Option Factor Momentum

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This version: March 15, 2023

Abstract

We document profitable cross-sectional and time-series momentum in a broad set of 56 option factors constructed from monthly sorts on daily delta-hedged option positions. Option factor returns are highly autocorrelated, but momentum profits of strategies with longer formation periods are mainly driven by high mean returns that persistently differ across factors. Momentum effects are the strongest in the factors' largest principal components, consistent with findings for stock factor momentum. Finally, we find a new form of momentum in options markets: momentum in single delta-hedged option returns. Option factor momentum fully subsumes option momentum, whereas option momentum cannot explain option factor momentum. Our findings provide insights into the channels that drive option momentum and have implications for designing profitable option trading strategies.

JEL classification: G11, G12, G14

Keywords: Options, momentum, factor momentum

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1. Introduction

The existence of momentum, the continuation of past, relative asset returns into the future, has questioned the efficiency of markets for over 30 years. The profitability of momentum strategies has been documented for various asset classes and investment regions.[1] Most recently, Heston, Jones, Khorram, Li, & Mo (2022) document momentum in option straddle returns. To explain momentum profits, a new strand of literature focuses on momentum in factors that describe the cross-section of returns. Gupta & Kelly (2019) show that strong autocorrelation in equity factors results in profitable time-series momentum strategies. Ehsani & Linnainmaa (2022) show that factor momentum subsumes stock momentum, and results of Arnott, Kalesnik, & Linnainmaa (2023) suggest that factor momentum also explains industry momentum. On the contrary, Heston et al. (2022) find that a momentum strategy based on seven option factors cannot explain the momentum inherent in straddle returns.

Our paper utilizes a large set of 56 option factors to assess factor momentum in an asset class which has attracted considerable interest from practitioners and academics alike. According to data from the Options Clearing Corporation, the average daily volume amounted to 41.1 million contracts in 2022 compared to just 11.4 million contracts in 2007.[2] Our sample of option factors largely coincides with those analyzed in Goyal & Saretto (2022), but we extend it by 12 more factors. We construct our factors from monthly returns on daily delta-hedged call positions from January 1996 to December 2021.

Using various formation periods, we form time-series and cross-sectional momentum strategies for option factors. For cross-sectional momentum strategies, we assign a long position to a factor with an above-median return in the formation period and a short position otherwise. For the time-series momentum strategy, we assign the positions based on the sign of each factor's formation period return. Strategies are rebalanced monthly. Compared to Ehsani & Linnainmaa (2022) and Arnott et al. (2023), who focus on the 1-year and 1-month formation periods respectively, we offer a more comprehensive sample of factor momentum strategies.

Time-series and cross-sectional factor momentum strategies across all formation peri-

[1] See Jegadeesh & Titman (1993) for U.S. stocks, Rouwenhorst (1998) for international stocks, Miffre & Rallis (2007) for commodity markets, Jostova, Nikolova, Philipov, & Stahel (2013) for corporate bonds, and Liu, Tsyvinski, & Wu (2022) for cryptocurrencies.

[2] `https://www.theocc.com/market-data/market-data-reports/volume-and-open-interest/historical-volume-statistics`

ods produce positive and statistically significant annualized mean returns, ranging from 5.56% (t-stat: 6.42) to 13.62% (t-stat: 9.87). The strategies offer returns distinct from an equal-weighted option factor portfolio and the option factor model of Horenstein, Vasquez, & Xiao (2020), with annualized information ratios ranging from 0.59 to 2.40.

Due to high unconditional mean returns in option factors with high cross-sectional variation, we conduct multiple momentum return decompositions, following Lo & MacKinlay (1990), Moskowitz, Ooi, & Pedersen (2012), and Leippold & Yang (2021). While autocovariance substantially drives momentum for the 1-month formation period, persistent differences in factor returns drive momentum for longer formation periods because returns over longer formation periods resemble unconditional mean returns more closely. This result contrasts the findings of Ehsani & Linnainmaa (2022) for the stock market. However, our results extend the findings of Leippold & Yang (2021) to the options market. Leippold & Yang (2021) show that alphas of factor momentum in stocks can be largely explained by a buy-and-hold strategy based on the factors' unconditional returns.

