Momentum, Reversal, and Seasonality in Option Returns*

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Abstract

Option returns display substantial momentum using formation periods ranging from 6 to 36 months long, with long/short portfolios obtaining annualized Sharpe ratios above 1.5. In the short term, option returns exhibit reversal. Options also show marked seasonality at multiples of three and 12 monthly lags. All of these results are highly significant and stable in the cross section and over time. They remain strong after controlling for other characteristics, and momentum and seasonality survive factor risk-adjustment. Momentum is mainly explained by an underreaction to past volatility and other shocks, while seasonality reflects unpriced seasonal variation in stock return volatility.

Keywords: options, momentum, reversal, seasonality

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I have nothing to disclose.

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1 Introduction

Momentum 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 2019; Gupta and Kelly 2019). In this paper we ask whether or not momentum exists within the options market.

We find, in fact, that momentum is a far stronger phenomenon in options than it is in other asset classes, with a Sharpe ratio at least three times higher than that of the standard cross-sectional momentum strategy for stocks. We also find, similarly to stocks, that one-month returns tend to reverse over the following month. This tendency is also stronger than it is for stocks and is highly significant. In addition, we show that option returns exhibit seasonality that is significant both statistically and economically. If a firm's options performed well in lags that are multiples of three or 12 months, then they are more likely to exhibit high current returns in the current month. This effect is distinct from momentum but close to it in terms of portfolio performance.

All of these effects are stable over our sample. Momentum, in particular, is significant in every five-year subsample, and seasonality nearly matches this performance. Furthermore, both momentum and seasonality are significant 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, momentum, reversal, and seasonality all remain significant. In addition, the profitability of momentum and seasonality are large and highly significant after factor adjustment using the model of

Horenstein et al. (2019) or an extension of that model. Reversal, however, turns insignificant.

All three strategies produce high Sharpe ratios, with a conventional momentum strategy having an annualized Sharpe ratio of 1.73. Furthermore, the returns to reversal, momentum, and most forms of seasonality are positively skewed, and all three strategies have relatively modest maximum drawdowns 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.

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 et al. (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 (2019) and Gupta and Kelly (2019). Several findings appear to make these strategies less interesting for options, however. 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. In fact, its alphas with respect to the Horenstein et al. (2019) model and our extension of it are both significantly negative.

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 et al. 1998, Grinblatt and Han 2005), delayed overreaction (Daniel et al. 1998), or a mixture of both (Hong and Stein 1999). Potentially rational explanations include cross-sectional variation in unconditional expected returns (e.g., Conrad and Kaul 1998), time-varying risk premia (e.g., Chordia and Shivakumar 2002, Kelly et al. 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 as a result of cross-sectional variation in unconditional expected returns.

The remaining two hypotheses that we consider, underreaction and time-varying risk premia, are somewhat difficult to distinguish. One possibility for doing so would be to follow the innovative approach of Kelly et al. (2020), who estimate time-varying factor loadings and risk premia under the assumption that conditional betas are functions of observable firm characteristics and find that stock momentum is largely explained by time-varying risk premia. While this procedure is potentially applicable in our setting, we take a more direct approach by exploiting the relationship, formalized by Bakshi and Kapadia (2003), between delta-hedged option returns and the gains from volatility swaps. Working with volatility swaps allows us to use highly effective methods, pioneered by Bollerslev et al. (2009), for disentangling volatility shocks from risk premia. When we use this approach, we find that momentum is primarily driven by past shocks, rather than risk premia. This implies that underreaction provides the best explanation of momentum in options.

In contrast, seasonality in straddle returns largely appears to be the result of unpriced seasonal variation in stock volatility. While realized volatilities display clear seasonal dependence, implied volatilities do not anticipate these predictable fluctuations. This also appears to be a new result in the literature.

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 et al. (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. Finally, in contemporaneous work, Heston and Li (2020) document a number of findings similar to our own, though their focus is on a type of variance swap rather than on the option straddles we analyze.

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 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. (2019) show that the existence of credit default swaps on a firm lowers expected option returns, while Christoffersen et al. (2018) find a negative relation between option liquidity and returns.

Our finding of short-term reversal in equity straddles 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 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 stock tend to reverse.

We also contribute to the growing literature showing the importance of seasonality in asset returns. In stocks, cross-sectional seasonality was first identified at the monthly level by Heston and Sadka (2008). Subsequent work has found seasonalities in intraday (Heston et al. 2010) and daily returns (Keloharju et al. 2016). Among these papers, there remains some debate about whether seasonality reflects risk or mispricing. Consistent with the recent work by Keloharju et al. (2019), our results provide support for the latter.

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 this section we also examine seasonality. In Section 5, we then subject these strategies to risk adjustment, check their consistency in the time series and cross section, and examine spanning relations between them. Section 6 examines volatility swap gains to disentangle underreaction from time-varying risk premia, and Section 7 concludes.

2 Data

We obtain call and put prices from the OptionMetrics database, which provides end-of-day bid-ask quotes on 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.

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 pair consists of 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

[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.

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 that the weights sum to one. Note that both weights are always positive.

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.[3] 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 show in the appendix that results obtained for non-dividend paying stocks, which are unlikely to be exercised early, are nearly identical. This is expected given that our analysis focuses on short-term near-the-money options, for which early exercise is rarely optimal.

We compute excess returns by subtracting the one-month Treasury bill rate imputed 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 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 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

[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.

[3] Alternatively, one could rebalance the straddle daily or use delta hedging to maintain delta neutrality throughout the holding period. Our approach is simple, transparent, and – because it uses monthly returns – unlikely to be affected by the biases documented by Duarte et al. (2019).

slope of the implied volatility curve (the "smile") 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.

Our primary dataset, which only includes options with positive open interest, contains about 450,000 observations. Given that our sample has 282 months, this translates to about 1,600 straddles per month. Straddle returns have negative means (-5.6% monthly) and large standard deviations (83% monthly), and substantial positive skewness. Out of these observations, we can measure a past average return over the traditional momentum formation period (lags two to 12) about 57% of the time. For the remainder, at least one month in the formation period is missing.[4]

3 Results

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

3.1 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

$$R_{i,t} = a_n + b_n R_{i,t-n} + \epsilon_{i,t},$$

where $R_{i,t}$ is the return on a straddle on stock i in month t. The lag, n, determines the placement on the horizontal axis. The top and bottom panels differ only with respect to the

[4]We provide more detailed summary statistics in the appendix.

range of lags displayed.

The top panel 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. Typically, these returns are aggregated using standard compounding. However, in our setting we find that this approach is inferior to one based on average returns. The reason for this is 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.

We therefore depart from standard practice by computing our momentum signal using the *average* return over the formation period.[5] This reduces the impact of return outliers and makes the momentum signal somewhat more symmetric. In the appendix we present results based on cumulative returns, which are still very strong.

Table 1 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

[5]We are not the only study to do so. Grundy and Martin (2001) also do not compound.

the formation period and report the mean and t-statistic of each quintile portfolio's returns.[6] As is standard, a long/short high-minus-low portfolio is reported as well. 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.

Panel B of Table 1 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. (2017). 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 "smile") 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 (IV-HV and the 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).

[6] 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.

Although the results presented in this table suggest that autocorrelation 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 autocorrelation 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. Nevertheless, we continue to use the term "auto-correlation" in order to reserve "cross-serial correlations" for use in referring to lead-lag relations between different stocks.

Digging in a little deeper, the straddle return in period t only depends on option prices at the end of period $t - 1$. This is because we hold options until expiration, implying that the final payoff depends only on the underlying stock price. Thus, if all option prices are simultaneously "too low" at the end of period t, this only impacts straddle returns in period $t + 1$, because period-t returns do not depend on period-t prices. Thus, short-term reversal is a much less intuitive finding in our setting. It does not arise simply due to a transitory component in option prices. Rather, it suggests that option payouts on one expiration date impact how non-expiring options are priced on the same day.

3.2 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 1.

From the regression results in Table 2, 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.[7]

3.3 Signal decay

One qualitative difference between stock and option autocorrelation 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

[7] In the appendix we show corresponding results for panel regressions. We find that 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 et al. (2020), for example, estimate a coefficient on past returns that is essentially zero when using the panel regression framework.

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, 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.

The regression results, shown in Table 3, provide a number of take-aways. First, by comparing regression (1) with the other five regressions in the table, we can see that 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 10% 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 as we require additional years of past straddle returns to be available. Overall, the table paints a clear picture.

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 et al. 1998). However, the complete lack of any evidence of 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 et al. 1998), or from market frictions, such as gradual information diffusion (Hong and Stein 1999).[8] At this point we also cannot rule out the

[8]The Barberis et al. (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.

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 3 also implies that variation in unconditional expected returns is also an unlikely 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.

4 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 et al. (2012), the industry momentum strategy of Moskowitz and Grinblatt (1999), and a factor momentum strategy similar to those of Gupta and Kelly (2019) and Ehsani and Linnainmaa (2019). We also examine seasonality, a phenomenon first identified in equity returns by Heston and Sadka (2008).

4.1 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 et al. (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 omits the scaling by lagged volatility that Moskowitz et al. (2012) use in their work. Our strategy also eliminates time variation in the degree to which the portfolio is net long, as our implementation always holds equal dollar values of long and short positions. In making these modifications, we avoid the critique of Goyal and Jegadeesh (2018), who argue that the strong performance of time series momentum is due to the fact that the degree to which it is net long varies over time. This variability is the result of volatility scaling and also the fact that the size of the positions taken is independent of the number of positions taken on that side of the trade (long or short).

Our time series momentum strategy is simple and follows Ehsani and Linnainmaa (2019). We long an equally weighted portfolio of all straddles whose past average excess returns (over some formation period) are positive and short an equally weighted portfolio of straddles with negative past average excess returns. The long and the short sides are therefore equal in value, and return volatilities are not taken into account. As in Ehsani and Linnainmaa (2019), we compare this strategy to a cross-sectional strategy in which winners and losers are determined based on whether past returns are higher or lower than contemporaneous cross-sectional medians.

Table 4 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 half of all stocks, 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 1, which is to be expected given the inclusion of stocks with less extreme past returns, but again the t-statistics do not change much. This suggests 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 very similar to the corresponding spreads from cross-sectional strategies. In no case does the cross-sectional strategy significantly under- or out-perform the time series version. In addition, the two types of strategies tend to be highly correlated, with correlations ranging from 0.79 to 0.91. Thus, we conclude that there is little to distinguish one class of strategies from the other.

These results differ substantially from those obtained in equity markets. Lewellen (2002) demonstrated that negative cross-serial correlations, the tendency of the return on a stock to negatively predict the future returns on another stock, can be an important component of momentum returns. Because this component represents the key difference between cross-sectional and time series momentum strategies, our results imply that this effect is absent in options.

We conclude from this analysis that the distinction between cross-sectional and time series strategies in straddles is less important than it is for stocks. For the remainder of the paper, we therefore limit our attention to the more common cross-sectional strategies.

4.2 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.[9] The results are shown in Panel A of Table 5.

To summarize the results in the table, there is strong evidence of momentum but no short-term reversal in industry option portfolios. The lack of short-term reversal is different from individual straddles, where reversal is strong. It is also different from industry stock portfolios, which 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 momentum, whereas for individual straddles even the "25 to 36" strategy delivered statistically significant average returns.

4.3 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 (2019) 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 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

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

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 lead to 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 smile, 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 differs from that of Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019). When we follow their approach, we find that results are mildly sensitive to how long/short factors are "signed." That is, they are sensitive to whether the long side of the factor portfolio is the one with the highest or the lowest values of the characteristic used to define the factor. We avoid the issue of signing factors by including both the long and short legs of the factor as separate portfolios, where the "short" side of the factor is also held as a long position. Thus, even though we start with seven factors, our factor momentum strategy analyzes 12 factor legs, all of which are held long. These include the long and short legs of the five long/short factors as well as the two short-only factors. This approach also has the potential advantage of expanding the cross section of portfolios in the sort, which would otherwise be extremely small.

From these 12 portfolios, we construct a momentum strategy by sorting the option factor legs by their own past returns over some formation period. The bottom three legs are assigned to the "low" portfolio, while the top three legs form the "high" portfolio. A long/short strategy is given by the difference between the two.

Panel B of Table 5 shows that factors appear to display momentum using all formation periods considered. Similar to the stock-based results of Ehsani and Linnainmaa (2019) and Gupta and Kelly (2019), momentum is found even at the very shortest formation periods. Even more surprisingly, highly delayed formation periods are also effective. The standard "2 to 12" strategy is actually less profitable than one based on returns from 13 to 36 months ago.

The profitability of strategies based on very long or very old formation periods suggests that factor momentum may not in fact be momentum at all. Rather, option factors may simply display a significant degree of variation in their unconditional returns, which is captured by any sort based on past returns.

While there may be substantial truth to this interpretation, it is incomplete. This is indicated by the fact that a highly effective version of factor momentum can be implemented using just a single month of past returns data. As the basis for estimates of unconditional expected returns, a single month of data should produce terrible results, when in fact they are nearly as good as the results based on 35 months of data. This suggests that the most recent month is special, i.e. there is serial dependence in factor returns.

4.4 Seasonality

Heston and Sadka (2008) show that stocks that perform relatively well in a particular month of the year are likely to do so again in the future. This is distinct from momentum, in that performance in that month appears to be persistent at horizons that far exceed those at which momentum applies. Keloharju et al. (2016) interpret this pattern as indicating that expected returns differ from month to month, where these differences vary across stocks.

In this section we reexamine the relation between past and future returns with a focus on seasonal relations. Unlike earlier work, we consider both quarterly and annual seasonalities.

This is in part motivated by the shorter sample period available for options research, but it also reflects the importance of certain quarterly events for options traders, such as futures expirations and earnings announcements.

As in earlier results, we utilize portfolio sorts and Fama-MacBeth regressions. In both, the explanatory variable of interest is the average past return computed over some set of periodic lags. These lags are multiples of either three or 12 months and go back either one or three years. We compare these variables against momentum, which is defined as the average return from lag two to lag N, where N is the longest lag included in the seasonality variable (i.e. either 12 or 36). For example, to investigate quarterly seasonality we will run the regression

$$R_{i,t} = \alpha + \beta\,\frac{1}{4}\sum_{\substack{k\in\{3,\\6,9,12\}}} R_{i,t-k} + \delta\,\frac{1}{11}\sum_{\substack{k\in\{2,\\3,\ldots,12\}}} R_{i,t-k} + \epsilon_{i,t}$$

A positive estimate of the β coefficient would indicate the presence of seasonality after controlling for momentum.

Panel A of Table 6 shows the results of quintile sorts on three different measures of seasonality. Below those results are comparable momentum sorts, which reproduce results already shown in Table 1. For all three seasonality measures, the high/low spread is statistically significant and large, roughly the same size as the momentum spread. The strongest result is obtained using quarterly seasonality with lags up to 36 months. The spread resulting from an annual seasonality sort is somewhat smaller but still highly significant. Given that this measure is based on just three lagged monthly returns (12, 24, and 36), its less impressive performance may simply be the result of excessive noise.

Panel B examines Fama-MacBeth regressions that include both seasonality and momentum variables. In short, both variables are important, but momentum appears to be somewhat more so. Still, the quarterly/36-month seasonality measure does come close to matching the corresponding momentum measure in terms of predictive ability, and both variables appear to offer some independent information about future returns.

