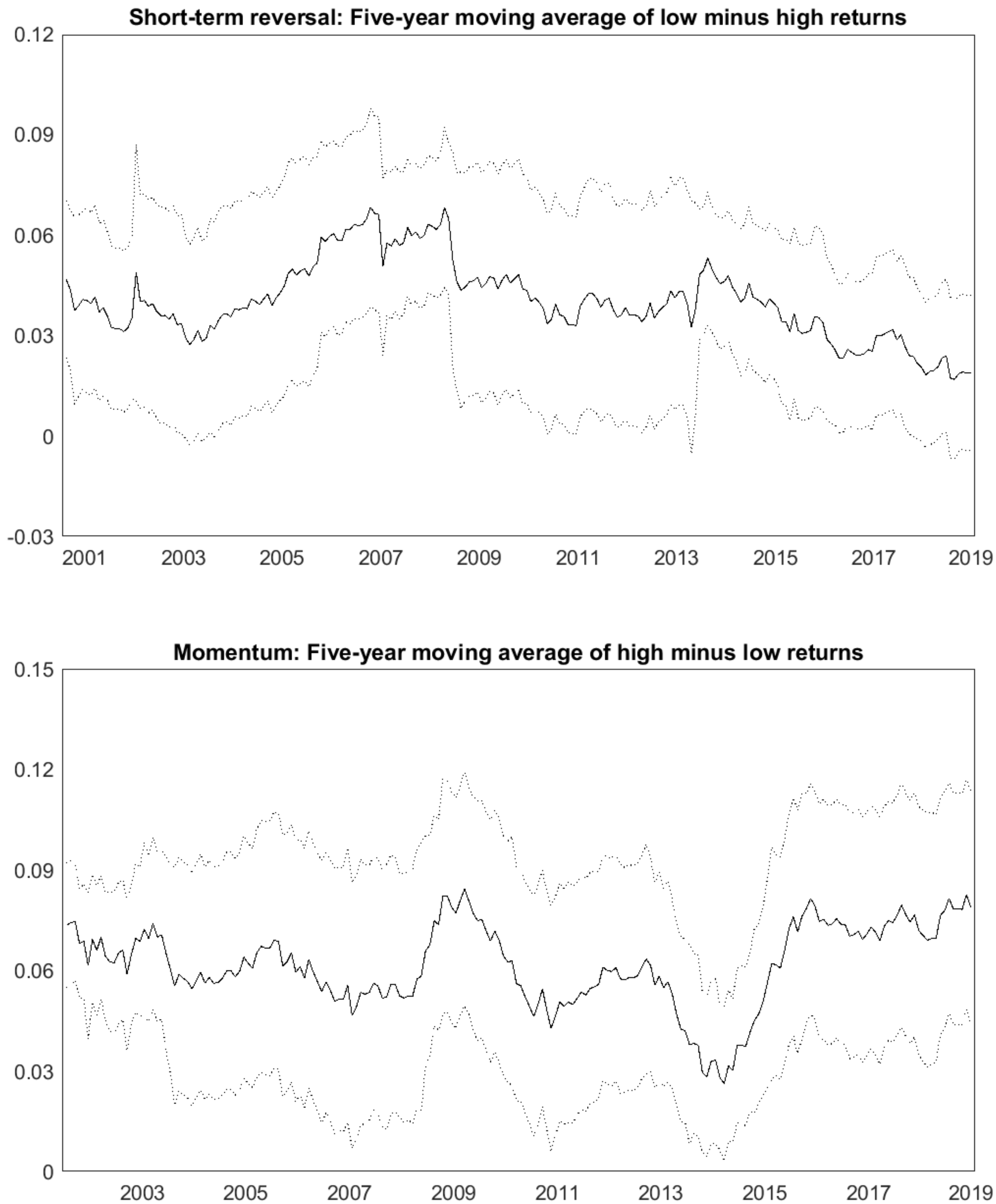

Figure 2. Five-year moving averages of strategy returns. This figure reports the rolling five-year average return on the short-term reversal (lag 1) and momentum (lags 2 to 12) factors. Dotted lines denote 95% confidence intervals, which use Newey-West standard errors with 3 lags.

Table I
Summary Statistics

This table reports summary statistics for main variables in this study. Returns are reported on a monthly basis. All the numbers are statistics on the full panel of each variable, except that we report time series statistics for number of firms in each month. Panel A includes the main sample used throughout the paper, which requires positive open interest for both the call and the put in the straddle. Straddles have one month until expiration and initially have zero delta. Returns are computed by holding the straddle until expiration. Implied volatility is an average of the values for the 30-day at-the-money call and put values. Historical volatility is a 250-day rolling standard deviation of stock returns. The IV term spread is the difference between the 60-day and 30-day at-the-money implied volatilities, while the IV smirk slope is the difference between the implied volatilities of the 30-day call with delta of 0.3 and the 30-day put with a delta of -0.3. Idiosyncratic volatility is the standard deviation of the residuals of a 22-day rolling regression using the Fama-French (1993) factors. Stock illiquidity is the Amihud ratio, averaged over the previous 12 months. Option liquidity is the weighted average of the bid-ask spreads of the call and put in each straddle, averaged over the previous 12 months. Panel B summarizes the subsample in which both straddle and VIX returns are non-missing with positive open interest. In this subsample we report returns on static strategies and on strategies that are dynamically delta hedged.

Panel A: Main sample

	Number of observations	Mean	Standard deviation	10th percentile	Median	90th percentile
Number of firms each month		1368.74	309.18	932	1442	1713
Straddle return	384672	-0.0528	0.8057	-0.8606	-0.2283	0.9403
Implied volatility (IV)	384540	0.4542	0.2416	0.2138	0.3970	0.7673
Historical volatility (HV)	374668	0.4531	0.2535	0.2122	0.3937	0.7657
IV - HV	374537	-0.0030	0.1646	-0.1387	-0.0008	0.1325
IV term spread	384540	-0.0067	0.0516	-0.0564	-0.0012	0.0363
IV smirk slope	384540	-0.0306	0.0863	-0.0986	-0.0296	0.0297
Equity market capitalization ($ billions)	383836	10.6489	31.0284	0.3995	2.4264	22.9442
Idiosyncratic volatility	383636	0.0225	0.0166	0.0084	0.0181	0.0414
Analyst coverage	363525	11.9698	7.7733	3.0000	10.0000	23.0000
Stock illiquidity	382174	0.0071	0.2112	0.0001	0.0008	0.0100
Option illiquidity	384672	0.1718	0.0955	0.0612	0.1549	0.3109

Panel B: Sample with VIX returns

	Number of observations	Mean	Standard deviation	10th percentile	Median	90th percentile
Number of firms each month		557.73	234.18	252	561	843
Static straddle return	156165	-0.0438	0.7904	-0.8570	-0.2139	0.9558
Dynamic straddle return	156165	-0.0512	0.6450	-0.6885	-0.1713	0.7056
Number of strikes in VIX portfolios		8.00	5.62	4	7	13
Static VIX return	156165	-0.0835	1.1881	-0.8894	-0.4832	1.1537
Dynamic VIX return	156165	-0.0752	0.6295	-0.5477	-0.1944	0.4622