Both in Ehsani & Linnainmaa (2022) and in Arnott et al. (2023), the largest principal components (PCs) of the set of equity factors subsume the momentum in lower PCs and in the underlying factors. The authors argue that predictable autocovariance only exists in factors with high systemic risk. Otherwise, there would be near arbitrage opportunities. In the case of options, while the largest 10 PCs capture the momentum in PCs 30-56, we still identify distinct momentum effects in PCs 11-30. We explain this deviation in two ways. First, in option factor momentum, expected returns play a larger role than autocovariances. This transmits into all PCs, not just the largest ones. Second, the amount of predictable PCs increases in the maximum squared Sharpe ratio (Haddad, Kozak, & Santosh, 2020). Since the squared Sharpe ratio is much higher in the optimal option factor portfolio than in the optimal equity factor portfolio, the predictability stretches to more PCs.

Finally, we document a new form of momentum in options markets: momentum in single delta-hedged option returns. Single-option return momentum strategies yield positive and significant profits for the 1-month, the 6-month, and the 1-year (excluding the most recent month) formation periods. Mean returns range from 2.96% (t-stat: 4.04) to 6.02% (t-stat: 4.50) per year. The strategies based on the latter two formation periods are robust to controlling for the risk factors proposed by Horenstein et al. (2020). In pairwise spanning tests, our factor momentum strategies can fully explain time-series and cross-sectional momentum in single options. On the other hand, significant alphas remain across all factor momentum strategies after controlling for option momentum, with

t-stats ranging from 6.46 to 11.16. The explanatory power of option factor momentum is concentrated in the largest eigenvalue principal components of the factor set.

The paper is structured as follows. In section 2, we summarize recent advances in research relevant to our paper. In section 3, we describe the data sources and daily delta-hedged option return and factor construction. In section 4, we present the main results. Section 5 concludes.

2. Related literature

Our study extends the nascent literature on factor momentum. Gupta & Kelly (2019) examine 65 characteristic-based equity factors and find significant positive autocorrelation in 49 factors. Ehsani & Linnainmaa (2022) build on a model of Kozak, Nagel, & Santosh (2018) and propose that persistence in sentiment-driven excess demand leads to persistence in factor returns. Rational arbitrageurs would have to carry a high risk to trade against the excess demand that lines up with high eigenvalue principal components of the factor set. Therefore predictability remains in those principal components. Ehsani & Linnainmaa (2022) show that the momentum in their factors' highest eigenvalue principal components subsumes not only the momentum in lower eigenvalue principal components but also various forms of stock momentum, such as residual momentum and intermediate horizon momentum. Additionally, Arnott et al. (2023) show that cross-sectional factor momentum subsumes industry momentum. Zhang (2022) finds that momentum in the dollar and carry factors subsumes currency momentum. Factor momentum is another addition to possible explanations for the existence of momentum effects in financial markets. Other explanations include behavioral-based explanations such as underreaction and overreaction theories (e.g., Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998; Hong & Stein, 1999; Grinblatt & Han, 2005), and risk-based explanations (e.g., Berk, Green, & Naik, 1999; Pástor & Stambaugh, 2003; Avramov, Chordia, Jostova, & Philipov, 2007; Kelly, Moskowitz, & Pruitt, 2021).

Naturally, momentum in option factors relies on the existence of factors with predictive power for the cross-section of option returns. Thus, our study also relates to the strand of literature that examines the predictability of options returns. In this context, many studies relate option returns and prices to various option and stock-related characteristics. Notably, Goyal & Saretto (2009) find that the difference between historical realized volatility and implied volatility negatively predicts future returns of straddles and delta-hedged call portfolios. Cao & Han (2013) document a negative relationship between the underlying stock's idiosyncratic volatility and delta-hedged option returns. By focusing on changes in implied volatility as a proxy for option returns, An, Ang, Bali, & Cakici (2014) show that positive (negative) past stock returns are associated with an increase (decrease) in implied volatility over the next month. Vasquez (2017) finds a positive relationship between the slope of the implied volatility term structure and the future return of straddle portfolios. Investigating variation in implied volatility levels, skew, and term structure using principal component analyses, Christoffersen, Fournier, & Jacobs (2018) unveil a strong factor structure inherent in equity options. More recently, Zhan, Han, Cao, & Tong (2022) provide evidence of predictability in the cross-section of delta-hedged option returns related to many stock-level characteristics such as stock price, profitability, or cash holdings.