For brevity, we relegate regressions with additional control variables to the appendix, but the bottom line is that including them has virtually no impact on the seasonality effect.

5 Risk, redundancy, and consistency

In this section we ask whether the profitability of option reversal, momentum, and seasonality 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.

5.1 Risk and consistency over time

In this section we 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 7 shows some basic performance statistics on 16 different portfolios. Panel A includes the cross-sectional momentum and reversal strategies, as well as the related strategies based on industry and factor portfolios. It also includes the three strategies based on seasonality. Panel B shows results for the seven factors based on prior research, as described in Section 4.3.

In this section only, 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.[10] For portfolios based on the standard momentum formation period, this results in going long the winners and short

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

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 and industries/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 momentum. We therefore examine the low-minus-high portfolio for individual straddles when sorting on the one month lag and the high-minus-low portfolio for industries and factors.

Overall, the results in Table 7 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 46%, while the equally weighted short portfolio is highly negatively skewed and suffers from a maximum drawdown greater than 100%.[11]

The momentum strategy on individual straddles has a Sharpe ratio of 0.498 on a monthly basis, which is an impressive 1.73 annualized. This approaches those of the two best performing factors, namely the implied minus historical volatility factor of Goyal and Saretto (2009) and the implied 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 of 95% or more. Industry momentum is 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 0.286, or 0.99

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

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 hold the past winners long, but they continue to suffer from greater volatility, and maximum drawdowns are large in both cases, above 100% for industries.

Seasonality-based strategies also produce strong risk-adjusted performance. The Sharpe ratios of the strategies based on quarterly seasonality have monthly Sharpe ratios of 0.452 or 0.425, which correspond to 1.57 or 1.47 on an annualized basis. Annual seasonality generates a somewhat lower average return and a lower Sharpe ratio.

A surprising result from the table is that almost all 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 short-term reversal, momentum, or seasonality represent compensation for return asymmetry. Thus, while skewness may be an important determinant of option prices, it is a poor explanation of relative returns.

In the stock market, Daniel and Moskowitz (2016) document that momentum portfolios "experience infrequent and persistent strings of negative returns," or "momentum crashes." If we measure the importance of momentum crashes by the maximum drawdown of the momentum strategy, then the size of the option momentum crash 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 1.72. 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. Thus, option momentum has a lower maximum drawdown but an average excess return that is perhaps ten times higher. While the tail risk in seasonality and cross-sectional short-term reversal is somewhat greater, the Calmar ratio for short-term reversal is 0.59, and the ratios for quarterly and annual seasonality are between 1.08 and 1.60. 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, reversal, or seasonality – at least when implemented with individual straddles – are justified on the basis of their exposure to crash risk.

In order to assess the stability of reversal, momentum, and seasonality, we examine five-year moving averages of the returns to each of these portfolios. We focus here on cross-sectional strategies formed using individual straddles, and the seasonality strategy shown is based on quarterly returns out to lag 36. The results, in Figure 2, show that these moving averages are positive for all three 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. The momentum effect appears to have strengthened slightly in the second half of the sample, though it is by an insignificant amount.

5.2 Factor risk adjustment

We now address the issue of whether the average returns on reversal and momentum returns can be explained by exposure to other factors. Though the literature gives little guidance on what factors to include, a notable exception is Horenstein et al. (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 smile 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 8 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. In the appendix we analyze strategies based on seasonality, for which factor adjustment has almost no effect.

To summarize, for strategies based on individual straddles, momentum survives factor adjustment while reversal does not. In particular, reversal is mostly explained by the loading on the volatility difference variable of Goyal and Saretto (2009), which has a much larger premium than most other factors. This suggests that reversal profits are related to the tendency of options with high implied volatility, relative to actual volatility, to underperform. It is possible that volatility differences reflect behavioral overreaction, in that high straddle returns in the recent past cause 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 8 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 moderately smaller than the unconditional mean in Table 7, but it is clear that momentum profits are not simply an expression of sensitivity to the other factors.

Industry-based strategies lead to different results under factor adjustment. The alpha of the short-term strategy is positive, suggesting that industry returns exhibit short-term persistence, but only after risk adjustment. Using the longer formation period, we find that factor adjustment explains part of the return on industry momentum. The alpha of the strategy is positive for both models, but it is only significant for the augmented model.

The strong short-term momentum of factor portfolios is completely explained by factor exposure. The positive return on the "2 to 12" momentum strategy actually becomes significantly negative after factor adjustment, which is mostly due to its strong exposure to the Goyal and Saretto (2009) factor.

To sum up, momentum in individual straddle returns is the only strategy whose average return is significant, with the same sign, both with and without factor adjustment, for both models.

5.3 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 as the dependent variable, while a different long/short momentum portfolio is the independent variable.[12] We also examine regressions in which the additional seven non-momentum factors are used as additional controls. The results are reported in Table 9.

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, it is fairly small. Factor momentum explains

[12] 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.

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.

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 5 shows that there is no short-term industry momentum for straddles, though after controlling for other factor exposures (Table 8) a small effect emerges. In the appendix we show that this effect is not spanned by other short-term strategy returns, though results are relatively weak.

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 (2019) 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, the table suggests that there are two distinct sources of priced momentum, individual and factor. As shown in Table 8, however, only the former survives risk adjustment. Our remaining analysis therefore focuses on the standard cross-sectional momentum strategy constructed from individual straddles.

5.4 Consistency in the cross section

In this section, we investigate how pervasive reversal, momentum, and seasonality 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 et al. 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 10. 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.

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 past 12 months; option illiquidity, measured by the average percentage bid-ask spread of the put and call that underly the straddle we examine, also averaged over the past 12 months; analyst coverage, measured by the number of analysts covering the stock and updated monthly[13]; and, finally, the most recent credit rating[14]

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 et al. 2000 and Zhang (2006)). Options on the stocks with lower 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 et al. (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 reversal, momentum, and seasonality 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

[13] The analyst coverage and forecast data are from I/B/E/S unadjusted summary history.

[14] Following Avramov et al. (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.

experienced a downgrade in the 12 months prior to the holding period.[15] The table shows that reversal is more pronounced for stocks with low impediments to arbitrage (large size, low stock or option illiquidity, and high analyst coverage), suggesting that mispricing from an overreaction to past shocks may not be the main explanation for reversal. Finally, we see that credit rating does not exhibit any relation to the profitability of reversal.

Panel B reports the same analyses for straddle momentum. Like reversal, momentum is pervasive in the cross section. Unlike reversal, however, momentum is somewhat 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 but stays marginally significant for high-grade stocks. This is similar to the results of Avramov et al. (2007), who find that stock momentum is completely absent for high-grade stocks, though not as dramatic. 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.

We apply the same analyses for the three seasonality strategies. To conserve space, Table 10 only reports results for the quarterly seasonal strategy based on lags from 3 to 36. Panel C of the table shows that seasonality is also pervasive throughout the cross section. Comparing terciles sorted by arbitrage impediments reveals no significant relation between them and the strength of return seasonality.

Results for the other two seasonality strategies are reported in the appendix. These are very similar, with two exceptions. One is that there is no significant annual seasonality in the small sample of firms experiencing recent downgrades. Another is that seasonality is

[15]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.

weaker, and in one case absent, among stocks with high credit ratings. This is in contrast to the results of Keloharju et al. (2016), who find that seasonality in stock returns is strongest among high-grade stocks.

The appendix also includes double sorts on past straddle returns and past stock returns, both over the standard “2 to 12” momentum formation period. Since straddle returns are approximately market neutral, the two sorting variables should be approximately uncorrelated. Consistent with this, we find that option momentum is strong regardless of past stock returns. In contrast, past stock returns appear unrelated to future straddle returns.

6 Learning from volatility swaps

The decay of the momentum signal appears to rule out explanations based on cross-sectional variation in unconditional returns (e.g. Conrad and Kaul 1998). The absence of long-term reversal excludes explanations based on overreaction (e.g., Daniel et al. 1998). The results we have presented do not, however, adequately distinguish between explanations based on underreaction or slowly moving risk premia.

There are a number of hypotheses put forth for why investors may underreact. Barberis et al. (1998) assume that investors are subject to conservatism bias, a behavioral bias that causes incomplete adjustments of beliefs to new information. In the model of Hong and Stein (1999), investor inattention causes gradual information diffusion. Grinblatt and Han (2005) propose that the disposition effect, arising from prospect theory, is responsible for the slow convergence of prices.

In contrast, other studies conclude that momentum in stocks is more likely the result of time-varying risk premia. Chordia and Shivakumar (2002) show that momentum profits can be explained by macroeconomic variables that drive conditional expected returns. More recently, Kelly et al. (2020) find that time-varying exposure to latent risk factors explains the vast majority of the momentum alpha.

To distinguish between underreaction and time-varying risk premia, we make use of the close connection between delta-hedged option returns and the difference between realized and implied volatilities, which represents the gain on a volatility swap. Bakshi and Kapadia (2003) demonstrate, in a general stochastic volatility framework, that the gain on a delta-hedged option position is approximately equal to the sum of the volatility risk premium and the volatility surprise, both multiplied by the option's vega (its first derivative with respect to instantaneous volatility).

This result holds exactly only when there are not jumps, and only when the delta hedge is rebalanced frequently. The former is ruled out by a large body of empirical work (e.g. Eraker 2004). The latter is inconsistent with how we compute straddle returns. Nevertheless, the connection with zero delta option positions is useful because it allows us to make use of relatively accurate measures of the volatility risk premium to distinguish between the two potential explanations of option momentum that remain.

6.1 Test design

To exploit the connection between straddles and volatility swaps, we perform a decomposition of the gains on a volatility swap, which are equal to the realized volatility from daily returns (RV) minus the volatility swap rate (IV). Specifically, we decompose these gains into a surprise component and a risk premium component:

$$\underbrace{\mathrm{RV}_{i,t+1} - \mathrm{IV}_{i,t}}_{\text{Volatility swap gain}} = \underbrace{\mathrm{RV}_{i,t+1} - \mathrm{E}_t\left[\mathrm{RV}_{i,t+1}\right]}_{\text{Volatility surprise}} + \underbrace{\mathrm{E}_t\left[\mathrm{RV}_{i,t+1}\right] - \mathrm{IV}_{i,t}}_{\text{Volatility risk premium}}$$

To the extent that volatility swap gains are related to straddle returns, a finding that past values of the volatility surprise are predictive of future straddle returns would indicate that momentum stems from underreaction. A finding that past values of the risk premium are more predictive would suggest that time-varying risk premia are more important.

In carrying out similar analyses, most prior work focuses on variance swaps rather than volatility swaps. This is likely due to the availability of an exact formula for the variance swap rate, which is equal to an integral involving the prices of options of all strikes. (e.g. Carr and Lee (2009)). Because of the requirement that there exist reasonably liquid puts and calls that are deep in-the-money, this work has largely analyzed stock indexes and very large stocks, which tend to have highly developed option markets.

Because we focus on a much larger set of stocks, this approach may be unreliable. Therefore, we instead focus on the volatility swap, making use of a convenient way to construct the $\text{IV}_{i,t}$ required in the previous decomposition. This approach uses just a single Black-Scholes implied volatility from an option that is close to at-the-money (Carr and Lee 2009). Specifically, we use the result of Rolloos and Arslan (2017), who find that the implied volatility of a particular near-the-money option provides an extremely accurate approximation of the one-month volatility swap rate, even when volatilities are stochastic and correlated with underlying prices.[16]

To obtain the value of $\text{IV}_{i,t}$ needed in the decomposition, we use implied volatilities from the OptionMetrics Volatility Surface File. Specifically, at the start of each holding period, we extract the set of one-month implied volatilities and use interpolation to obtain the value required by the Rolloos and Arslan (2017) approach. Because this option is always very close to at-the-money, these values are available for essentially all of our main sample.

Additionally, our analysis requires the expectation of future realized daily volatility, $E_t[\text{RV}_{i,t+1}]$. Bollerslev et al. (2009) show that measures of the variance risk premium benefit from the use of high frequency data on the underlying asset. We deviate somewhat from their approach by focusing on realized volatility, rather than variance, and by using a variant

[16] The option that Rolloos and Arslan (2017) choose is the one with zero vanna (the second order partial derivative with respect to stock price and volatility) and zero vomma (the second order partial derivative with respect to volatility). These options are those for which $d_2 = 0$ in the classic Black-Scholes formula.

of the HAR-RV model of Corsi (2009). This model has proven to be highly successful in forecasting volatility at relatively short horizons and can be estimated using OLS regression.

The dependent variable in the model is the realized volatility of daily returns over the period from one expiration Friday to the next, which we will informally refer to as a "month." The regressors include three high-frequency volatility measures from the previous month, as well as a dummy variable indicating whether the underlying stock return was negative during that month. The high-frequency volatilities are constructed from intraday data. For each firm on each day, we use the TAQ (monthly and daily) files to compute the sum of squared returns using the last transaction price in each five-minute interval.[17] The daily 5-minute return volatility, $\text{Vol5M}^d_{i,t}$, is simply the square root of this sum measured on the last day of month t. Following Corsi (2009), the model also includes the average 5-minute volatility over the last five days of the month, denoted $\text{Vol5M}^w_{i,t}$, as well as the average over the entire month, denoted $\text{Vol5M}^m_{i,t}$. Finally, for consistency with implied volatilities, all variables in the regression are annualized.

The model we estimate is then

$$\text{RV}_{i,t} \;=\; a \;+\; b_d \,\text{Vol5M}^d_{i,t-1} + \; b_w \,\text{Vol5M}^w_{i,t-1} + \; b_m \,\text{Vol5M}^m_{i,t-1} \;+\; c\, 1_{R^{\text{stock}}_{i,t-1}<0} \;+\; \epsilon_{i,t}.$$

Intuitively, the weekly and monthly averages of 5-minute volatility capture the more persistent components in volatility. The indicator variable allows the model to produce the typically negative correlation that is observed between returns and volatility shocks. The model is estimated monthly for each firm on a rolling out-of-sample basis, using up to five

[17] Following Andersen et al. (2001), we retain the last transaction price in each five minute interval during regular trading hours. If there is no transaction in an interval, then that interval is merged with the next. TAQ data are filtered before the five-minute returns are computed by excluding observations with zero price or zero size, corrected orders, and trades with condition codes B, G, J, K, L, O, T, W, or Z. We also eliminate observations that result in transaction-to-transaction return reversals of 25% or more as well as observations that are outside the CRSP daily high-low range. We include trades on all exchanges and compute size-weighted median prices for all transactions with the same time stamp.

years of data for each estimation. If a firm has fewer than three years of past data available, we exclude that firm/date from the analysis.