Table II
Univariate Sorts

This table reports means and T-statistics from univariate quintile sorts. On the third Friday of each month, one-month straddles are sorted into quintiles based on lagged returns (Panel A) or other stock-level characteristics (Panel B). Straddles are initially zero delta and approximately at the money. The table reports the average returns on equally weighted portfolios in which straddles are held to expiration. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Panel A: Portfolios formed on the basis of lagged straddle returns

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0408	-0.0453	-0.0483	-0.0607	-0.0817	-0.0409
		(-2.52)	(-2.77)	(-3.08)	(-3.76)	(-5.24)	(-6.18)
1	2	-0.0378	-0.0427	-0.0532	-0.0619	-0.0719	-0.0341
		(-2.41)	(-2.62)	(-3.22)	(-3.79)	(-4.54)	(-4.41)
1	6	-0.0584	-0.0571	-0.0536	-0.0459	-0.0392	0.0193
		(-3.54)	(-3.50)	(-3.07)	(-2.72)	(-2.38)	(2.32)
1	12	-0.0707	-0.0532	-0.0490	-0.0329	-0.0305	0.0402
		(-4.38)	(-3.06)	(-2.74)	(-1.88)	(-1.72)	(4.94)
2	12	-0.0777	-0.0617	-0.0453	-0.0355	-0.0155	0.0622
		(-4.80)	(-3.63)	(-2.58)	(-2.08)	(-0.85)	(7.97)
2	24	-0.0719	-0.0596	-0.0460	-0.0266	-0.0122	0.0596
		(-3.83)	(-3.45)	(-2.40)	(-1.40)	(-0.67)	(7.28)
2	36	-0.0820	-0.0717	-0.0375	-0.0311	-0.0240	0.0580
		(-4.33)	(-3.89)	(-1.88)	(-1.49)	(-1.27)	(6.51)
13	24	-0.0548	-0.0528	-0.0482	-0.0360	-0.0234	0.0314
		(-2.87)	(-2.89)	(-2.60)	(-1.96)	(-1.34)	(3.99)
13	36	-0.0686	-0.0651	-0.0411	-0.0380	-0.0288	0.0398
		(-3.64)	(-3.34)	(-2.08)	(-1.95)	(-1.56)	(4.18)
25	36	-0.0641	-0.0546	-0.0463	-0.0410	-0.0381	0.0261
		(-3.55)	(-2.97)	(-2.40)	(-2.10)	(-2.11)	(3.35)

Panel B: Portfolios formed on the basis of other lagged characteristics

Characteristic	Low	2	3	4	High	High - Low
IV - HV	-0.0186	-0.0365	-0.0454	-0.0682	-0.1220	-0.1034
	(-1.10)	(-2.18)	(-2.50)	(-4.12)	(-9.51)	(-9.48)
Idiosyncratic vol	-0.0543	-0.0474	-0.0476	-0.0540	-0.0793	-0.0249
	(-2.86)	(-2.75)	(-2.92)	(-3.59)	(-5.90)	(-1.99)
Market cap	-0.0815	-0.0501	-0.0441	-0.0530	-0.0573	0.0241
	(-6.09)	(-3.54)	(-2.71)	(-3.07)	(-3.11)	(2.07)
IV term spread	-0.0995	-0.0646	-0.0499	-0.0429	-0.0278	0.0717
	(-7.60)	(-4.12)	(-2.91)	(-2.44)	(-1.69)	(7.92)
IV smirk slope	-0.0675	-0.0543	-0.0476	-0.0531	-0.0626	0.0049
	(-4.80)	(-3.20)	(-2.84)	(-3.27)	(-4.11)	(0.78)

Table III
Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth regressions in which the dependent variable is the return on a one-month straddle that is held until expiration. Straddles are initially zero delta and approximately at the money. Independent variables include a measure of lagged returns and five other stock-level characteristics. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		Intercept	Past return	IV - HV	Idiosyncratic vol	Market cap	IV term spread	IV smirk slope	Avg. CS R^2
		-0.0357		-0.2045	-0.9812	0.0000	0.3491	0.0328	0.0154
		(-1.82)		(-7.60)	(-3.77)	(-1.03)	(5.62)	(1.53)	
1	1	-0.0581	-0.0202						0.0030
		(-3.72)	(-6.46)						
1	1	-0.0397	-0.0140	-0.2040	-0.8390	0.0000	0.3228	0.0499	0.0183
		(-1.98)	(-4.80)	(-7.20)	(-3.06)	(-0.84)	(5.09)	(1.94)	
1	2	-0.0577	-0.0231						0.0030
		(-3.71)	(-4.79)						
1	2	-0.0383	-0.0151	-0.2013	-0.8696	0.0000	0.3255	0.0576	0.0192
		(-1.92)	(-3.24)	(-6.83)	(-3.18)	(-0.76)	(4.84)	(1.94)	
1	6	-0.0525	0.0223						0.0031
		(-3.28)	(2.61)						
1	6	-0.0239	0.0373	-0.1866	-1.1848	0.0000	0.3589	0.0759	0.0211
		(-1.16)	(4.54)	(-5.95)	(-3.96)	(-0.79)	(4.76)	(1.94)	
1	12	-0.0449	0.0705						0.0040
		(-2.67)	(5.77)						
1	12	-0.0100	0.0796	-0.1958	-1.4372	0.0000	0.3877	0.0955	0.0248
		(-0.47)	(6.16)	(-4.87)	(-4.39)	(-2.27)	(4.46)	(1.96)	
2	12	-0.0424	0.0949						0.0044
		(-2.49)	(8.39)						
2	12	-0.0104	0.0964	-0.1713	-1.3680	0.0000	0.4486	0.0760	0.0252
		(-0.49)	(8.23)	(-4.37)	(-4.21)	(-2.20)	(4.69)	(1.72)	
2	24	-0.0350	0.1386						0.0051
		(-1.93)	(8.03)						
2	24	-0.0024	0.1392	-0.1513	-1.4197	0.0000	0.4864	0.1063	0.0300
		(-0.11)	(7.47)	(-3.32)	(-3.77)	(-3.04)	(4.12)	(1.57)	
2	36	-0.0383	0.1713						0.0063
		(-2.04)	(6.77)						
2	36	-0.0077	0.1769	-0.1353	-1.3825	0.0000	0.5037	0.0928	0.0372
		(-0.32)	(7.01)	(-2.70)	(-2.92)	(-2.93)	(3.70)	(0.91)	
13	24	-0.0382	0.0582						0.0033
		(-2.13)	(5.17)						
13	24	-0.0168	0.0535	-0.2007	-1.1641	0.0000	0.4741	0.0427	0.0252
		(-0.73)	(4.86)	(-5.06)	(-3.39)	(-1.76)	(4.65)	(0.87)	
13	36	-0.0411	0.0970						0.0051
		(-2.22)	(4.70)						
13	36	-0.0221	0.0978	-0.1598	-1.0789	0.0000	0.5392	0.0480	0.0318
		(-0.92)	(4.95)	(-3.43)	(-2.61)	(-2.09)	(4.48)	(0.61)	
25	36	-0.0466	0.0353						0.0034
		(-2.56)	(2.92)						
25	36	-0.0296	0.0366	-0.1269	-0.8479	0.0000	0.5043	0.0592	0.0249
		(-1.29)	(2.99)	(-3.22)	(-2.35)	(-1.38)	(4.84)	(1.04)	