Furthermore, a particular point of interest in the option return-related literature is the role of intermediaries and liquidity on option prices. For instance, Garleanu, Pedersen, & Poteshman (2008) empirically verify a demand-based option pricing model by showing that demand-pressure increases option prices as market makers cannot perfectly hedge their option exposure. Muravyev (2016) finds that imbalances in order flow increase option prices due to the increased inventory risk of market makers. Similarly, Christoffersen, Goyenko, Jacobs, & Karoui (2018) relate higher expected option returns to the existence of illiquidity premia as market makers are compensated for holding large illiquid option positions. In a related study, Kanne, Korn, & Uhrig-Homburg (2023) show that illiquidity premia are negative (positive) if there is net buying (selling) pressure by option end users.

Other studies point towards the impact of behavioral biases and effects on option returns. Bali & Murray (2013) find a negative relationship between option positions' risk-neutral skewness and returns, consistent with the notion of a positive skewness preference by investors. Byun & Kim (2016) show that lottery-like properties of underlying stocks lead to overvaluation in call options as investors exhibit gambling preferences. Moreover, Boulatov, Eisdorfer, Goyal, & Zhdanov (2022) show that investor inattention leads to investors perceiving options on low-priced stocks as cheap resulting in future underperformance of these options.

Given the abundance of possible option return predictors, recent research has applied machine learning techniques to determine the most important predictors. Bali, Beckmeyer, Moerke, & Weigert (2023) highlight the added benefits of using stock alongside option characteristics in forecasting option returns.

Finally, based on the empirically verified predictability of option returns, recent research has focused on option factor models that explain the cross-section of option returns. When making risk adjustments to options returns, many studies (e.g., Zhan et al., 2022) use common risk factors in the stock market as proposed in Fama & French (1993), Fama & French (2015), or Carhart (1997) and supplement them with aggregate option-based risk factors such as a delta-neutral straddle of S&P500 options (Coval & Shumway, 2001) to proxy for illiquidity risk. Büchner & Kelly (2022) use the methodology of instrumented principal component analysis, detailed in Kelly, Pruitt, & Su (2020), to propose a factor model for S&P 500 index options. Karakaya (2014) proposes a factor model that comprises a level, slope, and value factor constructed using delta-hedged returns on equity options. Zhan et al. (2022) show that a two-factor model using idiosyncratic volatility and stock illiquidity can explain returns to portfolios sorted by various stock-level characteristics. Bali, Cao, Song, & Zhan (2022) suggest a five-factor model comprising the option bid-ask spread, the option price, the model-free implied kurtosis, the difference between realized and implied volatilities and a dollar open-interest weighted average of all delta-hedged call returns. Moreover, Horenstein et al. (2020) propose a four-factor model consisting of the return on delta-hedged S&P500 calls, and three long-short factors based on sorting options by the idiosyncratic volatility and size of the underlying stock, as well as the difference between historical and implied volatility. Goyal & Saretto (2022) apply instrumented principal component analysis on a set of 44 option return-based factors and obtain a latent factor model that can explain the returns of most option trading strategies.

3. Data

Our primary data source is OptionMetrics IvyDB, which provides historical prices for all U.S. single equity options. We obtain option data from OptionMetrics for the period from January 1996 to December 2021. Additionally, we source interpolated volatility surface data from OptionMetrics. Volatility surface data is only required for constructing option-based characteristics, whereas option returns are based on historical option prices.