6.2 Volatility swap results

In Table 11 we compare the ability of past volatility swap gains, or their two components, to that of past straddle returns in forecasting future straddle returns. The table considers the formation periods that result in reversal, momentum, and seasonality. Because the relation between volatility swap gains and option returns is modulated by the option's vega, we multiply the volatility swap gain and its components by the straddle's normalized vega, which is equal to

$$\nu_{i,t} = w_{i,t}^{\text{call}} \frac{\text{vega}_{i,t}^{\text{call}}}{\text{price}_{i,t}^{\text{call}}} + w_{i,t}^{\text{put}} \frac{\text{vega}_{i,t}^{\text{put}}}{\text{price}_{i,t}^{\text{put}}},$$

where $w_{i,t}^{\text{call}}$ and $w_{i,t}^{\text{put}}$ denote the weights of the call and put in the straddle portfolio. Defined this way, $\nu_{i,t}$ measures the approximate sensitivity of straddle returns to changes in stock volatility. The new explanatory variables in our regressions are therefore average values, over the formation period, of $\nu_{i,t-1}\left(\text{RV}_{i,t} - \text{IV}_{i,t-1}\right)$, $\nu_{i,t-1}\left(\text{RV}_{i,t} - \text{E}_{t-1}\left[\text{RV}_{i,t}\right]\right)$, and $\nu_{i,t-1}\left(\text{E}_{t-1}\left[\text{RV}_{i,t}\right] - \text{IV}_{i,t-1}\right)$. Somewhat informally, we refer to these three terms as the volatility swap gain, the volatility surprise, and the volatility risk premium.

Panel A presents results for the short-run reversal effect. We begin by comparing the predictive ability of volatility swap gains, without decomposition, with that of past straddle returns. The purpose is to gauge whether reversal is entirely driven by the straddle's dependence on volatility risk, or whether the non-volatility-related portion of the straddle return is also important. As noted above, the straddle/swap relationship is tight only under assumptions that are unlikely to apply in practice. It is possible, for instance, that the momentum signal is predictive because of its sensitivity to jumps, which should have a greater impact on options than they will have on volatility swaps.

The first several regressions show that high past volatility swap gains (adjusted for vega) predict low future straddle returns in a way that is similar to past straddle returns. However, when both are included in the same regression, only the past straddle return retains its explanatory power. This implies that the straddle return is indeed related to volatility swaps, but that the straddle return contains other elements (e.g. jumps) that also show a tendency to reverse at short horizons.

The final two regressions in the panel examine the decomposition of the volatility swap gain. Whether or not the straddle return is included as an additional regressor, we observe that the volatility surprise is negatively related to future straddle returns, while the volatility risk premium is positively related. The former effect is consistent with a reversal interpretation, while the latter is not.

These regressions show that the role of the volatility swap gain in explaining short-term reversal combines two effects. One is that surprises are reversed. The other is that risk premia are persistent. Disentangling these effects using our simple decomposition leads to a closer fit and greater statistical significance.

Adding the past straddle return to the regression shrinks the coefficient on the volatility shock, but it raises the coefficient on the risk premium. This suggests that reversal in straddle returns has little to do with risk premia. Instead, reversal mainly arises from surprises in realized volatility and from the component of straddle returns that is orthogonal to volatility shocks.

Panel B repeats the same regressions, except that all explanatory variables are now averages over lags two to 12, the standard formation period for momentum. As with Panel A, volatility swap gains are highly predictive of future straddle returns, but past straddle returns subsume most of their explanatory power when both variables are included. Thus, momentum arises in part from the volatility channel, but non-volatility effects are also important.

When we decompose volatility swap gains, coefficient estimates for both components are positive and highly significant, suggesting that momentum may arise both from underreaction to volatility surprises and from risk premia. Adding the past average straddle return to the regression completely absorbs the volatility surprise effect, while reducing the coefficient on the volatility risk premium by about a third. Our interpretation is that past average straddle returns, to the extent they are driven by volatility effects, are predictive mainly because they capture volatility surprises, though non-volatility effects, like jumps, are also responsible for option momentum.

We conclude from this analysis that both momentum and reversal are primarily the result of delayed responses to surprises. In the case of reversal, this delayed response is negative. This is consistent with overreaction, but a liquidity-based explanation may be seen as more plausible. For momentum, the delayed response is positive and consistent with underreaction, such as that resulting from conservatism (Barberis et al. 1998) or gradual information diffusion (Hong and Stein 1999). While time-varying risk premia may also play a role, they appear to be the less important driver of option momentum.

Panels C and D examine the ability of volatility swap gains to explain seasonality effects. Panel C examines quarterly seasonality, while Panel D looks at annual seasonality.[18]

As in the reversal and momentum results, seasonality in straddle returns can also be uncovered by examining past volatility swap gains. In the first two regressions of Panels C and D, we observe that straddle returns and volatility swap gains are equally predictive. They are not the same, however, as the third regression in each panel shows that both regressors are important when included together. This is somewhat different from Panels A and B, in which the straddle return subsumes most or all of the explanatory power of the swap gain.

Using the two components of the volatility swap, we again see significance for both the

[18] Here we omit results based on lags 3, 6, 9, and 12, which are very similar to those presented in Panel C.

surprise and the risk premium. In both panels, the two coefficients are almost equal in magnitude. This is different from the momentum regressions, in which the risk premium had a relatively larger effect. Furthermore, when we add the average straddle return to the regression, the volatility surprise retains strong statistical significance. This is also much different from the momentum results in Panel B.

These results are consistent with seasonality in straddle returns being the result of unpriced seasonality in stock volatility. The volatility surprise is relatively important in these regressions because our model of expected volatility intentionally does not account for seasonalities. Hence, the surprise term naturally captures any omitted seasonal patterns. The fact that it retains its significance after controlling for past straddle returns indicates that the volatility surprise is the better measure of volatility seasonality. This is natural given that realized volatility, which is calculated from daily returns, is a less noisy proxy of true volatility than the monthly straddle return.

6.3 Seasonality in realized volatility

In this section we attempt to verify the conclusion of unpriced seasonality in realized volatility more directly. Specifically, we seek to determine whether realized volatility has seasonal patterns and, if so, whether they are reflected in option implied volatilities.

We begin by analyzing quarterly seasonality in realized volatilities, running the Fama-MacBeth regression

$$\mathrm{RV}_{i,t} = \alpha + \beta \, \frac{1}{36} \sum_{\substack{k \in \{1, \\ 2, \ldots, 36\}}} \mathrm{RV}_{i,t-k} + \delta \, \frac{1}{12} \sum_{\substack{k \in \{3, \\ 6, \ldots, 36\}}} \mathrm{RV}_{i,t-k} + \epsilon_{i,t},$$

where $\mathrm{RV}_{i,t}$ again denotes the realized volatility of daily returns within a month (i.e., one expiration Friday to the next). In this regression, the primary variable of interest is the seasonal average of past realized volatilities. Given that this regressor will correlate with the long-run mean of the realized volatility of the firms, we also include the average realized volatility over the most recent 36 months. The δ coefficient therefore measures the incremental predictive power of seasonal averages rather than merely persistence in volatility.

The results of this regression are in Table 12, which shows strong evidence of seasonality in realized volatility. This is indicated by the positive and highly significant coefficient on mean RV over lags 3, 6, ..., 36.

We then ask whether this quarterly seasonality is priced in the options market by replacing the seasonal average of realized volatilities with the seasonal average of implied volatilities, or

$$\mathrm{RV}_{i,t} = \alpha + \beta \, \frac{1}{36} \sum_{\substack{k \in \{1, \\ 2,\dots,36\}}} \mathrm{RV}_{i,t-k} + \delta \, \frac{1}{12} \sum_{\substack{k \in \{3, \\ 6,\dots,36\}}} \mathrm{IV}_{i,t-k-1} + \epsilon_{i,t},$$

where IV is the same implied volatility used previously as a proxy for the volatility swap rate. Note that these implied volatilities are lagged one month relative to the realized volatilities they replaced. This is because they are observed at the end of the month prior to the period that they forecast.

Table 12 shows that the seasonal average of implied volatilities is insignificantly related to future realized volatility. The coefficient becomes even smaller after controlling for the seasonal average of realized volatilities. This indicates that implied volatilities do not anticipate the seasonality in realized volatilities. While we cannot rule out an explanation based on seasonality in volatility risk premia, the more obvious explanation is mispricing.

In fact, seasonal mispricing has already been documented in the options market. Eisdorfer et al. (2020) show that options have much higher returns over expiration-to-expiration periods (what we informally refer to in this paper as "months") that are five weeks long relative to the more common four-week periods. This is a puzzle, because option returns are generally negative, so the five week return should be lower.

Importantly, the seasonal effect we document is unrelated to this one. This is because the Eisdorfer et al. (2020) seasonality is the same for all options, owing to the fact that all options follow the same expiration calendar. In contrast, the seasonality we document is in the *relative* performance of different straddles. This is seen by the fact that our analysis (sorts and Fama-MacBeth regression) is almost all cross-sectional in nature.

Table 12 also shows results that examine annual seasonality in realized volatility. These results are much different from the quarterly ones. The seasonal average of past realized volatilities now has a negative coefficient, suggesting some kind of seasonal reversal. Although the magnitude and significance of this result are both low, it nevertheless is puzzling, and it suggests that annual straddle seasonality might have an explanation other than seasonality in realized volatility.

7 Summary

This paper has documented a number of new serial correlation patterns in option returns that are highly significant, robust, and pervasive.

At short horizons, returns display cross-sectional reversal, in that firms with options that perform relatively well one month tend to have options that perform relatively poorly in the next month. While the effect is highly robust over time, its return can be explained by exposure to other option factors, most importantly the long/short factor formed on the basis of the difference between implied and historical volatilities (Goyal and Saretto 2009). A high option return in one month tends to raise implied volatility, which leads to lower future returns.

At longer horizons, option returns display momentum, meaning that firms whose options performed well in the previous six to 36 months are likely to see high option returns in the next month as well. This result holds whether we measure past performance on a relative basis ("cross-sectional momentum") or an absolute basis ("time series momentum"). Furthermore, momentum strategy returns are almost unaffected after controlling for other characteristics or for exposures to other risk factors. Momentum is far less risky than short straddle positions on the S&P 500 Index or on an equal weighted portfolio of stocks. Further, it shows no evidence of the momentum crashes that periodically affect stocks, though it is possible that our sample is too short to detect such phenomena.

We also show highly significant evidence of seasonal patterns in straddle returns, particularly at quarterly cycles. If a firm's straddles exhibited relatively high returns in a particular month of the quarter or the year, that pattern is likely to carry forward into the future. This effect appears to be complementary to momentum and is only slightly less predictive. Like momentum, it is present in almost all subperiods and in almost all subgroups of stocks that we examine.

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 et al. (2019) or an extension of it.

Our analysis suggests that momentum, reversal, and seasonality all have different explanations. While reversal is consistent with overreaction, rational liquidity-based explanations cannot be ruled out. Momentum appears to result from underreaction to shocks, such as an unexpectedly high level of stock volatility. Finally, seasonality in returns seems to arise mainly as a result of stock volatility having seasonal patterns that are insufficiently anticipated by the options market.

Our results have implications for the broader literature on momentum strategies. The finding that momentum can exist without long-term reversal supports the possibility that these are distinct phenomena, as Conrad and Yavuz (2017) conclude, rather than both having the same root cause. As noted by Hirshleifer (2001), this disconnect is inconsistent with the leading behavioral models of momentum and reversal. Our results also suggest that underreaction can exist without the disposition effect (Grinblatt and Han 2005). The straddle portfolios we analyze expire in just one month. An investor who is reluctant to exit a poorly performing trade simply does not have that option.

We leave many questions for future research. What is the behavioral bias that is responsible for the underreaction that underlies momentum? Is the momentum strategy itself predictable, as been well documented in the equity market? What explains the significant differences we see in the time-series patterns of stock and option returns, such as the finding that options do not experience long-run reversal? Answering any of these would be a significant but worthwhile undertaking.

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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.

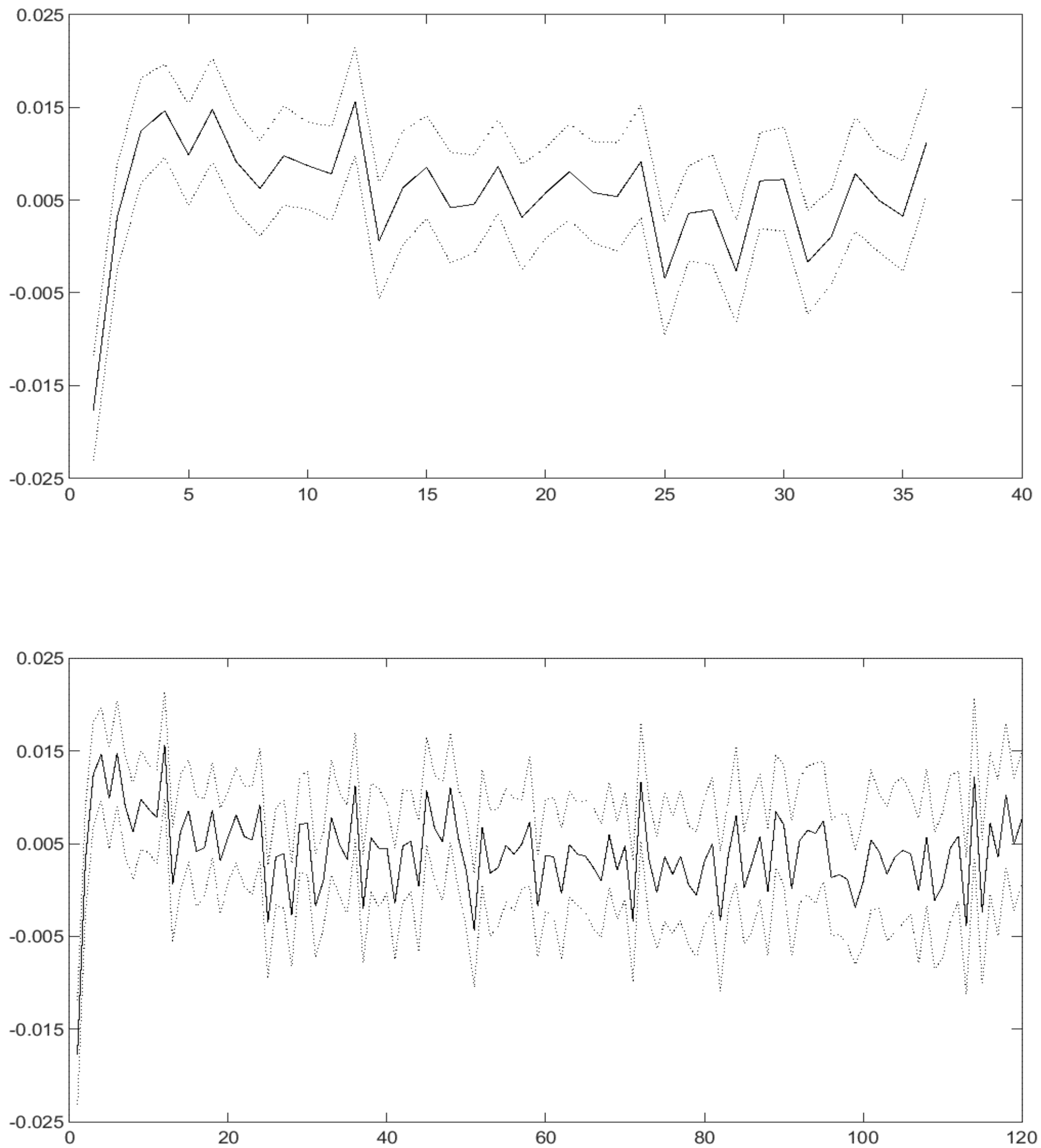

Figure 2

Five-year moving averages of strategy returns

This figure reports the rolling five-year average return on the short-term reversal (lag 1), momentum (lags 2 to 12), and quarterly seasonality (lags 3, 6, ..., 36) factors. Dotted lines denote 95% confidence intervals, which use Newey-West standard errors with 3 lags.