Table IV
Comparison of Option Benchmarks

Univariate quintile sorts on individual momentum for option returns. Four methodologies for computing option returns are considered. The sample examined is an intersection of the samples of straddle and VIX portfolio returns. When forming momentum signals, we require nonmissing return observations for at least two thirds of the formation period. Static hedges have zero delta only at the start of the holding period. Dynamic hedges rebalance to zero delta daily by taking a position in the underlying stock. If the delta of any option is missing, we estimate it from the current stock price and the most recent non-missing implied volatility from the same option. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		Straddle (static hedge)			Straddle (dynamic hedge)			VIX portfolio (static hedge)			VIX portfolio (dynamic hedge)		
		Low	High	High - Low	Low	High	High - Low	Low	High	High - Low	Low	High	High - Low
1	1	-0.0420	-0.0829	-0.0408	-0.0592	-0.0600	-0.0008	-0.0659	-0.1311	-0.0652	-0.1110	-0.0752	0.0358
		(-2.41)	(-4.95)	(-4.94)	(-4.18)	(-4.16)	(-0.09)	(-2.49)	(-5.39)	(-5.18)	(-8.83)	(-5.10)	(4.03)
1	2	-0.0259	-0.0675	-0.0415	-0.0574	-0.0483	0.0091	-0.0537	-0.1142	-0.0605	-0.1093	-0.0592	0.0501
		(-1.51)	(-3.97)	(-4.28)	(-4.20)	(-3.16)	(0.91)	(-2.02)	(-4.34)	(-4.38)	(-8.61)	(-3.80)	(4.98)
1	6	-0.0573	-0.0340	0.0233	-0.0755	-0.0350	0.0405	-0.0840	-0.0722	0.0118	-0.1180	-0.0506	0.0674
		(-3.23)	(-1.98)	(2.56)	(-5.52)	(-2.33)	(4.93)	(-3.27)	(-2.78)	(0.87)	(-9.60)	(-3.46)	(7.43)
1	12	-0.0687	-0.0323	0.0364	-0.0813	-0.0253	0.0559	-0.1031	-0.0730	0.0301	-0.1125	-0.0496	0.0630
		(-3.88)	(-1.79)	(4.13)	(-5.89)	(-1.67)	(7.47)	(-4.00)	(-2.69)	(2.67)	(-8.81)	(-3.34)	(7.66)
2	12	-0.0709	-0.0175	0.0534	-0.0817	-0.0161	0.0655	-0.1036	-0.0666	0.0370	-0.1187	-0.0453	0.0733
		(-4.04)	(-0.96)	(5.98)	(-5.75)	(-1.04)	(8.27)	(-4.11)	(-2.47)	(2.57)	(-9.40)	(-3.03)	(8.00)
2	24	-0.0711	-0.0257	0.0454	-0.0827	-0.0227	0.0600	-0.1235	-0.0665	0.0570	-0.1032	-0.0464	0.0568
		(-3.77)	(-1.37)	(4.40)	(-5.49)	(-1.44)	(6.93)	(-4.45)	(-2.23)	(3.89)	(-6.99)	(-2.92)	(4.75)
2	36	-0.0742	-0.0384	0.0358	-0.0782	-0.0249	0.0532	-0.1204	-0.0785	0.0419	-0.1091	-0.0519	0.0572
		(-3.84)	(-2.06)	(3.57)	(-4.86)	(-1.52)	(6.01)	(-4.58)	(-2.68)	(2.48)	(-7.79)	(-3.10)	(5.07)
13	24	-0.0579	-0.0275	0.0304	-0.0702	-0.0339	0.0363	-0.1145	-0.0605	0.0540	-0.1057	-0.0594	0.0463
		(-3.00)	(-1.51)	(2.62)	(-4.42)	(-2.10)	(4.53)	(-4.37)	(-1.94)	(2.88)	(-7.86)	(-3.98)	(5.92)
13	36	-0.0744	-0.0225	0.0485	-0.0663	-0.0350	0.0310	-0.1194	-0.0625	0.0545	-0.1002	-0.0641	0.0357
		(-4.03)	(-1.14)	(4.58)	(-4.02)	(-2.16)	(4.28)	(-4.67)	(-1.99)	(3.14)	(-7.06)	(-4.01)	(3.50)
25	36	-0.0639	-0.0390	0.0249	-0.0642	-0.0405	0.0238	-0.1024	-0.0869	0.0155	-0.0963	-0.0666	0.0297
		(-3.33)	(-2.08)	(2.51)	(-4.01)	(-2.43)	(3.38)	(-3.93)	(-2.95)	(0.99)	(-6.74)	(-4.31)	(3.25)

Table V
Fama-MacBeth Regressions with Longer Lags

This table reports the results of Fama-MacBeth regressions in which the dependent variable is the return on a one-month straddle that is held until expiration. Straddles are initially zero delta and approximately at the money. Independent variables include average returns over different past periods. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. The PT test column reports p-values of the Patton and Timmermann (2010) monotonicity test, whose null hypothesis is that the coefficients on different return lags (excluding lag 1) are constant or increasing, and whose alternative hypothesis is that the coefficients are decreasing.

		Return lag						Avg.	PT test	# of	Avg. obs.
	Intercept	1	2-12	13-24	25-36	37-48	49-60	CS R^2	p-value	months	/months
(1)	-0.0581	-0.0202						0.0030		280	1235.3
	(-3.72)	(-6.46)									
(2)	-0.0451	-0.0252	0.0968					0.0085		269	750.6
	(-2.63)	(-7.10)	(8.37)								
(3)	-0.0363	-0.0235	0.0888	0.0536				0.0141	0.0379	257	541.0
	(-1.99)	(-5.34)	(6.67)	(4.29)							
(4)	-0.0381	-0.0265	0.0809	0.0683	0.0301			0.0230	0.0357	245	414.2
	(-1.99)	(-5.08)	(5.05)	(4.46)	(2.11)						
(5)	-0.0422	-0.0259	0.0611	0.0619	0.0164	0.0408		0.0322	0.5784	233	325.7
	(-2.11)	(-4.57)	(2.85)	(3.13)	(1.06)	(2.40)					
(6)	-0.0395	-0.0264	0.0714	0.0445	-0.0060	0.0532	0.0121	0.0486	0.9084	221	261.2
	(-1.89)	(-3.46)	(3.10)	(1.97)	(-0.31)	(2.34)	(0.64)				