Historical prices for underlying stocks are obtained from CRSP. We retain only underlying stocks with share codes 10 or 11. Moreover, to avoid options on highly illiquid underlying stocks, we exclude stocks with a prior month's closing price below USD 5. We match CRSP with OpionMetrics using the linking algorithm provided by WRDS. Daily risk-free rates are taken from Kenneth French's online data library.[3]

3.1. Option returns

To construct option factor returns, we use the excess return of buying a delta-hedged call option on a daily rebalancing schedule. In line with previous literature (e.g., Horenstein et al., 2020), we focus on call options for our analyses as these contracts have a higher volume than puts (Bollen & Whaley, 2004). For the computation of delta-hedged returns, we first consider delta-hedged call gains following Bakshi, Kapadia, & Madan (2003) as the value of a self-financing portfolio consisting of a long call, hedged by a position in the underlying such that the portfolio is locally immune to changes in the stock price. To establish notation, consider the partition $\Pi = \{t = t_0 < \cdots < t_N = t + \tau\}$ of the interval from t to $t + \tau$. Assume that the long option position is hedged discretely N times at each of the dates $t_n, n = 0, \ldots, N - 1$. The discrete delta-hedged call option gain over the period $[t, t + \tau]$ is then given by

$$\begin{aligned}\Pi(t, t+\tau) = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{C,t_n} \left[S(t_{n+1}) - S(t_n)\right] \\ - \sum_{n=0}^{N-1} \frac{a_n r_n}{365} \left[C(t_n) - \Delta_{C,t_n} S(t_n)\right], \end{aligned} \tag{1}$$

where C_t denotes the price of the call option at time t, r_n is the risk-free rate at t_n, a_n is the number of calendar days between rehedging dates t_n and t_{n+1}, which we set to $a_n = 1$, and Δ_{C,t_n} is the observed delta of the call. We consider gains for investment horizons of one calendar month.[4] Finally, we define option returns following Cao & Han (2013) as

$$r_{t,t+\tau} = \frac{\Pi(t, t+\tau)}{\Delta_t S_t - C_t}. \tag{2}$$

As robustness checks, we alter the return definition in equation 2 to account for margin requirements. Details are given in Appendix B.1.

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] In case we have missing option data when we close an option position, we take the option's intrinsic value as a conservative estimate of the option price (Vasquez, 2017).

Table 1: **Summary statistics of individual options.**
This table reports summary statistics of our final sample of monthly call option data used to construct option factors. The sample is from February 1996 to December 2021. Daily delta-hedged option returns are the monthly returns of a delta-hedged call position that is daily adjusted to be immune to changes in the underlying. Details are outlined in section 3. Margin-adjusted option returns are delta-hedged returns scaled by the margin requirement for sustaining a delta-hedged option position over a monthly period. Details are outlined in Appendix B.1. Open interest is the call contract's open interest at the beginning of the month. Delta is the option's Black & Scholes (1973) delta as provided by OptionMetrics. Moneyness is the ratio of the option's strike price (K) over the underlying stock price (S). Time to maturity is the days until the option's expiration. The bid-ask spread is the option contract's bid-ask spread in proportion to the option mid price at the beginning of the month. Size is the underlying stock's total market capitalization at the beginning of the month. ILLIQ is the underlying stock's Amihud (2002) illiquidity measure at the beginning of the month.

Variable	N	Mean	SD	10^{th} pct.	Median	90^{th} pct.
# of underlying stocks each month	311	749.81	151.9	571	656.5	741
Option return (daily delta-hedged, in %)	233192	-0.07	6.83	-5.14	-0.57	5.05
Option return (margin-adjusted, in %)	233192	0.03	8.65	-6.65	-0.83	6.85
Open interest	233192	1205.05	5034.03	5	153	2448
Delta	233192	0.51	0.13	0.33	0.52	0.67
Moneyness (K/S)	233192	1.02	0.06	0.95	1.01	1.1
Time to maturity (in days)	233192	49.65	2.1	46	50	52
Bid-ask spread (in %)	233192	18.5	20.73	4.13	12.24	40
Size	233109	10.83	41.17	0.39	2.26	21.29
B/M	225296	0.44	0.46	0.08	0.32	0.9
ILLIQ	233192	3.41	16.65	0.07	0.71	7.36