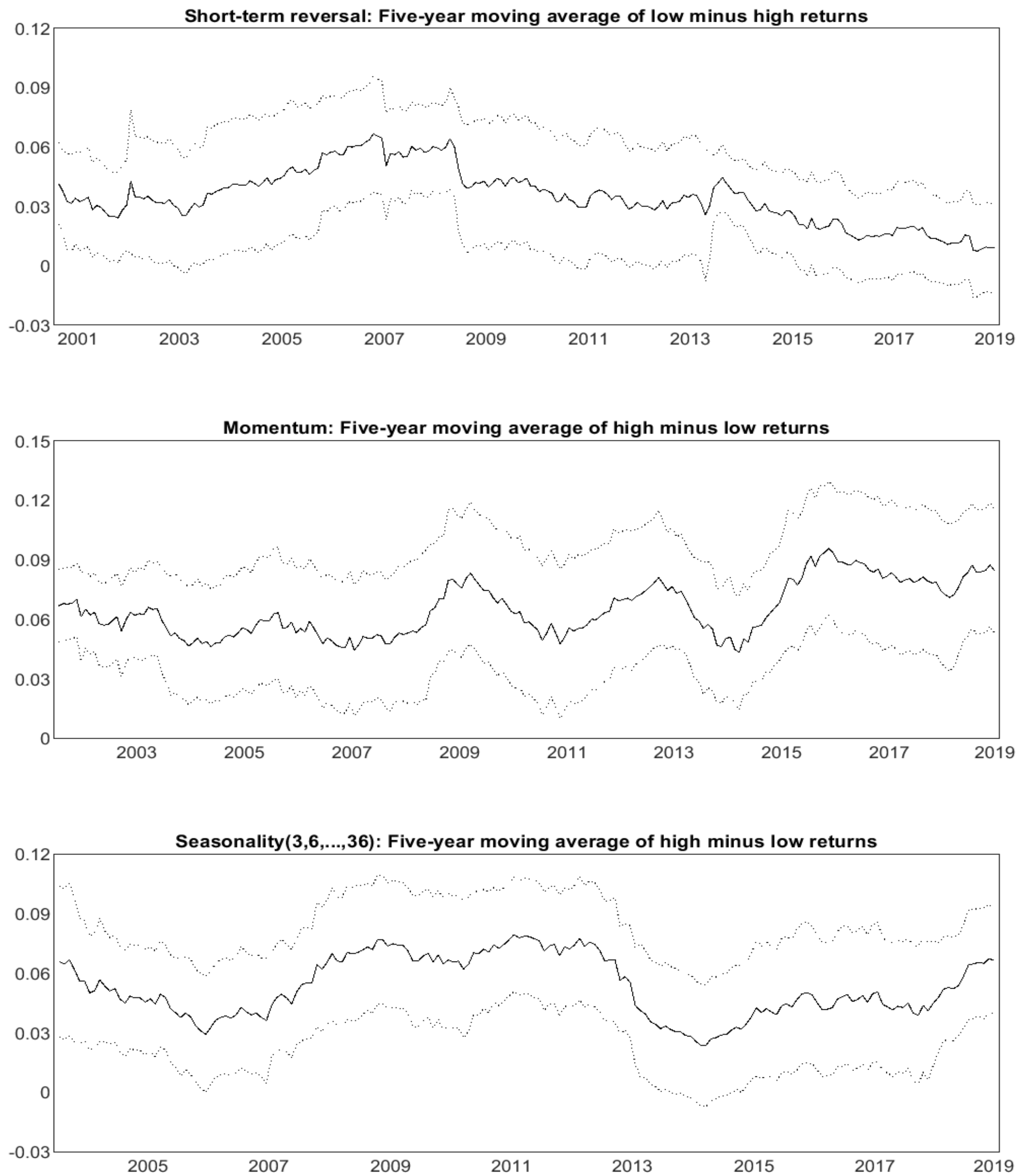

Table 1
Univariate sorts
This table reports means and t-statistics from univariate quintile sorts. Zero delta straddles are allocated to portfolios based on lagged returns (Panel A) or other stock-level characteristics (Panel B). Average returns are per month. T-statistics, in parentheses, are computed 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	-0.0456	-0.0480	-0.0557	-0.0603	-0.0798	-0.0342
		(-2.93)	(-3.03)	(-3.65)	(-3.81)	(-5.26)	(-5.23)
1	2	-0.0441	-0.0483	-0.0568	-0.0603	-0.0718	-0.0277
		(-2.88)	(-3.14)	(-3.51)	(-3.75)	(-4.55)	(-3.51)
1	6	-0.0654	-0.0618	-0.0520	-0.0489	-0.0378	0.0276
		(-4.11)	(-3.89)	(-3.09)	(-2.89)	(-2.36)	(3.37)
1	12	-0.0748	-0.0584	-0.0489	-0.0342	-0.0297	0.0451
		(-4.74)	(-3.44)	(-2.75)	(-2.02)	(-1.73)	(5.74)
2	12	-0.0824	-0.0625	-0.0510	-0.0332	-0.0166	0.0658
		(-5.28)	(-3.73)	(-2.92)	(-1.96)	(-0.95)	(8.91)
2	24	-0.0747	-0.0655	-0.0427	-0.0272	-0.0136	0.0611
		(-4.26)	(-3.79)	(-2.30)	(-1.42)	(-0.76)	(7.88)
2	36	-0.0781	-0.0679	-0.0388	-0.0316	-0.0229	0.0551
		(-4.11)	(-3.91)	(-2.01)	(-1.55)	(-1.25)	(6.67)
13	24	-0.0647	-0.0579	-0.0471	-0.0385	-0.0258	0.0389
		(-3.62)	(-3.27)	(-2.61)	(-2.14)	(-1.50)	(5.96)
13	36	-0.0691	-0.0603	-0.0464	-0.0358	-0.0320	0.0371
		(-3.73)	(-3.32)	(-2.45)	(-1.90)	(-1.80)	(4.50)
25	36	-0.0657	-0.0575	-0.0458	-0.0436	-0.0403	0.0254
		(-3.74)	(-3.24)	(-2.50)	(-2.28)	(-2.25)	(3.47)

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

Characteristic	Low	2	3	4	High	High - Low
IV - HV	-0.0202	-0.0336	-0.0456	-0.0743	-0.1423	-0.1220
	(-1.21)	(-2.02)	(-2.57)	(-4.75)	(-12.47)	(-12.28)
Idiosyncratic vol	-0.0567	-0.0503	-0.0492	-0.0583	-0.0873	-0.0306
	(-3.02)	(-2.96)	(-3.12)	(-4.00)	(-6.79)	(-2.53)
Market cap	-0.0920	-0.0607	-0.0478	-0.0551	-0.0571	0.0349
	(-7.10)	(-4.43)	(-3.12)	(-3.20)	(-3.14)	(2.80)
IV term spread	-0.1152	-0.0736	-0.0506	-0.0415	-0.0290	0.0862
	(-9.76)	(-4.80)	(-3.00)	(-2.38)	(-1.79)	(10.58)
IV smile slope	-0.0756	-0.0566	-0.0473	-0.0589	-0.0725	0.0031
	(-5.63)	(-3.45)	(-2.80)	(-3.68)	(-4.86)	(0.48)

Table 2
Fama-MacBeth regressions
This table reports the results of Fama-MacBeth regressions in which monthly zero delta straddle returns are the dependent variable. 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 smile slope	Avg. CS R^2
		-0.0377		-0.1959	-1.0444	-0.1369	0.4578	0.0190	0.0152
		(-1.98)		(-8.03)	(-4.27)	(-1.28)	(8.22)	(1.09)	
1	1	-0.0611	-0.0177						0.0027
		(-4.04)	(-6.14)						
1	1	-0.0412	-0.0124	-0.2023	-0.9640	-0.1213	0.4170	0.0054	0.0175
		(-2.11)	(-4.47)	(-8.03)	(-3.60)	(-1.15)	(7.29)	(0.27)	
1	2	-0.0604	-0.0180						0.0027
		(-4.00)	(-3.73)						
1	2	-0.0393	-0.0131	-0.1941	-1.0441	-0.1216	0.4160	0.0055	0.0179
		(-2.01)	(-2.91)	(-7.30)	(-3.89)	(-1.12)	(6.91)	(0.23)	
1	6	-0.0540	0.0280						0.0027
		(-3.44)	(3.45)						
1	6	-0.0237	0.0383	-0.1774	-1.3588	-0.1140	0.4182	0.0647	0.0190
		(-1.17)	(4.93)	(-6.80)	(-4.86)	(-1.09)	(6.17)	(2.03)	
1	12	-0.0461	0.0753						0.0036
		(-2.79)	(6.66)						
1	12	-0.0138	0.0808	-0.1672	-1.5160	-0.1790	0.4556	0.0534	0.0218
		(-0.66)	(6.89)	(-5.05)	(-5.18)	(-1.78)	(6.09)	(1.47)	
2	12	-0.0437	0.0976						0.0040
		(-2.61)	(9.34)						
2	12	-0.0139	0.0952	-0.1493	-1.4158	-0.1748	0.5095	0.0558	0.0224
		(-0.66)	(8.84)	(-4.46)	(-4.90)	(-1.75)	(6.21)	(1.62)	
2	24	-0.0361	0.1404						0.0043
		(-2.02)	(8.87)						
2	24	-0.0094	0.1380	-0.1166	-1.3741	-0.1743	0.5549	0.0897	0.0263
		(-0.42)	(8.39)	(-2.79)	(-4.00)	(-1.85)	(5.37)	(1.57)	
2	36	-0.0385	0.1529						0.0049
		(-2.11)	(6.83)						
2	36	-0.0178	0.1625	-0.1114	-1.1112	-0.1039	0.5345	0.1474	0.0313
		(-0.78)	(6.98)	(-2.27)	(-2.97)	(-1.00)	(4.42)	(1.80)	
13	24	-0.0415	0.0656						0.0028
		(-2.37)	(6.81)						
13	24	-0.0182	0.0632	-0.1722	-1.2684	-0.1482	0.4856	0.0457	0.0227
		(-0.81)	(6.85)	(-4.64)	(-3.94)	(-1.54)	(5.56)	(0.97)	
13	36	-0.0434	0.0836						0.0039
		(-2.41)	(4.69)						
13	36	-0.0286	0.0889	-0.1346	-0.9258	-0.0887	0.5183	0.0985	0.0282
		(-1.25)	(5.22)	(-2.98)	(-2.63)	(-0.91)	(5.00)	(1.49)	
25	36	-0.0485	0.0360						0.0029
		(-2.72)	(3.15)						
25	36	-0.0346	0.0369	-0.1411	-0.8102	-0.0979	0.5510	0.0724	0.0231
		(-1.57)	(3.13)	(-3.74)	(-2.53)	(-1.09)	(5.97)	(1.42)	

Table 3
Fama-MacBeth regressions with longer lags
This table reports the results of Fama-MacBeth regressions in which monthly zero delta straddle returns are the dependent variable. Independent variables include average returns over different past periods. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

	Intercept	1	2 to 12	13 to 24	25 to 36	37 to 48	49 to 60	Avg. CS R^2	# of months	Avg. obs. / month
(1)	-0.0611	-0.0177						0.0027	280	1474.0
	(-4.04)	(-6.14)								
(2)	-0.0465	-0.0228	0.0994					0.0074	269	940.7
	(-2.77)	(-6.96)	(9.24)							
(3)	-0.0380	-0.0238	0.0921	0.0529				0.0123	257	698.0
	(-2.11)	(-5.99)	(7.25)	(5.03)						
(4)	-0.0400	-0.0272	0.0846	0.0537	0.0238			0.0173	245	547.4
	(-2.14)	(-6.23)	(5.71)	(4.45)	(1.75)					
(5)	-0.0429	-0.0257	0.0768	0.0441	0.0059	0.0262		0.0236	233	441.8
	(-2.21)	(-5.46)	(4.38)	(2.93)	(0.43)	(1.92)				
(6)	-0.0374	-0.0232	0.0662	0.0419	-0.0096	0.0305	0.0250	0.0328	221	362.0
	(-1.89)	(-4.03)	(3.63)	(2.42)	(-0.67)	(1.84)	(1.62)			

Table 4

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. For cross-sectional (CS) strategies, portfolios are determined based on whether the lagged average straddle excess return is above or below the cross-sectional median. For time series (TS) strategies, portfolio assignment depends on whether the lagged average excess return is positive or negative. The "TS - CS" column reports the difference between the time series high minus low spread and the cross-sectional high minus low spread. Corr(CS, TS) is the correlation between the cross-sectional and time series high/low portfolios. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Min and max lag in formation period		Cross-Sectional Strategies (CS)			Time Series Strategies (TS)			TS - CS	Corr(CS, TS)
		Low	High	High - Low	Low	High	High - Low	Mean	
1	1	-0.0474	-0.0683	-0.0209	-0.0508	-0.0730	-0.0223	-0.0014	0.915
		(-3.07)	(-4.47)	(-5.10)	(-3.32)	(-4.78)	(-4.92)	(-0.66)	
1	2	-0.0488	-0.0637	-0.0149	-0.0520	-0.0689	-0.0169	-0.0019	0.892
		(-3.18)	(-4.07)	(-3.18)	(-3.44)	(-4.45)	(-3.29)	(-0.98)	
1	6	-0.0603	-0.0460	0.0144	-0.0619	-0.0443	0.0176	0.0033	0.875
		(-3.81)	(-2.83)	(3.14)	(-3.97)	(-2.76)	(3.98)	(1.36)	
1	12	-0.0642	-0.0340	0.0302	-0.0606	-0.0330	0.0276	-0.0026	0.843
		(-3.95)	(-1.99)	(6.82)	(-3.72)	(-1.94)	(6.13)	(-1.01)	
2	12	-0.0676	-0.0302	0.0374	-0.0642	-0.0242	0.0399	0.0026	0.873
		(-4.21)	(-1.76)	(8.66)	(-3.95)	(-1.41)	(8.77)	(1.18)	
2	24	-0.0646	-0.0247	0.0399	-0.0584	-0.0183	0.0401	0.0002	0.794
		(-3.73)	(-1.36)	(8.14)	(-3.33)	(-1.00)	(8.06)	(0.07)	
2	36	-0.0662	-0.0291	0.0371	-0.0590	-0.0248	0.0342	-0.0029	0.819
		(-3.70)	(-1.54)	(6.11)	(-3.25)	(-1.32)	(5.54)	(-0.75)	
13	24	-0.0582	-0.0350	0.0232	-0.0546	-0.0308	0.0238	0.0006	0.828
		(-3.33)	(-2.01)	(5.92)	(-3.12)	(-1.75)	(5.28)	(0.25)	
13	36	-0.0610	-0.0363	0.0247	-0.0548	-0.0359	0.0189	-0.0058	0.818
		(-3.35)	(-2.01)	(4.87)	(-3.01)	(-1.99)	(3.36)	(-1.62)	
25	36	-0.0593	-0.0420	0.0173	-0.0582	-0.0394	0.0188	0.0015	0.821
		(-3.37)	(-2.30)	(3.58)	(-3.31)	(-2.14)	(3.77)	(0.45)	