Table VI
Cross-Sectional Versus Time Series Reversal and Momentum

This table reports means and T-statistics of the returns on portfolios meant to capture cross sectional and time series reversal and momentum. Cross sectional (CS) strategies go long (short) an equal weighted portfolio of straddles whose lagged excess returns are above (below) the cross sectional mean. Time series (TS) strategies go long (short) straddles whose lagged excess returns are positive (negative) and size each straddle's position at $2/N, where N is the total number of straddles held long or short. The CSTVM strategy is constructed as the sum of CS strategy and the time-varying investment in the equal weighted portfolio of individual straddles. (Please refer to text for details.) The "TS - CS" ("TS - CSTVM") column reports the difference between the TS strategy's high minus low spread and the CS (CSTVM) strategy's high minus low spread. The next two columns show correlations between the TS and CS or CSTVM high/low portfolios. $ Long and $ Short are the average dollar sizes of long and short positions of the TS strategy. All portfolios are equaly weighted and use the same sample of straddles as Table II. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		CS High - Low	TS High - Low	CSTVM High - Low	TS - CS	TS - CSTVM	Corr. of TS w/ CS	Corr. of TS w/ CSTVM	$ Long	$ Short
1	1	-0.0264	0.0120	0.0126	0.0384	-0.0006	0.50	0.99	0.74	1.26
		(-5.87)	(1.08)	(1.15)	(3.82)	(-0.41)				
1	2	-0.0225	0.0141	0.0146	0.0367	-0.0005	0.50	0.98	0.77	1.23
		(-4.99)	(1.28)	(1.38)	(3.60)	(-0.26)				
1	6	0.0139	0.0380	0.0396	0.0242	-0.0016	0.44	0.97	0.78	1.22
		(2.97)	(3.35)	(3.44)	(2.20)	(-0.56)				
1	12	0.0246	0.0454	0.0486	0.0207	-0.0032	0.41	0.97	0.75	1.25
		(5.40)	(3.99)	(4.34)	(1.79)	(-1.00)				
2	12	0.0358	0.0522	0.0558	0.0163	-0.0037	0.42	0.97	0.76	1.24
		(7.72)	(4.84)	(5.18)	(1.48)	(-1.20)				
2	24	0.0372	0.0515	0.0588	0.0143	-0.0074	0.24	0.96	0.71	1.29
		(6.70)	(3.83)	(4.71)	(1.06)	(-1.79)				
2	36	0.0380	0.0620	0.0722	0.0240	-0.0102	0.25	0.93	0.68	1.32
		(5.60)	(4.21)	(5.15)	(1.64)	(-1.88)				
13	24	0.0177	0.0356	0.0393	0.0180	-0.0037	0.21	0.97	0.74	1.26
		(4.18)	(2.53)	(3.00)	(1.38)	(-1.22)				
13	36	0.0248	0.0509	0.0598	0.0261	-0.0088	0.24	0.95	0.70	1.30
		(3.68)	(3.43)	(4.08)	(1.90)	(-1.92)				
25	36	0.0171	0.0480	0.0504	0.0309	-0.0024	0.31	0.95	0.74	1.26
		(3.58)	(3.68)	(4.05)	(2.54)	(-0.67)				

Table VII
Industry and Factor Momentum

This table reports means and T-statistics on industry and factor momentum portfolios. For industry momentum in Panel A, we follow Moskowitz and Grinblatt (2004) and form 20 different industry portfolios, but of straddles instead of stocks. In each month, we rank all industries on the basis of their average returns over some formation period. We then form a portfolio from the top three, the bottom three, and the remaining 14. Factor momentum, in Panel B, is a time series momentum strategy implemented on seven straddle factors. These include five different long/short factors as well as the equally weighted straddle portfolio and the SPX straddle. In each month, we long factors whose past average excess returns (over some formation period) are positive and short factors with negative past average excess returns. Both panels show the performance of these strategies over the following month. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		Panel A: Industry portfolios				Panel B: Factor portfolios		
		Low 3	Middle 14	High 3	High - Low	Low	High	High - Low
1	1	-0.0430	-0.0551	-0.0443	-0.0013	-0.0168	0.0569	0.0720
		(-2.36)	(-3.29)	(-2.31)	(-0.08)	(-1.73)	(4.83)	(4.82)
1	2	-0.0430	-0.0543	-0.0459	-0.0029	-0.0144	0.0538	0.0684
		(-2.29)	(-3.20)	(-2.36)	(-0.19)	(-1.60)	(4.24)	(4.43)
1	6	-0.0607	-0.0524	-0.0252	0.0355	-0.0105	0.0498	0.0610
		(-3.40)	(-3.11)	(-1.15)	(2.09)	(-1.06)	(3.92)	(3.77)
1	12	-0.0731	-0.0497	-0.0104	0.0627	-0.0128	0.0507	0.0636
		(-4.03)	(-2.88)	(-0.51)	(3.88)	(-1.26)	(3.89)	(3.75)
2	12	-0.0684	-0.0489	-0.0187	0.0497	-0.0074	0.0453	0.0527
		(-3.55)	(-2.87)	(-0.93)	(3.22)	(-0.70)	(3.21)	(2.77)
2	24	-0.0610	-0.0478	-0.0146	0.0464	-0.0158	0.0515	0.0673
		(-3.10)	(-2.68)	(-0.69)	(2.81)	(-1.70)	(3.70)	(4.01)
2	36	-0.0578	-0.0533	-0.0143	0.0435	-0.0255	0.0626	0.0881
		(-2.99)	(-2.89)	(-0.65)	(2.41)	(-4.23)	(4.17)	(5.75)
13	24	-0.0417	-0.0475	-0.0351	0.0066	-0.0229	0.0587	0.0816
		(-1.90)	(-2.75)	(-1.67)	(0.43)	(-2.32)	(4.63)	(5.26)
13	36	-0.0693	-0.0456	-0.0387	0.0306	-0.0198	0.0569	0.0767
		(-3.59)	(-2.45)	(-1.84)	(1.78)	(-2.82)	(3.89)	(4.96)
25	36	-0.0567	-0.0489	-0.0361	0.0207	-0.0140	0.0511	0.0651
		(-2.75)	(-2.66)	(-1.74)	(1.27)	(-1.94)	(3.41)	(4.01)

Table VIII
Risk and Return for Alternative Strategies

This table reports risk and return measures for 13 different portfolios constructed from zero delta straddles. Panel A includes strategies from Tables II and VII, except that in all cases the long side is chosen to have the higher average return. Panel B includes factors from prior literature, again constructed to have positive means. The first five are long/short factors sorted on the difference between implied and historical volatilities (Goyal and Saretto, 2009), idiosyncratic volatility (Cao and Han, 2013), market capitalization (Cao at al., 2021), the implied volatility term structure slope (Vasquez, 2017), and the slope of the implied volatility smirk. The last two factors are short only, where the short position is either an at-the-month S&P 500 Index straddle or an equally weighted portfolio of straddles on individual equities. All straddles have a one-month maturity, are approximately at the money, and are held in equally weighted portfolios until expiration. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Panel A: Factors formed on the basis of lagged straddle returns

Formation period:	Lag 1 only			Lags 2 to 12		
	Individual (low - high)	Industry (low - high)	Factor (high - low)	Individual (high - low)	Industry (high - low)	Factor (high - low)
Mean	0.0409	0.0013	0.0720	0.0622	0.0497	0.0527
	(6.18)	(0.08)	(4.82)	(7.97)	(3.22)	(2.77)
Standard deviation	0.124	0.256	0.266	0.141	0.266	0.264
Sharpe ratio	0.330	0.005	0.271	0.441	0.187	0.200
Skewness	0.636	0.078	-0.498	0.267	-0.857	-1.081
Excess kurtosis	11.86	1.10	2.64	0.46	5.87	2.87
Maximum drawdown	0.738	>1	>1	0.557	>1	>1