3.2. Option filters

We closely follow the filters of Zhan et al. (2022) to obtain our final option sample from which we construct characteristics-based option portfolios. First, at the end of each month and for each stock, we select the call option closest to being at-the-money which has the shortest maturity among contracts that do not expire in the next month. Second, we only retain calls if the underlying stock did not pay dividends during the option's remaining life until expiration. Third, we only keep options with a positive trading volume and a positive bid quote, a bid price strictly smaller than the ask price, and a mid-price between the ask and bid quote of at least USD 0.125. Fourth, we exclude observations that violate clear no-arbitrage conditions such as $S \geq C \geq \max(0, Ke^{-rt})$. Fourth, we exclude options with a strike-to-spot ratio, K/S, lower than 0.8 or larger than 1.2. Fifth, as most options at the end of each month have the same maturity, we discard observations with different expiration dates from the majority of all other options selected on that day. Finally, for the remaining calls in our sample, we compute daily rebalanced delta-hedged returns from the selection month's end to the end of the next month.

Table 1 shows summary statistics for our final pooled sample of monthly call option observations. In total, the sample contains 233,192 option-month observations for 6,721 unique underlyings. On average, our sample consists of 750 unique underlying stocks per month. Overall, contract-level characteristics are similar to the options in the sample of Zhan et al. (2022). The average daily delta-hedged option return is -0.07% whereas the median amounts to -0.57%. By construction, the options' moneyness and delta are on average close to 1 and 0.5. The options have an average remaining time until expiration of approximately 50 days with a standard deviation of 2 days. The market capitalization of the underlying stocks is, on average, USD 10.83 billion, and the book-to-market ratio averages 0.44.

3.3. Factor construction

We construct option return factors using various stock- and option-level characteristics. Precisely, we consider a mixture of characteristics that have shown explanatory power for delta-hedged option returns in the existing literature as well as readily-available and common stock-/ option-level characteristics. In total, we collect 56 characteristics. We provide details on all characteristics in Appendix A. Notably, our sample of option factors largely coincides with the factors analyzed in Goyal & Saretto (2022). In general, we distinguish between three categories of characteristics:

1. Single option contract-level characteristics such as implied volatility, option Greeks, open interest, option prices, and option bid-ask spreads.
2. Stock-level characteristics derived from *options* data such as the volatility or the slope of implied volatilities and risk-neutral skewness or kurtosis measures.
3. Stock-level characteristics derived from *stock* prices and accounting data such as stock illiquidity, stock return volatility, leverage, or profitability measures.

Based on our characteristics, we compute monthly factor returns by sorting all available options at the end of each month into quintiles. We define factor returns as the equal-weighted high-minus-low quintile returns over the subsequent month. Table 2 provides an overview of the monthly returns of our 56 factors. The returns are in percent. t-statistics of mean returns are based on Newey & West (1987) standard errors with 4 lags.

Our factor sample largely exhibits significantly negative mean returns in line with the findings in Goyal & Saretto (2022). The sign of the mean return is significantly negative at the 5% level for 30 out of the 56 factors. There are 14 significantly positive mean factor returns at the same significance level. In addition, the magnitude of absolute returns is large with up to 1.72% per month highlighting the strong predictive power on delta-hedged returns of some stock and option characteristics. Moreover, large absolute Sharpe ratios (SR) indicate persistently high or low returns on some factors over time.

Table 2: **Overview of individual factor returns.**

This table reports the mean ($E[R]$), standard deviation (SD), Sharpe ratio (SR), and skewness of monthly returns for each of our 56 option factors. t-stats of mean returns account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987). The sample period is from February 1996 to December 2022. Detailed descriptions of the characteristics used for factor construction are documented in Appendix A.