Table 5

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 constructed from a total of 12 different long-only straddle portfolios. These include the high and the low quintiles behind five different long/short factors as well as the equally weighted straddle portfolio and the SPX straddle. In each month, we rank all 12 long-only portfolios 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 six. 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 3	Middle 6	High 3	High - Low
1	1	-0.0424	-0.0595	-0.0387	0.0037	-0.1019	-0.0752	-0.0532	0.0487
		(-2.33)	(-3.73)	(-1.93)	(0.24)	(-5.86)	(-5.17)	(-2.80)	(4.03)
1	2	-0.0503	-0.0535	-0.0564	-0.0061	-0.1066	-0.0707	-0.0551	0.0515
		(-2.89)	(-3.25)	(-2.93)	(-0.39)	(-6.14)	(-4.74)	(-3.01)	(4.39)
1	6	-0.0669	-0.0538	-0.0273	0.0396	-0.1100	-0.0721	-0.0472	0.0628
		(-4.08)	(-3.27)	(-1.28)	(2.44)	(-6.78)	(-4.73)	(-2.43)	(5.32)
1	12	-0.0694	-0.0534	-0.0178	0.0517	-0.1024	-0.0748	-0.0389	0.0635
		(-4.27)	(-3.16)	(-0.89)	(3.53)	(-5.69)	(-5.04)	(-1.93)	(4.52)
2	12	-0.0746	-0.0519	-0.0197	0.0549	-0.1028	-0.0726	-0.0430	0.0597
		(-4.24)	(-3.11)	(-1.01)	(3.80)	(-5.80)	(-4.81)	(-2.16)	(4.28)
2	24	-0.0650	-0.0498	-0.0230	0.0420	-0.1075	-0.0692	-0.0367	0.0708
		(-3.47)	(-2.85)	(-1.09)	(2.49)	(-6.27)	(-4.33)	(-1.77)	(5.42)
2	36	-0.0674	-0.0556	-0.0175	0.0499	-0.1091	-0.0720	-0.0434	0.0657
		(-3.99)	(-3.06)	(-0.82)	(3.30)	(-6.34)	(-4.21)	(-2.22)	(5.46)
13	24	-0.0498	-0.0494	-0.0404	0.0094	-0.1042	-0.0740	-0.0306	0.0736
		(-2.39)	(-2.93)	(-1.94)	(0.60)	(-5.94)	(-4.73)	(-1.44)	(5.29)
13	36	-0.0697	-0.0494	-0.0445	0.0253	-0.1116	-0.0735	-0.0378	0.0737
		(-3.69)	(-2.76)	(-2.12)	(1.59)	(-6.33)	(-4.50)	(-1.85)	(5.97)
25	36	-0.0687	-0.0492	-0.0464	0.0222	-0.1027	-0.0710	-0.0518	0.0509
		(-3.85)	(-2.73)	(-2.23)	(1.51)	(-5.30)	(-4.28)	(-2.78)	(4.21)

Table 6
Seasonality

This table examines seasonality in straddle returns. A seasonality signal is defined for each stock as the average return over some set of lags, either {3, 6, 9, 12}, {3, 6, ..., 36}, or {12, 24, 36}. Panel A reports the results of quintile sorts on these signals, along with roughly comparable momentum sorts that replicate results in Table 1. Panel B shows the results of Fama-MacBeth regressions in which the seasonality and momentum signals are used as independent variables. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Panel A: Univariate sorts

Lags included	Low	2	3	4	High	High - Low
			Seasonality			
{3,6,9,12}	-0.0762	-0.0604	-0.0534	-0.0393	-0.0242	0.0520
	(-4.85)	(-3.67)	(-3.25)	(-2.26)	(-1.37)	(7.02)
{3,6,...,36}	-0.0805	-0.0616	-0.0471	-0.0380	-0.0231	0.0574
	(-4.54)	(-3.53)	(-2.51)	(-2.00)	(-1.23)	(6.76)
{12, 24, 36}	-0.0710	-0.0627	-0.0582	-0.0413	-0.0335	0.0375
	(-4.09)	(-3.54)	(-3.28)	(-2.18)	(-1.83)	(5.24)
			Momentum			
{2,3,…,12}	-0.0824	-0.0625	-0.0510	-0.0332	-0.0166	0.0658
	(-5.28)	(-3.73)	(-2.92)	(-1.96)	(-0.95)	(8.91)
{2,3,…,36}	-0.0781	-0.0679	-0.0388	-0.0316	-0.0229	0.0551
	(-4.11)	(-3.91)	(-2.01)	(-1.55)	(-1.25)	(6.67)

Panel B: Fama-MacBeth regressions

	Intercept	Seasonality	Momentum	Avg. CS R^2
	-0.0493	0.0461		0.0028
	(-3.01)	(7.22)		
Seasonality lags: {3,6,9,12}	-0.0436		0.0976	0.0040
Momentum lags: {2,3,…,12}	(-2.61)		(9.34)	
	-0.0448	0.0206	0.0740	0.0063
	(-2.72)	(2.69)	(6.00)	
	-0.0446	0.0897		0.0041
	(-2.48)	(7.15)		
Seasonality lags: {3,6,...,36}	-0.0385		0.1529	0.0049
Momentum lags: {2,3,…,36}	(-2.11)		(6.83)	
	-0.0378	0.0716	0.0826	0.0086
	(-2.07)	(4.16)	(2.97)	
	-0.0498	0.0354		0.0029
	(-2.79)	(6.18)		
Seasonality lags: {12, 24, 36}	-0.0385		0.1529	0.0049
Momentum lags: {2,3,…,36}	(-2.11)		(6.83)	
	-0.0372	0.0253	0.1284	0.0092
	(-2.03)	(3.10)	(5.25)	

Table 7

Risk and return for alternative strategies

This table reports risk and return measures for 16 different portfolios constructed from zero delta straddles. Panel A includes strategies from Tables 1, 5, and 6, 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., 2017), the implied volatility term structure slope (Vasquez, 2017), and the implied volatility smile slope (related to Bali and Murray, 2013). 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 values are in monthly decimal terms. 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 -------------------			------------- Seasonal (high - low) -------------		
	Individual (low - high)	Industry (high - low)	Factor (high - low)	Individual (high - low)	Industry (high - low)	Factor (high - low)	Quarterly 3, 6, 9, 12	Quarterly 3, 6, ..., 36	Annual 12, 24, 36
Mean	0.0342	0.0037	0.0487	0.0658	0.0549	0.0597	0.0520	0.0574	0.0375
	(5.23)	(0.24)	(4.03)	(8.91)	(3.80)	(4.28)	(7.02)	(6.76)	(5.24)
Standard deviation	0.120	0.260	0.221	0.132	0.252	0.214	0.115	0.135	0.117
Sharpe ratio	0.286	0.014	0.220	0.498	0.218	0.279	0.452	0.425	0.322
Skewness	0.570	-0.552	0.653	0.337	-0.385	0.106	1.076	-0.003	0.851
Excess kurtosis	10.05	2.20	3.17	0.78	1.78	3.02	3.27	1.48	3.09
Maximum drawdown	0.694	> 1	0.874	0.460	> 1	0.947	0.389	0.585	0.415

Panel B: Factors based on prior research

	IV - HV	Idiosyncratic volatility	Market cap	IV term spread	IV smile slope	Short SPX straddle	Short EW stock straddle
Mean	0.1221	0.0306	0.0349	0.0862	0.0031	0.1020	0.0598
	(12.28)	(2.52)	(2.80)	(10.57)	(0.47)	(2.45)	(3.98)
Standard deviation	0.156	0.197	0.183	0.132	0.107	0.703	0.237
Sharpe ratio	0.782	0.155	0.190	0.651	0.029	0.145	0.252
Skewness	1.180	1.025	0.567	1.924	1.339	-1.319	-3.209
Excess kurtosis	3.05	5.28	0.90	10.13	6.14	2.22	17.20
Maximum drawdown	0.405	0.972	0.989	0.511	0.962	> 1	> 1

Table 8

Factor risk adjustment for the reversal and momentum strategies

This table reports the results of regressions in which a reversal or momentum factor is 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 smile slope	Short SPX straddle	Short EW stock straddle	R^2
					Individual Straddles					
1	1	-0.0014	0.2229	0.1857	0.0470			-0.0180		0.1295
		(-0.09)	(2.65)	(2.50)	(0.71)			(-1.03)		
1	1	0.0035	0.1453	0.1493	0.0272	-0.1637	-0.0369	-0.0224	-0.0006	0.1508
		(0.23)	(1.85)	(2.33)	(0.39)	(-1.93)	(-0.50)	(-1.02)	(-0.01)	
2	12	0.0437	-0.1777	0.1619	0.1660			0.0074		0.0805
		(3.21)	(-2.68)	(2.06)	(2.70)			(0.42)		
2	12	0.0565	-0.1469	0.1824	0.1782	-0.0502	0.0260	0.0333	-0.1289	0.1003
		(3.34)	(-1.56)	(2.52)	(2.93)	(-0.52)	(0.28)	(1.63)	(-1.53)	
					Industries					
1	1	0.0299	0.0949	-0.0501	-0.3449			-0.0418		0.0399
		(1.33)	(0.72)	(-0.37)	(-2.64)			(-1.39)		
1	1	0.0557	0.1580	-0.0609	-0.3635	-0.0831	-0.1443	0.0090	-0.2642	0.0630
		(2.11)	(1.04)	(-0.46)	(-2.52)	(-0.42)	(-0.68)	(0.23)	(-2.15)	
2	12	0.0358	-0.1908	0.4394	0.3007			0.0028		0.0732
		(1.64)	(-1.40)	(3.12)	(2.34)			(0.09)		
2	12	0.0710	-0.0472	0.5078	0.3352	-0.0401	0.0405	0.0825	-0.3873	0.1233
		(3.00)	(-0.30)	(3.25)	(2.53)	(-0.24)	(0.24)	(2.08)	(-3.56)	
					Factors					
1	1	-0.0059	-0.3708	-0.3517	-0.1687			0.0463		0.0951
		(-0.29)	(-3.55)	(-3.72)	(-1.34)			(1.20)		
1	1	-0.0091	-0.3776	-0.3621	-0.1764	0.0143	-0.0261	0.0399	0.0303	0.0956
		(-0.41)	(-3.16)	(-3.19)	(-1.43)	(0.11)	(-0.14)	(0.85)	(0.22)	
2	12	-0.0409	-0.7160	-0.1962	-0.0456			0.1171		0.2429
		(-2.68)	(-7.77)	(-1.95)	(-0.55)			(3.33)		
2	12	-0.0278	-0.5650	-0.1323	-0.0148	0.1405	0.0357	0.1614	-0.1966	0.2707
		(-1.50)	(-5.09)	(-1.18)	(-0.18)	(1.37)	(0.28)	(3.85)	(-1.60)	

Table 9

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 8 included as controls. All momentum strategies use 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									
0.0658				0	0.0565				0.1003
(8.91)					(3.34)				
0.0541		0.2135		0.1658	0.0434		0.1851		0.2095
(7.54)		(5.91)			(2.77)		(5.77)		
0.0610			0.0803	0.0169	0.0574			0.0305	0.1021
(7.32)			(2.21)		(3.36)			(0.76)	
Panel B: Dependent variable is industry momentum									
0.0549				0	0.0710				0.1233
(3.80)					(3.00)				
0.0038	0.7765			0.1658	0.0339	0.6559			0.2297
(0.27)	(7.55)				(1.54)	(6.54)			
0.0591			-0.0712	0.0037	0.0655			-0.2000	0.1443
(3.94)			(-0.63)		(2.88)			(-1.82)	
Panel C: Dependent variable is factor momentum									
0.0597				0	-0.0278				0.2707
(4.28)					(-1.50)				
0.0459	0.2105			0.0169	-0.0315	0.0649			0.2722
(3.02)	(2.18)				(-1.59)	(0.76)			
0.0625		-0.0513		0.0037	-0.0193		-0.1199		0.2882
(4.08)		(-0.62)			(-1.11)		(-1.75)		

Table 10

Pervasiveness of reversal, momentum, and seasonality

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 average the percentage bid-ask spread of the put and the call 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	-0.0156	-0.0422	-0.0424	-0.0164	-0.0427	No downgrade	-0.0383
	(-2.12)	(-5.80)	(-6.41)	(-2.58)	(-4.79)		(-5.50)
Medium	-0.0265	-0.0279	-0.0256	-0.0267	-0.0410	Downgrade	-0.0283
	(-3.62)	(-4.01)	(-3.88)	(-3.94)	(-4.51)		(-2.42)
High	-0.0449	-0.0112	-0.0138	-0.0437	-0.0369	No rating	-0.0203
	(-6.71)	(-1.65)	(-1.88)	(-6.10)	(-4.14)		(-3.33)
High - Low	-0.0293	0.0310	0.0286	-0.0272	0.0058		
	(-3.17)	(3.46)	(3.33)	(-3.30)	(0.50)		

Panel B: Formation period includes lags 2 to 12

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
Low	0.0549	0.0399	0.0461	0.0668	0.0645	No downgrade	0.0442
	(6.06)	(4.83)	(6.27)	(8.74)	(5.90)		(5.90)
Medium	0.0586	0.0551	0.0437	0.0506	0.0378	Downgrade	0.0381
	(7.45)	(7.85)	(5.78)	(6.98)	(3.71)		(2.11)
High	0.0426	0.0684	0.0694	0.0462	0.0220	No rating	0.0592
	(5.32)	(7.47)	(7.76)	(5.53)	(1.81)		(9.15)
High - Low	-0.0123	0.0285	0.0233	-0.0209	-0.0425		
	(-1.06)	(2.43)	(2.19)	(-2.18)	(-2.71)		

Panel C: Formation period includes lags 3, 6, …, and 36

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
Low	0.0386	0.0494	0.0494	0.0456	0.0527	No downgrade	0.0489
	(3.64)	(5.33)	(5.23)	(4.34)	(4.27)		(6.56)
Medium	0.0488	0.0340	0.0470	0.0527	0.0550	Downgrade	0.0409
	(4.88)	(3.64)	(5.62)	(5.62)	(4.36)		(2.39)
High	0.0507	0.0560	0.0478	0.0422	0.0302	No rating	0.0470
	(5.36)	(5.97)	(4.72)	(4.12)	(2.46)		(5.43)
High - Low	0.0121	0.0066	-0.0016	-0.0033	-0.0225		
	(0.90)	(0.54)	(-0.13)	(-0.25)	(-1.56)		

Table 11

Explaining return predictability with volatility swap returns

This table examines Fama-MacBeth regressions in which straddle returns are predicted using averages, over some formation period, of volatility swap returns or the two components of their decomposition, namely the volatility surprise and risk premium. Past average straddle returns are an additional predictor. Each panel differs only with respect to the formation period in which the predictors are computed. The volatility swap return is defined and then decomposed as

$$\nu_{i,t}\left(\mathrm{RV}_{i,t+1}-\mathrm{IV}_{i,t}\right) \quad = \quad \nu_{i,t}\left(\mathrm{RV}_{i,t+1}-\mathrm{E}_t\left[\mathrm{RV}_{i,t+1}\right]\right) \quad + \quad \nu_{i,t}\left(\mathrm{E}_t\left[\mathrm{RV}_{i,t+1}\right]-\mathrm{IV}_{i,t}\right)$$

where v is the straddle's normalized vega, RV is the realized volatility of the underlying stock, and IV is the implied volatility used to proxy for the volatility swap rate. We refer to the left hand side expression as the volatility swap gain and the two terms on the right hand side as the volatility surprise and the volatility risk premium, respectively. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