Panel B: Factors based on prior research

	IV - HV	Idiosyncratic volatility	Market cap	IV term spread	IV smirk slope	Short SPX straddle	Short EW stock straddle
Mean	0.1034	0.0249	0.0241	0.0717	0.0049	0.1049	0.0567
	(9.48)	(1.99)	(2.07)	(7.92)	(0.78)	(2.52)	(3.65)
Standard deviation	0.160	0.202	0.172	0.133	0.106	0.702	0.243
Sharpe ratio	0.646	0.123	0.140	0.538	0.046	0.149	0.234
Skewness	0.824	1.046	0.650	1.913	1.312	-1.316	-3.093
Excess kurtosis	2.62	5.35	1.44	10.60	6.80	2.22	15.88
Maximum drawdown	0.547	0.985	0.983	0.798	0.889	> 1	> 1

Table IX
Factor Risk Adjustment for Reversal and Momentum Strategies

This table reports the results of regressions in which reversal or momentum strategy returns are risk-adjusted using the four-factor model of Horenstein, Vasquez, and Xiao (2019) or an extended model with three additional factors. *T*-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		Intercept	IV - HV	Idio. volatility	Market cap	IV term spread	IV smirk slope	Short SPX straddle	Short EW stock straddle	R^2
					Individual Straddles					
1	1	-0.0155	0.1903	0.1585	-0.0277			-0.0134		0.1340
		(-1.12)	(2.11)	(2.18)	(-0.34)			(-0.76)		
1	1	-0.0103	0.0728	0.1263	-0.0391	-0.2407	0.0044	-0.0180	-0.0007	0.1702
		(-0.74)	(0.92)	(2.05)	(-0.48)	(-2.89)	(0.05)	(-0.79)	(-0.01)	
2	12	0.0497	-0.1188	0.1563	0.1818			0.0051		0.0497
		(3.48)	(-1.42)	(1.57)	(2.57)			(0.26)		
2	12	0.0646	-0.0970	0.1929	0.1984	-0.0966	0.0952	0.0478	-0.1961	0.0955
		(4.24)	(-0.96)	(2.35)	(2.93)	(-0.90)	(0.83)	(2.10)	(-2.34)	
					Industries					
1	1	0.0220	0.1012	-0.0680	-0.4066			-0.0460		0.0486
		(1.00)	(0.81)	(-0.53)	(-2.65)			(-1.52)		
1	1	0.0311	0.1787	-0.0163	-0.3826	0.0512	0.0966	-0.0103	-0.1497	0.0592
		(1.24)	(1.17)	(-0.12)	(-2.47)	(0.29)	(0.50)	(-0.27)	(-1.20)	
2	12	0.0485	-0.1263	0.4831	0.1476			-0.0286		0.0859
		(2.26)	(-0.89)	(2.54)	(0.89)			(-0.87)		
2	12	0.0723	0.0642	0.5421	0.1693	0.1247	-0.0658	0.0737	-0.4386	0.1570
		(3.43)	(0.41)	(2.87)	(1.09)	(0.70)	(-0.46)	(1.88)	(-4.41)	
					Factors					
1	1	0.0176	-0.3514	-0.3076	-0.1416			0.1276		0.0992
		(0.91)	(-3.06)	(-2.35)	(-1.10)			(2.85)		
1	1	0.0051	-0.3218	-0.2708	-0.1302	0.1372	0.1586	0.0887	0.1805	0.1151
		(0.20)	(-2.43)	(-1.87)	(-1.02)	(0.73)	(0.76)	(1.94)	(0.95)	
2	12	-0.0379	-0.6326	-0.1419	-0.0089			0.2431		0.3375
		(-1.90)	(-7.77)	(-1.25)	(-0.07)			(6.37)		
2	12	-0.0533	-0.5103	-0.0930	0.0075	0.3215	0.0885	0.2142	0.1525	0.3587
		(-1.95)	(-3.95)	(-0.70)	(0.06)	(2.17)	(0.65)	(6.57)	(0.96)	

Table X
Time-Varying Factor Exposures

This table examines the effects of time-varying betas on momentum strategy returns. It reports estimates of full and restricted versions of the regression

$$\begin{aligned} r_{HL,t} = a &+ [\ m_{down}\ D_t^{down,mkt} + m_{flat}\ D_t^{flat,mkt} + m_{up}\ D_t^{up,mkt}\ ]\ r_{mkt,t} \\ &+ [\ v_{down}\ D_t^{down,vol} + v_{flat}\ D_t^{flat,vol} + v_{up}\ D_t^{up,vol}\ ]\ r_{vol,t} \\ &+ [\ j_{down}\ D_t^{down,jmp} + j_{flat}\ D_t^{flat,jmp} + j_{up}\ D_t^{up,jmp}\ ]\ r_{jmp,t} + \epsilon_t, \end{aligned}$$

The three risk factors represent the excess returns on the S&P 500 Index, an at-the-money index straddle, and an out-of-the-money index put. The dummy variables indicate whether the referenced factor had a low, medium, or high realization during the formation period. All regressions use equally weighted portfolios based on the "2 to 12" formation period. The table reports coefficient estimates and t-statistics (in parentheses, using Newey-West standard errors with three lags), R-squares, differences between coefficients, and average hedged momentum returns, where hedge ratios are time-varying and estimated using a rolling window of the most recent 60 months (with a minimum of 36 months). For comparison, unhedged returns have a mean of .0603 and a t-statistic of 6.87.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a	0.0646	0.0649	0.0618	0.0677	0.0627	0.0645	0.0648
	(8.08)	(7.99)	(7.78)	(8.04)	(7.87)	(8.04)	(8.05)
m_{down}	0.2205			0.2811	0.0681		-0.0952
	(0.49)			(0.64)	(0.15)		(-0.23)
m_{flat}	-0.4511			-0.4599	-0.5830		-0.9692
	(-1.57)			(-1.56)	(-1.68)		(-2.40)
m_{up}	0.0359			-0.0755	0.0401		-0.2161
	(0.06)			(-0.13)	(0.07)		(-0.34)
v_{down}		-0.0153		-0.0182		-0.0329	0.0071
		(-0.77)		(-0.90)		(-1.01)	(0.21)
v_{flat}		0.0076		0.0083		0.0109	0.0404
		(0.46)		(0.48)		(0.53)	(1.71)
v_{up}		0.0541		0.0582		0.0633	0.0906
		(1.62)		(1.75)		(1.60)	(2.32)
j_{down}			0.0054		0.0007	0.0113	-0.0073
			(0.74)		(0.11)	(1.00)	(-0.56)
j_{flat}			0.0012		-0.0046	-0.0007	-0.0201
			(0.19)		(-0.62)	(-0.09)	(-1.81)
j_{up}			-0.0083		-0.0128	-0.0154	-0.0341
			(-1.05)		(-1.54)	(-1.39)	(-2.83)
R^2	0.0148	0.0104	0.0028	0.0270	0.0186	0.0187	0.0452
$m_{up} - m_{down}$	-0.1846			-0.3566	-0.0279		-0.1209
	(-0.25)			(-0.49)	(-0.04)		(-0.16)
$v_{up} - v_{down}$		0.0693		0.0765		0.0962	0.0835
		(1.79)		(1.97)		(2.07)	(1.79)
$j_{up} - j_{down}$			-0.0137		-0.0135	-0.0268	-0.0269
			(-1.29)		(-1.41)	(-1.94)	(-2.08)
Average hedged returns	0.0610	0.0609	0.0603	0.0605	0.0599	0.0592	0.0574
	(6.98)	(6.95)	(6.83)	(6.93)	(6.86)	(6.48)	(6.34)