	$E[R]$	$t(E[R])$	SD	SR	Skew
Panel A: Option contract characteristics					
1. Delta (*delta*)	-0.60	-5.36	1.48	-0.41	-1.03
2. Embedded leverage (*embedlev*)	1.63	10.83	1.95	0.84	0.13
3. Gamma (*gamma*)	-0.20	-1.72	1.43	-0.14	-1.41
4. Implied volatility (*iv*)	-1.72	-10.10	2.19	-0.78	0.01
5. Moneyness (*moneyness*)	0.08	0.80	1.51	0.05	0.38
6. Open interest (*oi*)	-0.60	-10.31	1.07	-0.56	-0.92
7. Option bid-ask spread (*optspread*)	0.19	2.19	1.34	0.14	-0.02
8. Option mid price (*mid*)	-0.05	-0.37	1.56	-0.03	0.53
9. Theta (*theta*)	-0.05	-0.38	1.50	-0.03	-1.31
10. Vega (*vega*)	0.89	6.16	1.69	0.52	0.61
11. Volga (*volga*)	-1.13	-6.76	1.98	-0.57	-0.73
Panel B: Stock-level characteristics derived from options data					
12. ATM implied volatility(*atmiv*)	-1.34	-8.36	2.14	-0.63	0.30
13. Call minus put ATM IV (*civpiv*)	-0.77	-11.81	1.01	-0.76	-1.05
14. Demand pressure (*demand_pressure*)	-0.77	-8.30	1.52	-0.50	0.02
15. Implied volatility skew (*skewiv*)	0.39	5.37	1.13	0.35	0.17
16. Implied volatility term structure (*ivterm*)	-0.88	-8.21	1.47	-0.60	-0.07
17. Risk-neutral kurt., 30 days ($rnk30$)	1.28	12.65	1.39	0.92	0.84
18. Risk-neutral kurt., 365 days ($rnk365$)	0.99	8.25	1.68	0.59	-0.39
19. Risk-neutral skew, 30 days ($rns30$)	0.79	9.74	1.18	0.67	0.40
20. Risk-neutral skew, 365 days ($rns365$)	-0.37	-3.04	1.69	-0.22	-0.02
21. Stochastic volatility risk (*sr*)	-0.43	-6.40	1.07	-0.40	-0.47
22. Volatility of implied volatility (*ivvol*)	-0.41	-6.50	1.09	-0.38	0.36

Table 2 cont.: **Overview of individual factor returns.**

	$E[R]$	$t(E[R])$	SD	SR	Skew
Panel C: Stock-level characteristics derived from stock price and accounting data					
23. 1-year new stock issues ($issue\_1y$)	-0.35	-3.38	1.36	-0.26	0.28
24. 5-year new stock issues ($issue\_5y$)	-0.55	-6.26	1.29	-0.43	-0.38
25. Altman Z-score (z_score)	0.35	3.23	1.41	0.25	1.46
26. Analyst dispersion ($market\_equity$)	-0.48	-5.92	1.24	-0.39	-0.06
27. Autocorrelation (ac)	0.01	0.14	0.92	0.01	0.36
28. Avg. of 10 highest returns, past 3m ($max10$)	-0.50	-3.74	1.90	-0.26	0.86
29. Book to market equity ($assets$)	0.05	0.42	1.52	0.04	-0.77
30. Cash-to-assets ($cash\_at$)	-0.55	-4.68	1.67	-0.33	0.30
31. Cash flow volatility ($ocfq\_saleq\_std$)	-0.70	-8.86	1.27	-0.56	-0.01
32. Debt to total assets ($debt\_at$)	-0.10	-1.13	1.24	-0.08	-0.45
33. Default risk ($defrisk$)	-0.41	-3.08	1.57	-0.26	0.81
34. Financial debt ($debt$)	0.15	1.29	1.51	0.10	-0.21
35. Idiosyncratic skewness ($iskew$)	-0.14	-2.17	0.97	-0.14	-0.73
36. Idiosyncratic volatility ($ivol$)	-0.71	-5.67	1.71	-0.42	1.18
37. Implied minus realized volatility ($ivrv$)	-0.97	-7.68	1.44	-0.68	-1.03
38. Institutional ownership ($insti$)	0.72	6.22	1.48	0.49	1.18
39. Institutional ownership concentration ($insti\_hhi$)	-0.64	-5.53	1.39	-0.46	-0.71
40. Market equity ($market\_equity$)	0.59	4.23	1.62	0.36	0.48
41. Net equity issuance ($eqnetis\_at$)	-0.44	-4.37	1.49	-0.30	1.03
42. Net total issuance ($netis\_at$)	-0.27	-2.71	1.50	-0.18	0.51
43. Operating profits-to-book equity (ope_be)	0.59	6.03	1.49	0.40	-0.33
44. Profit margin ($ebit\_sale$)	0.66	7.16	1.39	0.47	-0.05
45. Realized kurtosis ($kurtosis$)	-0.59	-7.33	1.09	-0.54	0.07
46. Realized minus risk-neutral kurt. ($diff\_kurt$)	-0.88	-10.14	1.08	-0.81	-0.51
47. Realized minus risk-neutral skew. ($diff\_skew$)	-0.40	-5.19	1.12	-0.36	-0.61
48. Realized skewness ($skew$)	-0.12	-1.74	0.99	-0.13	-0.14
49. Realized volatility (vol)	-0.60	-4.26	2.07	-0.29	1.06
50. Share turnover ($turnover\_126d$)	-0.30	-2.84	1.54	-0.19	1.02
51. Short-term stock return reversal (ret_1_0)	0.03	0.26	1.56	0.02	-0.57
52. Short interest (rsi)	-0.19	-2.73	1.10	-0.17	-0.07
53. Stock illiquidity ($amihud$)	-0.44	-3.32	1.59	-0.28	-0.36
54. Stock price (log_price)	1.00	6.98	1.69	0.59	0.59
55. Stock return momentum (ret_12_1)	0.09	0.73	1.55	0.06	0.09
56. Total assets ($assets$)	0.50	4.30	1.69	0.29	-0.13