Panel A: Formation period includes lag 1 only

Intercept	Straddle return	Volatility swap gain	Volatility surprise	Volatility risk premium	Avg. CS R^2
-0.0637	-0.0193				0.0028
(-4.10)	(-6.64)				
-0.0627		-0.0237			0.0018
(-3.99)		(-3.67)			
-0.0631	-0.0181	-0.0044			0.0047
(-4.04)	(-5.14)	(-0.57)			
-0.0527			-0.0427	0.0952	0.0049
(-3.27)			(-6.80)	(7.35)	
-0.0531	-0.0158		-0.0257	0.1102	0.0077
(-3.32)	(-4.46)		(-3.45)	(7.94)	

Panel B: Formation period includes lags 2 to 12

Intercept	Straddle return	Volatility swap gain	Volatility surprise	Volatility risk premium	Avg. CS R^2
-0.0464	0.1012				0.0044
(-2.74)	(9.21)				
-0.0443		0.1405			0.0040
(-2.55)		(6.07)			
-0.0446	0.0882	0.0526			0.0075
(-2.56)	(7.49)	(2.15)			
-0.0373			0.1077	0.2212	0.0070
(-2.11)			(4.39)	(8.16)	
-0.0366	0.0935		0.0105	0.1396	0.0106
(-2.07)	(7.92)		(0.40)	(5.06)	

Panel C: Formation period includes lags 3, 6, …, and 36

Intercept	Straddle return	Volatility swap gain	Volatility surprise	Volatility risk premium	Avg. CS R^2
-0.0453	0.0968				0.0047
(-2.48)	(6.97)				
-0.0385		0.2062			0.0047
(-2.04)		(7.09)			
-0.0382	0.0657	0.1383			0.0086
(-2.04)	(4.38)	(4.28)			
-0.0323			0.1946	0.2249	0.0078
(-1.68)			(6.45)	(6.12)	
-0.0316	0.0666		0.1242	0.1641	0.0116
(-1.65)	(4.47)		(3.73)	(4.16)	

Panel D: Formation period includes lags 12, 24, and 36

Intercept	Straddle return	Volatility swap gain	Volatility surprise	Volatility risk premium	Avg. CS R^2
-0.0516	0.0355				0.0030
(-2.83)	(6.30)				
-0.0483		0.0843			0.0029
(-2.63)		(6.01)			
-0.0477	0.0251	0.0595			0.0057
(-2.59)	(3.81)	(3.65)			
-0.0455			0.0843	0.0807	0.0054
(-2.43)			(5.85)	(3.91)	
-0.0446	0.0253		0.0588	0.0589	0.0082
(-2.38)	(3.89)		(3.49)	(2.73)	

Table 12

Seasonality in realized volatility

This table examines seasonality in realized volatilities (RV), which are calculated as the standard deviation of daily returns from one expiration Friday to the next. We run Fama-MacBeth regressions in which RV is predicted using the average monthly value of RV in the 36 months prior to the period being forecast as well as averages of RV and IV (the implied volatility used in Table 11 as a proxy of the volatility swap rate) over selected lags, corresponding to either quarterly or annual seasonality. The table reports Fama-MacBeth coefficients with t-statistics, in parentheses, that are computed using Newey-West standard errors with three lags.

Intercept	Mean RV over lags 1 to 36	Mean RV over lags 3, 6, …, 36	Mean IV over lags 3, 6, …, 36	Avg. CS R^2
		Panel A: Quarterly seasonality		
0.0311	0.7030	0.1937		0.3557
(4.16)	(12.11)	(6.36)		
0.0284	0.7897		0.1003	0.3592
(3.73)	(9.12)		(1.77)	
0.0291	0.6619	0.1854	0.0459	0.3654
(3.84)	(7.38)	(7.08)	(0.81)	

Panel B: Annual seasonality

Intercept	Mean RV over lags 1 to 36	Mean RV over lags 12, 24, and 36	Mean IV over lags 12, 24, and 36	Avg. CS R^2
0.0308	0.9373	-0.0450		0.3536
(4.18)	(18.11)	(-2.04)		
0.0334	0.9431		-0.0577	0.3579
(4.44)	(12.91)		(-1.31)	
0.0325	0.9580	-0.0242	-0.0478	0.3617
(4.37)	(12.66)	(-1.85)	(-1.16)	

Internet appendix for

Momentum, Reversal and Seasonality in Option Returns

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A Additional results

This appendix contains additional results that were omitted from the main text.

A.1 Summary statistics

Table A1 shows a number of summary statistics for our main sample. Straddle returns have very negative means and large standard deviations, and a median that is well below the mean indicates substantial positive skewness. Average straddle returns over the "2 to 12" momentum formation period have about the same mean as the full sample. Their standard deviation is lower, as expected, almost exactly by a factor of $\sqrt{11}$.

A.2 Alternative sorts

In the main text, we use quintiles for most portfolio sorts. Table A2 shows results for terciles and deciles. For the latter, we report only the extreme portfolios and the high-minus-low portfolio.

The table shows that all results are robust to using alternative sorts. Using terciles, the average return on "2 to 12" momentum is lower than quintiles, but the t-statistic is higher. For deciles, the avearage return is higher, but the t-statistic is lower.

A.3 Alternative return measures

In all the results in our paper, we only examine straddles for which the call option has a delta that is between 0.25 and 0.75. During the formation period, there must be a non-missing straddle return in each month, but there is no requirement that the straddle has positive open interest. In contrast, the straddle must have positive open interest at the beginning of the holding period.

Table A3 relaxes the requirement of positive open interest in the holding period. Doing so weakens the short-run reversal effect, though it remains significant. In contrast, the momentum and seasonality results are strengthened.

In Table A4, we require positive open interest both in the holding period and in the formation period. This strengthens short-run reversal but slightly weakens momentum and seasonality. All results remain highly significant, both economically and statistically.

Table A5 also eliminates the requirement of positive open interest, both in the formation period and the holding period. However, rather than using the single straddle that is closest to at-the-money for each firm, it examines the equally weighted portfolio return constructed from all straddles within the 0.25 to 0.75 delta range for a given firm. Doing so substantially weakens short-run reversal, but both momentum and seasonality are markedly stronger.

Table A6 uses the same open interest requirements as our main results, but it discards the straddle of any firm that pays a dividend during the holding period. This exclusion is designed to eliminate any possibility that early exercise is affecting our results. The table shows results that are nearly identical to those in the main text.

Table A7 replicates the main portfolio sorts in Table 1 of the paper, but it uses cumulative returns over the formation period rather than average returns. For short-term reversal, these two sets of results are identical. For momentum, using cumulative returns reduces the high-minus-low spread by about one quarter. The corresponding t-statistic is 7.45, which is lower than the value from Table 2 but nevertheless highly significant.

A.4 Double sorting using stock and option momentum

Table A8 reports the results of sequential tercile sorts based on average stock and option returns over the "2 to 12" formation period. The table shows that option momentum is significant within all stock momentum terciles, though it is weakest in the middle tercile. In contrast, there is no difference in average returns for straddle portfolios with different levels of stock momentum. The table therefore confirms that stock and option momentum are distinct.

A.5 Panel regressions

Table 2 of the main text uses Fama-MacBeth regressions to control for other option return predictors. Table A9 repeats this analysis using panel regressions instead.

Overall, results are weaker relative to Fama-MacBeth regressions. The short-run reversal phenomenon disappears, and the control variables mostly lose their statistical significance. The standard "2 to 12" momentum effect remains strong, however, with slightly smaller coefficient estimates. T-statistics are also reduced, but they nevertheless indicate strong statistical significance for most formation periods. Furthermore, as discussed in the text, stock momentum is often insignificant in panel regressions (e.g., Kelly, Moskowitz, and Pruitt 2020), so in one respect these results are comparatively strong.

A.6 Spanning regressions for short-term strategies

The spanning regressions in Table 9 only examined the "2 to 12" formation period. In Table A10, we analyze strategies in which the formation period includes just the most recent month.

The table shows a weak connection between the strategy based on individual straddles and the strategy based on factors. Factors also do not appear to explain industries, nor do industries explain factors.

As in Table 9, there is a stronger relation between the strategy based on individual straddles and the strategy based on industries. Regressing the industry strategy on individual straddles actually results in a positive alpha on the industry-based strategy, whose unconditional mean is close to zero. Industries also explain some of the variation in the individual straddle portfolio, though they do not explain that portfolio's mean return.

A.7 Additional seasonality results

A number of seasonality results are omitted from the main text because of their similarity to results that were presented.

Table A11 examines Fama-MacBeth regressions in which we add additional controls to one of the regressions from Table 6. This is similar to Table 2, which analyzed reversal and momentum. It is evident from these results that adding these controls has almost no effect on the effect of seasonality.

Table A12 uses the Horenstein, Vasquez, and Xiao (2019) model, or our extension of it, to adjust seasonality returns for factor exposures. This table is analogous to Table 8 in the main text, which examined reversal and momentum only. We find that adding controls has a minor effect on the two strategies based on quarterly seasonality and a somewhat larger effect on the annual seasonality strategy. Nevertheless, all regressions show statistically significant alphas, indicating that seasonality is not explained by other risk factors.

Table A13 examines straddle seasonality by subgroup for the two seasonality strategies that were not considered in Table 10. As noted in the main text, there is one difference between the results in these two tables, which is that we find the seasonality effect to be significantly weaker for firms with high credit ratings, though in one of the cases in Table A13 these firms nevertheless display a significant amount of seasonality.

Table A14 shows results for the one seasonality strategy not examined in Table 11. This quarterly strategy, based on lags 3, 6, 9, and 12, is qualitatively similar to the quarterly strategy examined in Panel C of Table 11, which uses up to lag 36. Consistent with the rest of our results, using only four quarterly lags results in smaller coefficients and t-statistics, but all estimates remain highly significant.

A.8 Performance graphs

Figure A1 shows histograms of the monthly returns on all the portfolios in Table 7 in addition to the time series reversal and momentum strategies from Table 4. Consistent with results from that table, the figure shows that most long/short portfolios based on individual straddles display positive skewness. Few outliers are observed for short-term reversal, momentum, or seasonality strategies based on individual straddles.

Figure A2 shows the performance of factors over time, representing the performance of an investor who follows each of the strategies in Table 7 on top of a 100% base position in Treasury bills. Because the cumulative returns on some of the portfolios dip below -100%, we choose to show portfolio values corresponding to a delevered position in each strategy, in which the trader takes only a 25% position. The figure shows that the returns to reversal, momentum, and seasonality, when based on individual straddles, are fairly consistent over time, similar to some but not all of the other factors.

Table A1
Summary statistics
This table reports summary statistics for main variables in this study. Returns are reported on a monthly basis.

Variable	Number of Observations	Mean	Standard Deviation	10th percentile	Median	90th percentile
Straddle return	450119	-0.0559	0.8253	-0.8619	-0.2354	0.9385
Average straddle return (lags 2-12)	257629	-0.0491	0.2438	-0.3424	-0.0693	0.2679
Implied volatility (IV)	449364	0.4657	0.2500	0.2162	0.4059	0.7935
Historical volatility (HV)	381423	0.4675	0.2599	0.2193	0.4063	0.7887
IV - HV	380831	0.0011	0.1710	-0.1406	0.0013	0.1434
IV term spread	449364	-0.0081	0.0567	-0.0597	-0.0017	0.0367
IV smile slope	449364	-0.0269	0.1098	-0.1059	-0.0286	0.0475
Equity market capitalization ($ billions)	391805	9.6651	29.9569	0.3243	1.9637	20.0150
Idiosyncratic volatility	391525	0.0235	0.0175	0.0086	0.0188	0.0436
Analyst coverage	423474	11.3801	7.6969	3.0000	10.0000	22.0000
Stock illiquidity	446387	0.0103	0.3951	0.0001	0.0011	0.0137
Option illiquidity	416473	0.1235	0.1226	0.0311	0.0843	0.2603
Realized volatility (RV)	390226	0.4384	0.3052	0.1787	0.3593	0.7825

Table A2

Univariate tercile and decile sorts

Panel A of this table is identical to Panel A of Table 1, except that it uses deciles and terciles rather than quintiles. Panel B is similar to Panel A of Table 6, but again uses deciles and terciles. For brevity, we only report extreme deciles.

Panel A: Reversal and momentum sorts

Min and max lag in formation period		Terciles Low	Terciles Medium	Terciles High	Terciles High - Low	Deciles Low	Deciles High	Deciles High - Low
1	1	-0.0463	-0.0551	-0.0722	-0.0259	-0.0461	-0.0880	-0.0419
		(-2.95)	(-3.62)	(-4.69)	(-5.01)	(-2.95)	(-5.78)	(-5.00)
1	2	-0.0456	-0.0558	-0.0672	-0.0217	-0.0473	-0.0723	-0.0249
		(-3.02)	(-3.49)	(-4.27)	(-3.52)	(-2.97)	(-4.54)	(-2.48)
1	6	-0.0655	-0.0519	-0.0424	0.0231	-0.0684	-0.0380	0.0303
		(-4.18)	(-3.13)	(-2.62)	(3.76)	(-4.10)	(-2.37)	(2.88)
1	12	-0.0688	-0.0478	-0.0308	0.0380	-0.0826	-0.0175	0.0650
		(-4.29)	(-2.78)	(-1.80)	(6.59)	(-5.25)	(-0.98)	(6.51)
2	12	-0.0762	-0.0483	-0.0225	0.0537	-0.0829	-0.0090	0.0739
		(-4.81)	(-2.81)	(-1.32)	(9.74)	(-5.45)	(-0.50)	(7.83)
2	24	-0.0724	-0.0431	-0.0186	0.0538	-0.0820	-0.0090	0.0731
		(-4.18)	(-2.37)	(-1.02)	(8.49)	(-4.31)	(-0.50)	(6.93)
2	36	-0.0759	-0.0408	-0.0265	0.0494	-0.0839	-0.0203	0.0635
		(-4.23)	(-2.17)	(-1.41)	(6.51)	(-4.10)	(-1.08)	(5.37)
13	24	-0.0606	-0.0505	-0.0288	0.0319	-0.0725	-0.0203	0.0522
		(-3.46)	(-2.83)	(-1.66)	(6.08)	(-3.94)	(-1.15)	(5.58)
13	36	-0.0656	-0.0466	-0.0337	0.0320	-0.0746	-0.0323	0.0422
		(-3.64)	(-2.48)	(-1.87)	(4.64)	(-3.77)	(-1.77)	(3.80)
25	36	-0.0650	-0.0479	-0.0391	0.0259	-0.0609	-0.0451	0.0159
		(-3.75)	(-2.62)	(-2.13)	(4.42)	(-3.38)	(-2.43)	(1.62)

Panel B: Seasonality sorts

Formation period	Terciles Low	Terciles Medium	Terciles High	Terciles High - Low	Deciles Low	Deciles High	Deciles High - Low
3,6,9,12	-0.0699	-0.0525	-0.0295	0.0404	-0.0824	-0.0198	0.0627
	(-4.43)	(-3.19)	(-1.69)	(6.74)	(-5.36)	(-1.07)	(6.42)
3,6,...,36	-0.0735	-0.0502	-0.0266	0.0469	-0.0942	-0.0157	0.0785
	(-4.21)	(-2.72)	(-1.44)	(6.93)	(-5.18)	(-0.84)	(7.08)
12,24,36	-0.0681	-0.0565	-0.0353	0.0328	-0.0733	-0.0266	0.0466
	(-4.00)	(-3.15)	(-1.90)	(5.33)	(-4.17)	(-1.40)	(4.98)

Table A3

Univariate sorts with no positive open interest requirement in the holding period

Panel A of this table is identical to Panel A of Table 1, except that straddles without positive open interest at the start of the holding period are also included in the portfolio sorts. Panel B replicates Panel A of Table 6, but again without a positive open interest requirement.