Table XI
Spanning Tests for Alternative Momentum Strategies

This table performs spanning tests that compare the individual firm, industry, and factor momentum strategies. In each panel, we report regressions in which we regress a single momentum strategy on a different momentum strategy, with or without the seven additional option factors (coefficients unreported) from Table IX included as controls. All momentum strategies use equally weighted portfolios based on the "2 to 12" formation period. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Without additional factors					With 7 additional option factors				
Intercept	Individual	Industry	Factor	R^2	Intercept	Individual	Industry	Factor	R^2
Panel A: Dependent variable is individual straddle momentum									
0.0622				N/A	0.0646				0.0955
(7.97)					(4.24)				
0.0514		0.2172		0.1679	0.0500		0.2007		0.2164
(6.59)		(7.09)			(3.52)		(6.46)		
0.0603			0.0352	0.0043	0.0671			0.0483	0.1007
(7.24)			(1.02)		(4.34)			(0.95)	
0.0485		0.2210	0.0515	0.1772	0.0534		0.2067	0.0714	0.2277
(5.92)		(7.57)	(1.57)		(3.81)		(7.05)	(1.56)	
Panel B: Dependent variable is industry momentum									
0.0497				N/A	0.0723				0.1570
(3.22)					(3.43)				
0.0016	0.7731			0.1679	0.0293	0.6659			0.2696
(0.10)	(7.23)				(1.49)	(5.85)			
0.0536			-0.0740	0.0054	0.0664			-0.1117	0.1648
(3.60)			(-1.02)		(2.83)			(-0.99)	
0.0062	0.7856		-0.1016	0.1780	0.0205	0.6832		-0.1447	0.2827
(0.41)	(7.41)		(-1.45)		(0.95)	(6.17)		(-1.41)	
Panel C: Dependent variable is factor momentum									
0.0527				N/A	-0.0533				0.3587
(2.77)					(-1.95)				
0.0450	0.1228			0.0043	-0.0610	0.1196			0.3624
(2.04)	(1.01)				(-1.97)	(1.01)			
0.0563		-0.0726		0.0054	-0.0473		-0.0833		0.3647
(2.92)		(-1.10)			(-1.60)		(-1.03)		
0.0452	0.2151	-0.1194		0.0164	-0.0574	0.2022	-0.1239		0.3739
(2.06)	(1.53)	(-1.60)			(-1.86)	(1.66)	(-1.48)		

Table XII
Pervasiveness of Reversal and Momentum

This table reports return means and t-statistics from sequential double sorts on straddles. Every third Friday, we sort straddles into 3 portfolios based on a conditioning variable shown in the column header and then, within each tercile, sort straddles into 3 portfolios based on past average returns over some formation period. Within each tercile of the conditioning variable, we then compute equal-weighted portfolio returns and take long and short positions in the top and bottom terciles. Numbers reported are the resulting high-minus-low return spreads within each tercile of the conditioning variable. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags. We consider five conditioning variables. The first, firm size, is the stock's most recent equity capitalization. Stock illiquidity is proxied by the average Amihud (2002) measure over the most recent 12 months. Option illiquidity is the weighted average of the percentage bid-ask spread of the options in each straddle, averaged over the past 12 months. Analyst coverage is the number of analysts covering the stock, updated monthly. Credit rating is measured following Avramov et al. (2007) and is updated monthly. "No downgrade" reports the high-minus-low return spread for the sample of stocks that have a credit rating but were not downgraded in the 12 months prior to the holding period. "Downgrade" reports the high-minus-low return spread for the sample of stocks that have a credit rating and were downgraded in that period. "No rating" reports the high-low return spread for the sample of stocks without a credit rating.

Panel A: Formation period includes lag 1 only

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
Low	-0.0209	-0.0443	-0.0450	-0.0199	-0.0509	No downgrade	-0.0457
	(-3.00)	(-5.33)	(-6.27)	(-2.95)	(-5.24)		(-6.26)
Medium	-0.0366	-0.0384	-0.0346	-0.0363	-0.0471	Downgrade	-0.0334
	(-5.39)	(-5.40)	(-5.01)	(-4.84)	(-4.80)		(-2.70)
High	-0.0461	-0.0152	-0.0236	-0.0478	-0.0407	No rating	-0.0269
	(-6.05)	(-2.25)	(-3.39)	(-6.03)	(-4.06)		(-4.41)
High - Low	-0.0252	0.0292	0.0215	-0.0279	0.0102		
	(-2.75)	(3.01)	(2.46)	(-2.98)	(0.81)		

Panel B: Formation period includes lags 2 to 12

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
Low	0.0544	0.0395	0.0435	0.0561	0.0571	No downgrade	0.0378
	(5.12)	(4.60)	(5.40)	(6.20)	(4.79)		(4.83)
Medium	0.0528	0.0484	0.0501	0.0505	0.0438	Downgrade	0.0509
	(6.48)	(5.74)	(6.33)	(5.90)	(4.12)		(2.44)
High	0.0422	0.0585	0.0507	0.0452	0.0143	No rating	0.0546
	(4.91)	(5.77)	(5.48)	(4.74)	(1.12)		(7.32)
High - Low	-0.0122	0.0189	0.0072	-0.0109	-0.0428		
	(-0.94)	(1.48)	(0.67)	(-0.86)	(-2.50)		

Table XIII
After-Cost Performance of Liquidity-Taking Strategies

This table reports after-cost average returns on reversal and momentum strategies. It also examines a composite strategy based on a combination of those strategies' rankings. We report results for the baseline strategies and for strategies that optimize for transactions costs by using extreme deciles rather than quintiles and by using only options with percentage bid-ask spreads below 10%. We report results under a variety of assumptions about the size of transactions costs, ranging from zero to the full quoted half-spread. Intermediate cases include the algo, adjusted, and effective spreads, which are 20.3%, 51.6%, and 75.8%, respectively, as large as the quoted spreads (following Muravyev and Pearson 2020). We include results with and without a cost for liquidating the stock position acquired by exercising in-the-money options, where the cost is assumed to be one half of the closing bid-ask spread on the underlying stock. The last column of the table reports the average return after adjustment for the required margin. These values do not account for transactions costs. All straddles are zero delta with a one-month maturity, are approximately at the money, and are held in equally weighted portfolios until expiration. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

	Zero exercise costs					Nonzero exercise costs					Margin-adjusted
Option bid-ask spread:	None	Algo	Adjusted	Effective	Quoted	None	Algo	Adjusted	Effective	Quoted	
Panel A: Reversal											
Main sample	0.0409	0.0107	-0.0359	-0.0722	-0.1090	0.0094	-0.0208	-0.0674	-0.1037	-0.1406	0.0185
	(6.18)	(1.61)	(-5.26)	(-10.21)	(-14.72)	(1.23)	(-2.73)	(-8.76)	(-13.21)	(-17.36)	(4.72)
Main sample with deciles	0.0496	0.0196	-0.0266	-0.0627	-0.0993	0.0195	-0.0105	-0.0567	-0.0928	-0.1295	0.0233
	(5.61)	(2.21)	(-2.95)	(-6.80)	(-10.45)	(2.14)	(-1.15)	(-6.17)	(-9.94)	(-13.52)	(4.57)
Low-cost with deciles	0.0806	0.0682	0.0493	0.0346	0.0199	0.0614	0.0490	0.0301	0.0153	0.0006	0.0396
	(6.63)	(5.62)	(4.07)	(2.85)	(1.64)	(5.11)	(4.08)	(2.49)	(1.27)	(0.05)	(5.75)
Panel B: Momentum											
Main sample	0.0622	0.0362	-0.0040	-0.0356	-0.0678	0.0374	0.0114	-0.0290	-0.0607	-0.0930	0.0294
	(7.97)	(4.81)	(-0.56)	(-5.04)	(-9.63)	(4.52)	(1.41)	(-3.68)	(-7.77)	(-11.85)	(7.85)
Main sample with deciles	0.0729	0.0465	0.0056	-0.0265	-0.0592	0.0482	0.0218	-0.0192	-0.0515	-0.0844	0.0345
	(7.10)	(4.65)	(0.58)	(-2.78)	(-6.28)	(4.65)	(2.14)	(-1.94)	(-5.25)	(-8.63)	(7.38)
Low-cost with deciles	0.0723	0.0599	0.0408	0.0260	0.0112	0.0551	0.0427	0.0236	0.0088	-0.0061	0.0347
	(4.84)	(4.02)	(2.74)	(1.75)	(0.75)	(3.66)	(2.84)	(1.57)	(0.58)	(-0.40)	(4.44)
Panel C: Composite											
Main sample	0.0591	0.0271	-0.0222	-0.0606	-0.0995	0.0268	-0.0051	-0.0543	-0.0928	-0.1317	0.0277
	(9.92)	(4.60)	(-3.74)	(-9.90)	(-15.46)	(3.61)	(-0.71)	(-7.60)	(-12.92)	(-17.96)	(8.32)
Main sample with deciles	0.0641	0.0316	-0.0186	-0.0578	-0.0977	0.0326	0.0001	-0.0500	-0.0894	-0.1293	0.0302
	(8.23)	(4.09)	(-2.39)	(-7.27)	(-11.85)	(3.68)	(0.02)	(-5.82)	(-10.35)	(-14.74)	(7.33)
Low-cost with deciles	0.0815	0.0690	0.0498	0.0348	0.0198	0.0589	0.0463	0.0270	0.0120	-0.0030	0.0391
	(6.10)	(5.16)	(3.71)	(2.59)	(1.47)	(4.30)	(3.37)	(1.96)	(0.87)	(-0.21)	(5.33)

Internet Appendix for

Option Momentum

STEVEN L. HESTON, CHRISTOPHER S. JONES, MEHDI KHORRAM,

SHUAIQI LI, and HAITAO MO*

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In Section IV.C of our paper, we considered the possibility, raised by Grundy and Martin (2001), that momentum portfolio returns exhibited time-varying factor loadings. We examined a model that included market return, volatility, and jump factors. Our proxies for these were, respectively, return on the S&P 500 Index, the return on the one-month at-the-money S&P 500 Index straddle, and the return on the one-month S&P 500 put option with Black-Scholes delta closest to -0.25. We found that factor loadings varied slightly, but that accounting for this variation had virtually no effect on the profitability of the momentum strategy.

In this appendix we analyze whether this conclusion is robust to other proxies of volatility and jump risk. One alternative formulation follows Cremers, Halling, and Weinbaum (2015), who use S&P 500 Index straddles of different maturities to construct a portfolio with nonzero vega but zero gamma, which is interpreted as a pure volatility factor, and another portfolio with zero vega but nonzero gamma, which is interpreted as a jump factor. The other formulation we consider uses the CBOE's VIX and SKEW indexes to construct volatility and jump factors.

To construct the Cremers, Halling, and Weinbaum (2015) volatility and jump factors, we begin by selecting the one-month and two-month straddles on the SPX index that are closest to at-the-money (call delta = 0.5). We compute the vega and gamma of each straddle by taking the weighted averages of the vegas and gammas of the component puts and calls. To construct a portfolio of these two straddles that is sensitive to volatility risk but not jump risk, we find the combination that has a positive vega, a zero gamma, and portfolio weights that sum to one. The volatility factor is the 1-month return on this portfolio. The jump factor is constructed similarly, except that it has a zero vega and positive gamma.

The final set of factors are constructed using the VIX and SKEW indexes from the CBOE. The volatility factor is equal to ratio of a realized variance measure and an implied variance, minus one. The realized variance is the squared excess S&P 500 Index return over the period from one expiration Friday to the next.[1] The implied variance is the square of the VIX index at the start of the month divided by $N/365$, where N is the number of calendar days between expiration Fridays.

The skewness factor is based on the CBOE's SKEW index, whose relation with risk neutral skewness S is given by

$$SKEW = 100 - 10\,S.$$

To construct a "realized SKEW," note that the risk-neutral skewness can be written as

$$S = \frac{\mathrm{E}^Q\left[(R - r_f)^3\right]}{(N/365)^{1.5}\,\mathrm{VIX}^3}.$$

The skewness factor is based on the realization of the numerator of S. The factor is

$$\frac{100 - 10\,\text{Realized}\,S}{SKEW} - 1,$$

where

$$\text{Realized}\,S = \frac{(R - r_f)^3}{(N/365)^{1.5}\,\mathrm{VIX}^3}.$$

Tables AI and AII report regression results that are analogous to those in Table X but use

[1] More commonly, the realized variance is computed as the sum of squared daily excess returns. Under the risk-neutral measure, the expected sum of squared daily returns and the expected squared monthly excess return are identical, because return autocorrelation under risk neutrality is always zero. We base our realized variance measure based on monthly returns rather than daily returns both because it results in higher R-squares and because the skewness factor we construct can only be computed from monthly returns.

these alternative factor models. The results are easy to summarize. Aside from intercepts, we find no significant coefficients in any regression, suggesting that the momentum portfolio exhibits little to no dependence on market, volatility, jump, or skewness factors, either unconditionally or conditional on the sign of past returns.

It is important to emphasize that the long and short legs of the momentum strategy individually do exhibit significant factor risk exposures, with regression R-squares that are generally above 30%. In particular, option returns have a strongly positive and highly significant relationship with the volatility factor, and jump risk is also significant in some cases. The momentum portfolio's lack of any significant loadings on these factors is simply a reflection of the very similar factor loadings of the long and short legs of the strategy.

References

Cremers, Martijn, Michael Halling, and David Weinbaum (2015), "Aggregate jump and volatility risk in the cross-section of stock returns." *Journal of Finance*, 70, 577–614.