Panel A: Reversal and momentum sorts

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0560	-0.0578	-0.0643	-0.0635	-0.0721	-0.0162
		(-3.64)	(-3.74)	(-4.24)	(-3.96)	(-4.60)	(-2.42)
1	2	-0.0574	-0.0567	-0.0631	-0.0593	-0.0668	-0.0094
		(-3.80)	(-3.72)	(-3.93)	(-3.65)	(-4.14)	(-1.17)
1	6	-0.0729	-0.0640	-0.0529	-0.0487	-0.0366	0.0363
		(-4.63)	(-3.98)	(-3.09)	(-2.88)	(-2.25)	(4.33)
1	12	-0.0783	-0.0597	-0.0487	-0.0338	-0.0283	0.0500
		(-4.91)	(-3.48)	(-2.74)	(-1.98)	(-1.63)	(6.21)
2	12	-0.0861	-0.0620	-0.0504	-0.0346	-0.0160	0.0702
		(-5.47)	(-3.62)	(-2.91)	(-2.02)	(-0.91)	(9.54)
2	24	-0.0776	-0.0659	-0.0410	-0.0266	-0.0122	0.0654
		(-4.41)	(-3.79)	(-2.21)	(-1.38)	(-0.68)	(8.39)
2	36	-0.0806	-0.0671	-0.0371	-0.0296	-0.0225	0.0580
		(-4.24)	(-3.81)	(-1.89)	(-1.47)	(-1.22)	(7.16)
13	24	-0.0667	-0.0576	-0.0476	-0.0385	-0.0241	0.0426
		(-3.70)	(-3.25)	(-2.61)	(-2.14)	(-1.39)	(6.34)
13	36	-0.0712	-0.0572	-0.0453	-0.0336	-0.0314	0.0399
		(-3.84)	(-3.08)	(-2.41)	(-1.78)	(-1.74)	(5.00)
25	36	-0.0681	-0.0596	-0.0429	-0.0432	-0.0398	0.0283
		(-3.90)	(-3.36)	(-2.28)	(-2.26)	(-2.19)	(4.09)

Panel B: Seasonality sorts

Formation period	Low	2	3	4	High	High - Low
3,6,9,12	-0.0802	-0.0644	-0.0546	-0.0385	-0.0227	0.0575
	(-5.12)	(-3.90)	(-3.26)	(-2.21)	(-1.27)	(7.95)
3,6,...,36	-0.0825	-0.0611	-0.0463	-0.0357	-0.0219	0.0606
	(-4.67)	(-3.44)	(-2.45)	(-1.88)	(-1.15)	(7.58)
12,24,36	-0.0733	-0.0637	-0.0592	-0.0416	-0.0332	0.0401
	(-4.27)	(-3.56)	(-3.32)	(-2.19)	(-1.77)	(5.65)

Table A4

Univariate sorts with a positive open interest requirement in the formation period

Panel A of this table is identical to Panel A of Table 1, except that straddles must have positive open interest at the start of each month in the formation period. Panel B replicates Panel A of Table 6, but again with a positive open interest requirement.

Panel A: Reversal and momentum sorts

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0392	-0.0452	-0.0517	-0.0573	-0.0818	-0.0426
		(-2.51)	(-2.83)	(-3.40)	(-3.60)	(-5.41)	(-6.29)
1	2	-0.0330	-0.0417	-0.0476	-0.0580	-0.0719	-0.0389
		(-2.15)	(-2.69)	(-2.93)	(-3.67)	(-4.60)	(-4.85)
1	6	-0.0539	-0.0525	-0.0449	-0.0473	-0.0354	0.0185
		(-3.34)	(-3.34)	(-2.67)	(-2.79)	(-2.23)	(2.21)
1	12	-0.0585	-0.0582	-0.0422	-0.0363	-0.0262	0.0323
		(-3.65)	(-3.36)	(-2.36)	(-2.10)	(-1.53)	(3.65)
2	12	-0.0679	-0.0599	-0.0452	-0.0313	-0.0157	0.0522
		(-4.29)	(-3.54)	(-2.57)	(-1.84)	(-0.90)	(6.50)
2	24	-0.0650	-0.0633	-0.0293	-0.0191	-0.0137	0.0513
		(-3.76)	(-3.65)	(-1.48)	(-0.97)	(-0.78)	(5.87)
2	36	-0.0730	-0.0599	-0.0316	-0.0222	-0.0223	0.0507
		(-3.74)	(-3.25)	(-1.67)	(-1.09)	(-1.19)	(5.13)
13	24	-0.0557	-0.0506	-0.0429	-0.0313	-0.0214	0.0343
		(-3.11)	(-2.82)	(-2.31)	(-1.69)	(-1.25)	(4.14)
13	36	-0.0598	-0.0585	-0.0403	-0.0337	-0.0283	0.0315
		(-3.14)	(-3.16)	(-2.09)	(-1.75)	(-1.53)	(3.08)
25	36	-0.0552	-0.0619	-0.0416	-0.0412	-0.0330	0.0222
		(-3.03)	(-3.49)	(-2.21)	(-2.16)	(-1.79)	(2.45)

Panel B: Seasonality sorts

Formation period	Low	2	3	4	High	High - Low
3,6,9,12	-0.0710	-0.0558	-0.0458	-0.0381	-0.0231	0.0479
	(-4.41)	(-3.48)	(-2.69)	(-2.22)	(-1.31)	(6.09)
3,6,...,36	-0.0780	-0.0558	-0.0426	-0.0363	-0.0203	0.0577
	(-4.36)	(-3.03)	(-2.21)	(-1.84)	(-1.10)	(5.84)
12,24,36	-0.0676	-0.0555	-0.0552	-0.0373	-0.0292	0.0384
	(-3.84)	(-3.04)	(-3.07)	(-1.95)	(-1.59)	(4.93)

Table A5

Univariate sorts of individual momentum

Panel A of this table is identical to Panel A of Table 1, except that instead of using the straddle that is closest to at-the-money, we construct an equal weighted portfolio for each stock consisting of all straddles whose call delta is between 0.25 and 0.75, including options with zero open interest. These average returns are used both for the formation and holding periods. Panel B replicates Panel A of Table 6 but uses the same average straddle returns.

Panel A: Reversal and momentum sorts

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0614	-0.0566	-0.0670	-0.0663	-0.0736	-0.0121
		(-4.03)	(-3.67)	(-4.47)	(-4.20)	(-4.79)	(-1.91)
1	2	-0.0604	-0.0612	-0.0624	-0.0626	-0.0681	-0.0078
		(-4.03)	(-4.03)	(-3.89)	(-3.95)	(-4.29)	(-0.96)
1	6	-0.0772	-0.0631	-0.0564	-0.0491	-0.0416	0.0356
		(-4.91)	(-3.92)	(-3.47)	(-2.89)	(-2.61)	(4.31)
1	12	-0.0824	-0.0583	-0.0544	-0.0375	-0.0306	0.0518
		(-5.26)	(-3.51)	(-3.08)	(-2.20)	(-1.80)	(7.10)
2	12	-0.0903	-0.0642	-0.0516	-0.0368	-0.0201	0.0702
		(-5.87)	(-3.86)	(-3.00)	(-2.16)	(-1.16)	(10.02)
2	24	-0.0805	-0.0653	-0.0407	-0.0357	-0.0139	0.0666
		(-4.61)	(-3.93)	(-2.25)	(-1.84)	(-0.79)	(9.14)
2	36	-0.0823	-0.0662	-0.0448	-0.0357	-0.0221	0.0602
		(-4.52)	(-3.71)	(-2.35)	(-1.81)	(-1.20)	(7.19)
13	24	-0.0698	-0.0592	-0.0478	-0.0430	-0.0256	0.0442
		(-4.01)	(-3.43)	(-2.58)	(-2.42)	(-1.48)	(6.30)
13	36	-0.0732	-0.0583	-0.0498	-0.0365	-0.0335	0.0397
		(-4.02)	(-3.18)	(-2.66)	(-2.01)	(-1.84)	(4.80)
25	36	-0.0699	-0.0613	-0.0484	-0.0454	-0.0412	0.0287
		(-4.09)	(-3.49)	(-2.60)	(-2.45)	(-2.26)	(4.01)

Panel B: Seasonality sorts

Time period	Low	2	3	4	High	High - Low
3,6,9,12	-0.0816	-0.0693	-0.0547	-0.0438	-0.0237	0.0579
	(-5.32)	(-4.30)	(-3.31)	(-2.52)	(-1.33)	(7.97)
3,6,...,36	-0.0859	-0.0635	-0.0486	-0.0425	-0.0217	0.0642
	(-5.00)	(-3.62)	(-2.66)	(-2.20)	(-1.17)	(7.93)
12,24,36	-0.0749	-0.0664	-0.0616	-0.0475	-0.0329	0.0420
	(-4.41)	(-3.79)	(-3.49)	(-2.54)	(-1.78)	(6.07)

Table A6
Univariate sorts of individual momentum

Panel A of this table is identical to Panel A of Table 1, except that straddles are only included if the underlying stock does not pay a dividend during the holding period. Panel B replicates Panel A of Table 6, but again with sample that does not pay dividends.

Panel A: Reversal and momentum sorts

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0418	-0.0461	-0.0509	-0.0586	-0.0808	-0.0391
		(-2.76)	(-2.95)	(-3.42)	(-3.72)	(-5.37)	(-5.89)
1	2	-0.0401	-0.0443	-0.0517	-0.0612	-0.0717	-0.0316
		(-2.68)	(-2.94)	(-3.19)	(-3.88)	(-4.64)	(-3.96)
1	6	-0.0621	-0.0589	-0.0489	-0.0480	-0.0397	0.0223
		(-4.02)	(-3.77)	(-2.90)	(-2.91)	(-2.54)	(2.82)
1	12	-0.0718	-0.0551	-0.0492	-0.0329	-0.0283	0.0435
		(-4.67)	(-3.21)	(-2.81)	(-2.00)	(-1.67)	(5.59)
2	12	-0.0778	-0.0616	-0.0485	-0.0325	-0.0160	0.0619
		(-5.00)	(-3.74)	(-2.84)	(-1.94)	(-0.94)	(8.36)
2	24	-0.0700	-0.0648	-0.0376	-0.0239	-0.0143	0.0557
		(-4.04)	(-3.79)	(-2.04)	(-1.26)	(-0.82)	(6.92)
2	36	-0.0718	-0.0677	-0.0370	-0.0265	-0.0229	0.0488
		(-3.83)	(-3.85)	(-1.94)	(-1.32)	(-1.27)	(5.24)
13	24	-0.0630	-0.0555	-0.0435	-0.0367	-0.0243	0.0387
		(-3.65)	(-3.11)	(-2.45)	(-2.06)	(-1.45)	(5.69)
13	36	-0.0656	-0.0594	-0.0414	-0.0329	-0.0296	0.0360
		(-3.52)	(-3.27)	(-2.18)	(-1.76)	(-1.72)	(3.92)
25	36	-0.0630	-0.0565	-0.0401	-0.0440	-0.0356	0.0274
		(-3.63)	(-3.23)	(-2.21)	(-2.32)	(-2.02)	(3.49)

Panel B: Seasonality sorts

Time period	Low	2	3	4	High	High - Low
3,6,9,12	-0.0758	-0.0589	-0.0518	-0.0368	-0.0218	0.0540
	(-4.95)	(-3.63)	(-3.18)	(-2.15)	(-1.25)	(6.95)
3,6,...,36	-0.0760	-0.0578	-0.0457	-0.0370	-0.0201	0.0559
	(-4.32)	(-3.34)	(-2.45)	(-1.99)	(-1.10)	(6.71)
12,24,36	-0.0698	-0.0601	-0.0538	-0.0376	-0.0320	0.0378
	(-4.03)	(-3.47)	(-3.04)	(-2.04)	(-1.77)	(4.99)

Table A7

Univariate sorts based on cumulative straddle returns

This table is identical to Panel A of Table 1, except that we sort based on cumulative return rather than average return over the formation period.

Min and max lag in formation period		Low	2	3	4	High	High - Low
1	1	-0.0456	-0.0480	-0.0557	-0.0603	-0.0798	-0.0342
		(-2.93)	(-3.03)	(-3.65)	(-3.81)	(-5.26)	(-5.23)
1	2	-0.0486	-0.0465	-0.0576	-0.0603	-0.0686	-0.0200
		(-3.21)	(-2.97)	(-3.62)	(-3.82)	(-4.32)	(-2.83)
1	6	-0.0619	-0.0559	-0.0566	-0.0471	-0.0444	0.0175
		(-3.90)	(-3.51)	(-3.49)	(-2.80)	(-2.74)	(2.94)
1	12	-0.0633	-0.0578	-0.0503	-0.0436	-0.0301	0.0331
		(-3.95)	(-3.38)	(-2.99)	(-2.62)	(-1.70)	(4.74)
2	12	-0.0682	-0.0603	-0.0535	-0.0422	-0.0196	0.0486
		(-4.33)	(-3.54)	(-3.22)	(-2.49)	(-1.11)	(7.45)
2	24	-0.0612	-0.0566	-0.0457	-0.0359	-0.0233	0.0379
		(-3.38)	(-3.26)	(-2.52)	(-1.98)	(-1.27)	(5.53)
2	36	-0.0585	-0.0553	-0.0535	-0.0355	-0.0332	0.0253
		(-3.10)	(-2.89)	(-2.86)	(-1.81)	(-1.82)	(3.49)
13	24	-0.0553	-0.0517	-0.0483	-0.0439	-0.0329	0.0224
		(-3.16)	(-2.98)	(-2.65)	(-2.41)	(-1.92)	(4.14)
13	36	-0.0569	-0.0498	-0.0513	-0.0457	-0.0378	0.0191
		(-3.08)	(-2.67)	(-2.75)	(-2.45)	(-2.10)	(2.61)
25	36	-0.0561	-0.0591	-0.0517	-0.0474	-0.0386	0.0175
		(-3.04)	(-3.36)	(-2.84)	(-2.61)	(-2.07)	(2.39)

Table A8

Two-way sorts by stock momentum and option momentum

This table shows the average returns of portfolios formed from sequential tercile sorts, first on average stock returns and then on average straddle returns, both from the formation period starting at lag 12 and ending at lag 2. T-statistics, in parentheses, are computed using Newey-West standard errors with three lags.