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Table AI
Time-varying factor exposures using the Cremers, Halling, and Weinbaum (2015) factors

This table examines the effects of time-varying betas on momentum strategy returns. Panel A reports estimates of full and restricted versions of the regression

$$\begin{aligned} r_{HL,t} = a &+ [\ m_{down}\ D_t^{down,mkt} + m_{flat}\ D_t^{flat,mkt} + m_{up}\ D_t^{up,mkt}\ ]\ r_{mkt,t} \\ &+ [\ v_{down}\ D_t^{down,vol} + v_{flat}\ D_t^{flat,vol} + v_{up}\ D_t^{up,vol}\ ]\ r_{vol,t} \\ &+ [\ j_{down}\ D_t^{down,jmp} + j_{flat}\ D_t^{flat,jmp} + j_{up}\ D_t^{up,jmp}\ ]\ r_{jmp,t} + \epsilon_t, \end{aligned}$$

The three risk factors represent the excess returns on the S&P 500 Index, a delta-neutral portfolio constructed to have positive vega and zero gamma, and another delta-neutral portfolio constructed to have positive gamma and zero vega. The dummy variables indicate whether the referenced factor had a low, medium, or high realization during the formation period. All regressions use equally weighted portfolios based on the "2 to 12" formation period. The table reports coefficient estimates and t-statistics (in parentheses, using Newey-West with three lags), R-squares, differences between coefficients, and average hedged momentum returns, where hedge ratios are time-varying and estimated using a rolling window of the most recent 60 months (with a minimum of 36 months). For comparison, unhedged returns have a mean of .0603 and a t-statistic of 6.87.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a	0.0646	0.0615	0.0630	0.0635	0.0658	0.0627	0.0650
	(8.08)	(7.68)	(7.98)	(7.81)	(8.12)	(7.59)	(7.65)
m_{down}	0.2205			0.2141	0.2659		0.2713
	(0.49)			(0.48)	(0.61)		(0.63)
m_{flat}	-0.4511			-0.5044	-0.4574		-0.4971
	(-1.57)			(-1.77)	(-1.53)		(-1.66)
m_{up}	0.0359			0.0473	0.0765		0.0912
	(0.06)			(0.08)	(0.12)		(0.14)
v_{down}		-0.0241		-0.0408		-0.0144	-0.0292
		(-0.45)		(-0.73)		(-0.23)	(-0.44)
v_{flat}		0.0112		0.0040		0.0190	0.0138
		(0.30)		(0.12)		(0.51)	(0.41)
v_{up}		-0.0220		-0.0539		-0.0246	-0.0560
		(-0.34)		(-0.79)		(-0.38)	(-0.80)
j_{down}			-0.0067		-0.0115	-0.0053	-0.0128
			(-0.20)		(-0.32)	(-0.15)	(-0.35)
j_{flat}			0.0143		0.0205	0.0175	0.0219
			(0.53)		(0.75)	(0.62)	(0.76)
j_{up}			0.0452		0.0430	0.0475	0.0447
			(0.73)		(0.68)	(0.75)	(0.69)
R^2	0.0148	0.0013	0.0030	0.0181	0.0190	0.0047	0.0223
$m_{up} - m_{down}$	-0.1846			-0.1668	-0.1895		-0.1800
	(-0.25)			(-0.22)	(-0.25)		(-0.23)
$v_{up} - v_{down}$		0.0021		-0.0131		-0.0102	-0.0268
		(0.03)		(-0.15)		(-0.11)	(-0.27)
$j_{up} - j_{down}$			0.0519		0.0545	0.0527	0.0575
			(0.73)		(0.74)	(0.73)	(0.77)
Average hedged	0.0575	0.0596	0.0581	0.0589	0.0582	0.0580	0.0580
returns	(6.52)	(6.77)	(6.61)	(6.65)	(6.57)	(6.60)	(6.60)

Table AII
Time-varying factor exposures using factors based on the VIX and SKEW indices

This table examines the effects of time-varying betas on momentum strategy returns. Panel A reports estimates of full and restricted versions of the regression

$$\begin{aligned} r_{HL,t} = a &+ [\; m_{down}\; D_t^{down,mkt} + m_{flat}\; D_t^{flat,mkt} + m_{up}\; D_t^{up,mkt}\;]\; r_{mkt,t} \\ &+ [\; v_{down}\; D_t^{down,vix} + v_{flat}\; D_t^{flat,vix} + v_{up}\; D_t^{up,vix}\;]\; r_{vix,t} \\ &+ [\; j_{down}\; D_t^{down,skew} + j_{flat}\; D_t^{flat,skew} + j_{up}\; D_t^{up,skew}\;]\; r_{skew,t} + \epsilon_t, \end{aligned}$$

The three risk factors represent the excess returns on the S&P 500 Index, the return on a squared return claim (vix), and the return on a cubed return claim (skew). The dummy variables indicate whether the referenced factor had a low, medium, or high realization during the formation period. All regressions use equally weighted portfolios based on the "2 to 12" formation period. The table reports coefficient estimates and t-statistics (in parentheses, using Newey-West with three lags), R-squares, differences between coefficients, and average hedged momentum returns, where hedge ratios are time-varying and estimated using a rolling window of the most recent 60 months (with a minimum of 36 months). For comparison, unhedged returns have a mean of .0603 and a t-statistic of 6.87.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a	0.0646	0.0651	0.0677	0.0668	0.0613	0.0721	0.0655
	(8.08)	(7.29)	(6.10)	(7.19)	(5.31)	(5.67)	(4.89)
m_{down}	0.2205			0.2253	0.2467		0.1318
	(0.49)			(0.48)	(0.53)		(0.32)
m_{flat}	-0.4511			-0.3795	-0.5365		-0.4131
	(-1.57)			(-1.34)	(-1.55)		(-1.27)
m_{up}	0.0359			0.0817	-0.0038		0.0565
	(0.06)			(0.13)	(-0.01)		(0.09)
v_{down}		0.0114		0.0067		0.0047	0.0092
		(1.18)		(0.68)		(0.32)	(0.67)
v_{flat}		-0.0014		-0.0018		-0.0006	0.0031
		(-0.17)		(-0.19)		(-0.04)	(0.22)
v_{up}		0.0417		0.0374		0.0490	0.0427
		(1.57)		(1.34)		(1.64)	(1.49)
j_{down}			0.0591		0.0052	0.0660	0.0140
			(1.05)		(0.09)	(0.97)	(0.21)
j_{flat}			0.0346		-0.0313	0.0394	-0.0264
			(0.60)		(-0.46)	(0.53)	(-0.31)
j_{up}			-0.0083		0.0063	-0.0344	-0.0355
			(-0.17)		(0.14)	(-0.42)	(-0.49)
R^2	0.0148	0.0165	0.0036	0.0274	0.0160	0.0230	0.0289
$m_{up} - m_{down}$	-0.1846			-0.1436	-0.2505		-0.0753
	(-0.25)			(-0.18)	(-0.33)		(-0.10)
$v_{up} - v_{down}$		0.0303		0.0307		0.0443	0.0335
		(1.08)		(1.05)		(1.35)	(1.08)
$j_{up} - j_{down}$			-0.0674		0.0011	-0.1004	-0.0495
			(-0.92)		(0.02)	(-1.15)	(-0.64)
Average hedged	0.0610	0.0615	0.0709	0.0617	0.0649	0.0675	0.0601
returns	(6.98)	(7.02)	(7.34)	(7.11)	(7.21)	(6.73)	(6.47)