		Individual straddle momentum			
		Low	2	High	High - Low
Stock momentum	1	-0.0656	-0.0330	-0.0134	0.0522
		(-4.21)	(-1.90)	(-0.72)	(5.03)
	2	-0.0761	-0.0585	-0.0396	0.0365
		(-4.27)	(-3.04)	(-2.10)	(4.85)
	3	-0.0771	-0.0493	-0.0254	0.0517
		(-4.65)	(-2.76)	(-1.46)	(7.45)
	High - Low	-0.0115	-0.0163	-0.0120	-0.0005
		(-1.20)	(-1.44)	(-0.87)	(-0.04)

Table A9
Panel regressions
This table reports the results of panel regressions in which monthly zero delta straddle returns are the dependent variable. Independent variables include a measure of average lagged returns and five other stock-level characteristics. T-statistics, in parentheses, are computed using standard errors that cluster by date.

Min and max lag in formation period		Intercept	Past return	IV - HV	Idiosyncratic vol	Market cap	IV term spread	IV smile slope	Pooled R^2
		-0.0366		-0.0472	-0.8445	0.1254	0.2816	0.0094	0.0011
		(-1.92)		(-1.06)	(-2.17)	(1.49)	(3.19)	(0.18)	
1	1	-0.0543	-0.0066						0.0000
		(-3.56)	(-0.94)						
1	1	-0.0346	-0.0027	-0.0434	-0.8486	0.1065	0.2579	0.0130	0.0010
		(-1.72)	(-0.39)	(-0.93)	(-1.93)	(1.25)	(2.73)	(0.22)	
1	2	-0.0521	-0.0017						0.0000
		(-3.33)	(-0.18)						
1	2	-0.0318	0.0022	-0.0335	-0.8750	0.0936	0.2541	0.0158	0.0009
		(-1.53)	(0.22)	(-0.68)	(-1.94)	(1.12)	(2.55)	(0.24)	
1	6	-0.0453	0.0325						0.0002
		(-2.77)	(2.07)						
1	6	-0.0202	0.0403	-0.0136	-0.9944	0.0491	0.2623	0.0530	0.0010
		(-0.94)	(2.68)	(-0.24)	(-2.06)	(0.58)	(2.31)	(0.60)	
1	12	-0.0386	0.0660						0.0004
		(-2.24)	(2.84)						
1	12	-0.0104	0.0818	0.0402	-1.0875	0.0068	0.3272	0.0572	0.0012
		(-0.45)	(3.37)	(0.53)	(-2.06)	(0.08)	(2.48)	(0.54)	
2	12	-0.0381	0.0742						0.0005
		(-2.22)	(3.39)						
2	12	-0.0117	0.0859	0.0470	-1.0086	0.0165	0.3445	0.0572	0.0014
		(-0.52)	(3.80)	(0.62)	(-1.96)	(0.19)	(2.62)	(0.57)	
2	24	-0.0357	0.0971						0.0004
		(-2.07)	(3.50)						
2	24	-0.0064	0.1228	0.0915	-1.1463	0.0215	0.3829	0.0872	0.0015
		(-0.28)	(4.12)	(1.08)	(-2.03)	(0.27)	(2.61)	(0.82)	
2	36	-0.0320	0.1255						0.0005
		(-1.74)	(3.73)						
2	36	0.0060	0.1705	0.1237	-1.5599	0.0203	0.3635	0.1398	0.0020
		(0.23)	(4.33)	(1.34)	(-2.42)	(0.24)	(2.17)	(1.23)	
13	24	-0.0439	0.0371						0.0001
		(-2.67)	(1.78)						
13	24	-0.0200	0.0452	0.0431	-1.0138	0.0852	0.3350	0.0723	0.0011
		(-0.91)	(2.11)	(0.56)	(-1.97)	(1.05)	(2.64)	(0.86)	
13	36	-0.0385	0.0720						0.0002
		(-2.17)	(2.66)						
13	36	-0.0079	0.0948	0.0766	-1.3284	0.0639	0.3526	0.1066	0.0015
		(-0.32)	(3.15)	(0.91)	(-2.25)	(0.75)	(2.34)	(1.13)	
25	36	-0.0426	0.0390						0.0001
		(-2.38)	(1.69)						
25	36	-0.0160	0.0473	0.0459	-1.2248	0.0748	0.3404	0.0768	0.0012
		(-0.65)	(1.90)	(0.61)	(-2.10)	(0.84)	(2.42)	(0.95)	

Table A10

Spanning tests for alternative short-term strategies

This table is identical to Table 9 except that it is based on a formation period that includes just a single month at lag 1. In each panel, the dependent variable is the return on a portfolio that goes long past winners and short past losers.

-------------------- 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 based on individual straddle returns									
-0.0342				0	0.0035				0.1508
(-5.23)					(0.23)				
-0.0348		0.1607		0.1223	-0.0050		0.1527		0.2543
(-5.40)		(3.70)			(-0.36)		(5.04)		
-0.0367			0.0518	0.0092	0.0046			0.1208	0.1959
(-5.79)			(1.44)		(0.31)			(3.84)	
Panel B: Dependent variable is based on industry returns									
0.0037				0	0.0557				0.0630
(0.24)					(2.11)				
0.0297	0.7609			0.1223	0.0528	0.7979			0.1772
(2.04)	(6.24)				(2.22)	(6.00)			
0.0026			0.0212	0.0003	0.0561			0.0544	0.0650
(0.18)			(0.27)		(2.13)			(0.79)	
Panel C: Dependent variable is based on factor returns									
0.0487				0	-0.0091				0.0956
(4.03)					(-0.41)				
0.0548	0.1770			0.0092	-0.0107	0.4398			0.1436
(4.17)	(1.19)				(-0.53)	(3.42)			
0.0486		0.0153		0.0003	-0.0112		0.0379		0.0974
(4.03)		(0.27)			(-0.51)		(0.79)		

Table A11
Additional controls for seasonality regressions
This table is similar to Panel B of Table 6 but uses other firm characteristics as control variables.

Intercept	Seasonality	IV - HV	Idio. volatility	Market cap	IV term spread	IV smile slope	Avg. CS R^2
			lags {3,6,9,12}				
-0.0493	0.0461						0.0028
(-3.01)	(7.22)						
-0.0201	0.0457	-0.1725	-1.3697	0.0000	0.4915	0.0651	0.0197
(-0.98)	(7.34)	(-5.77)	(-4.90)	(-1.86)	(7.07)	(2.15)	
			lags {3,6,...,36}				
-0.0446	0.0897						0.0041
(-2.48)	(7.15)						
-0.0217	0.0933	-0.1089	-1.1541	0.0000	0.5629	0.1565	0.0260
(-0.98)	(7.62)	(-2.69)	(-3.35)	(-1.22)	(5.41)	(2.61)	
			lags {12,24,36}				
-0.0498	0.0354						0.0029
(-2.79)	(6.18)						
-0.0322	0.0359	-0.1476	-0.9484	0.0000	0.5394	0.0747	0.0209
(-1.47)	(6.73)	(-4.01)	(-3.13)	(-1.23)	(6.03)	(2.06)	

Table A12

Factor risk adjustment for seasonality strategies

This table is identical to Table 8 except that it examines factor adjustment for seasonality strategies rather than reversal and momentum strategies.

Intercept	IV - HV	Idio. volatility	Market cap	IV term spread	IV smile slope	Short SPX straddle	Short EW stock straddle	R^2
				lags {3,6,9,12}				
0.0405	-0.1093	0.1232	0.0834			-0.0024		0.0459
(4.04)	(-1.70)	(2.21)	(1.33)			(-0.14)		
0.0571	-0.0605	0.1698	0.1152	-0.0551	0.0991	0.0325	-0.1681	0.0970
(4.27)	(-0.82)	(2.71)	(1.97)	(-0.63)	(1.10)	(1.75)	(-1.91)	
				lags {3,6,...,36}				
0.0559	-0.0355	0.2482	0.1694			-0.0097		0.0672
(4.83)	(-0.44)	(2.67)	(2.66)			(-0.57)		
0.0641	-0.0054	0.2787	0.1871	-0.0175	0.0762	0.0084	-0.0849	0.0793
(4.46)	(-0.07)	(3.44)	(2.73)	(-0.16)	(0.68)	(0.41)	(-1.69)	
				lags {12,24,36}				
0.0218	-0.1427	0.0196	0.0208			-0.0012		0.0409
(2.15)	(-2.16)	(0.31)	(0.35)			(-0.07)		
0.0261	-0.1758	0.0274	0.0322	-0.0905	0.0716	-0.0001	-0.0126	0.0486
(2.01)	(-2.29)	(0.44)	(0.51)	(-1.19)	(0.78)	(-0.00)	(-0.21)	

Table A13

Pervasiveness of alternative seasonality strategies

This table is identical to Table 10 except that it reports results for the two seasonality strategies not considered in that table.

Panel A: Subgroup results for the annual seasonality strategy, which includes lags 12, 24, and 36

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
L	0.0371	0.0273	0.0349	0.0277	0.0371	No downgrade	0.0316
	(4.32)	(3.48)	(4.33)	(3.21)	(3.57)		(3.89)
M	0.0293	0.0328	0.0233	0.0320	0.0310	Downgrade	0.0243
	(3.54)	(4.06)	(3.02)	(3.97)	(2.47)		(1.96)
H	0.0333	0.0376	0.0360	0.0303	-0.0001	No rating	0.0378
	(4.14)	(4.42)	(4.35)	(3.91)	(-0.01)		(4.89)
H-L	-0.0038	0.0103	0.0011	0.0026	-0.0372		
	(-0.37)	(1.07)	(0.11)	(0.30)	(-2.70)		

Panel B: Subgroup results for the alternative quarterly seasonality strategy, which includes lags 3, 6, 9, and 12

	Firm Size	Stock Illiquidity	Option Illiquidity	Analyst Coverage	Credit Rating		
L	0.0463	0.0352	0.0391	0.0433	0.0475	No downgrade	0.0325
	(5.26)	(5.07)	(4.92)	(5.70)	(4.19)		(4.25)
M	0.0446	0.0337	0.0366	0.0374	0.0206	Downgrade	0.0213
	(6.58)	(4.85)	(5.19)	(4.78)	(2.19)		(1.21)
H	0.0345	0.0488	0.0399	0.0381	0.0221	No rating	0.0480
	(4.49)	(5.68)	(4.65)	(4.61)	(2.20)		(7.51)
H-L	-0.0119	0.0137	0.0008	-0.0052	-0.0254		
	(-1.20)	(1.56)	(0.08)	(-0.55)	(-2.14)		

Table A14
Explaining seasonality with volatility swap returns
This table is identical to Panel C of Table 11 except that it examines the quarterly seasonality strategy that is based only on lags 3, 6, 9, and 12.

Formation period includes lags 3, 6, 9, and 12

Intercept	Straddle return	Volatility swap return	Volatility surprise	Volatility risk premium	Avg. CS R^2
-0.0525	0.0464				0.0030
(-3.15)	(6.97)				
-0.0469		0.1112			0.0032
(-2.77)		(8.05)			
-0.0479	0.0306	0.0788			0.0059
(-2.84)	(4.06)	(5.02)			
-0.0400			0.1005	0.1601	0.0056
(-2.33)			(7.15)	(8.05)	
-0.0404	0.0328		0.0646	0.1310	0.0084
(-2.36)	(4.26)		(3.93)	(6.54)	

Figure A1

Factor return distributions

This figure shows histograms of the monthly returns on 18 different factor portfolios. They include the 16 portfolios analyzed in Table 7, in addition to two of the time-series strategies examined in Table 4. Each portfolio is composed of zero delta straddles.

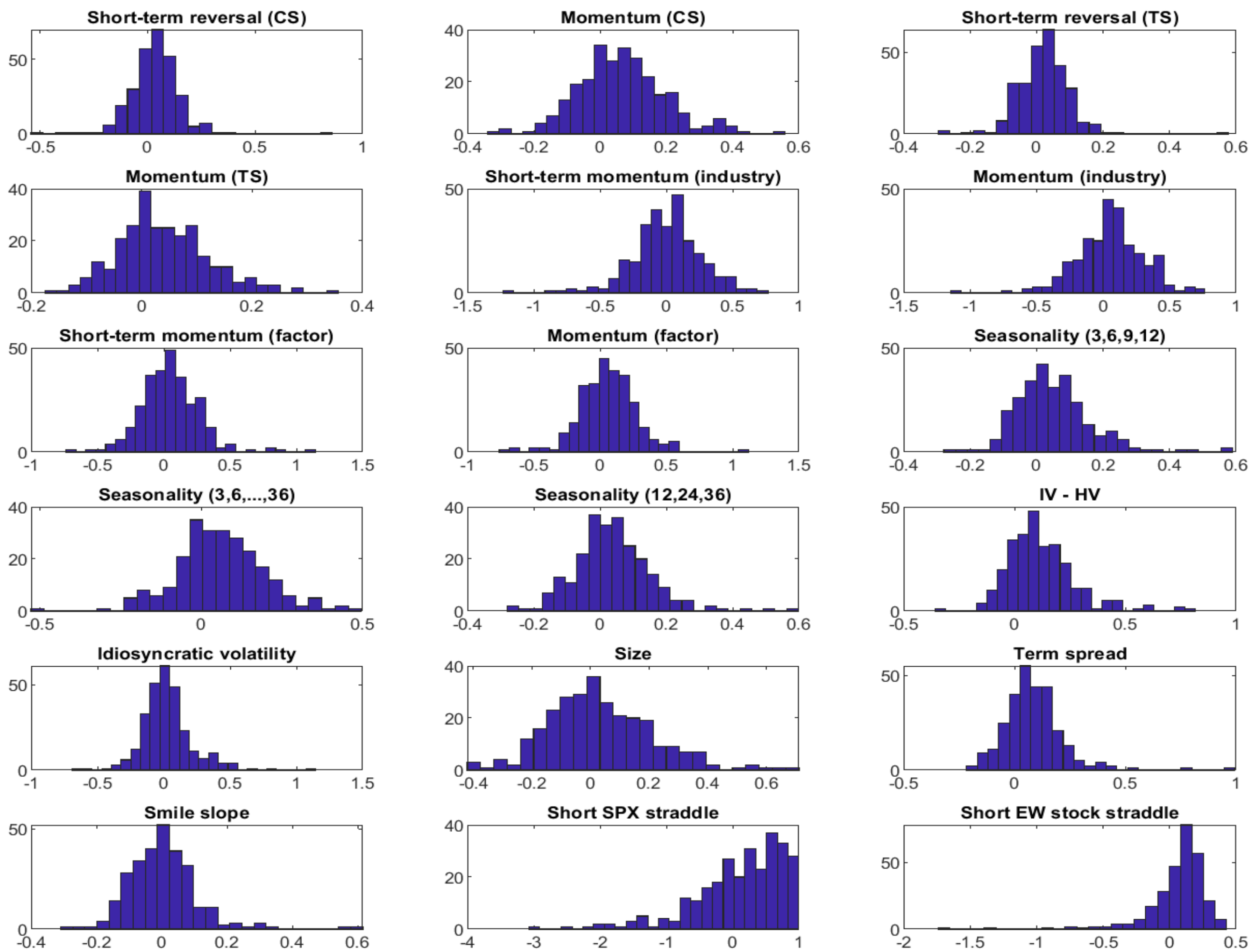

Figure A2

Cumulative performance of factor portfolios

This figure shows the cumulative performance of 18 delevered factor portfolios. They include the 16 portfolios analyzed in Table 7, in addition to two of the time-series strategies examined in Table 4. Each delevered portfolio represents a 100% position in Treasury bills and a 25% position in a zero-cost straddle portfolio.