4. Main results

4.1. Autocorrelation of option factor returns

We start our analysis of momentum in option factor returns by first considering their autocorrelation. Significant autocorrelation in returns is a main driver of profitable momentum strategies. The grey bars in Figure 1 show the correlation coefficients ρ between factor i's return in month t, $F_{i,t}$, and the same factor's average return over the formation period $-t$, $F_{i,-t}$. We depict three different formation periods: $t-1$ (month-on-month), $t-2$ to $t-12$ (year-on-month with the omission of the most recent month), and $t-13$ to $t-60$ (long-term autocorrelation, potentially testing for long-term reversal). Bootstrapped 95% confidence intervals are depicted in black color.

For the formation month $t-1$, we document significantly positive ρ-coefficients for 44 out of 56 with a maximum correlation of 40%. Turning to the 1-year formation period, the exhibited serial correlation tends to get even stronger. Moreover, factors such as *ivrv* that display high autocorrelation for the 1-month formation period are also among the strongest serially correlated factors for the 1-year formation period. As autocorrelation is a typical property of return series that display momentum, the strong autocorrelation inherent in returns up to lags of one year is a strong indicator of profitable momentum in option factor returns. Finally, as depicted in Panel C for a formation period of 5 years, there is mostly no long-term autocorrelation. Moreover, as there are barely any factors with significantly negative serial correlation for this formation period, we do not find preliminary evidence for long-term reversal and, thus, no confirmation of overreaction theories in our option factor return data.

4.2. Baseline option factor momentum strategies

Before testing for momentum, we flip the sign of returns for factors such that their full-sample mean return is positive. For equity factors, researchers usually construct high-minus-low factors in the same way as the original study that finds a positive factor premium. Since not all of our option factors have been studied in detail, we follow Heston et al. (2022) and construct factors so that their mean returns are positive. The flipping of factors should not change the main findings, especially since time-series strategies are invariant to such rotation. Additionally, a static factor investor who equally weighs all factors – a strategy we use as a benchmark – would also construct the factors such that the factors are expected to earn a premium.

Using all flipped factors, we construct both time-series (TSFM) and cross-sectional factor momentum strategies (CSFM) with monthly rebalancing. For the TSFM strategies, we assign the positions based on the sign of each factor's formation period return. For the CSFM strategy, we assign a long position to a factor with an above-median return in the formation period and a short position otherwise. We consider a holding period of one month and eight different formation periods ranging from the prior month up to 60 months.

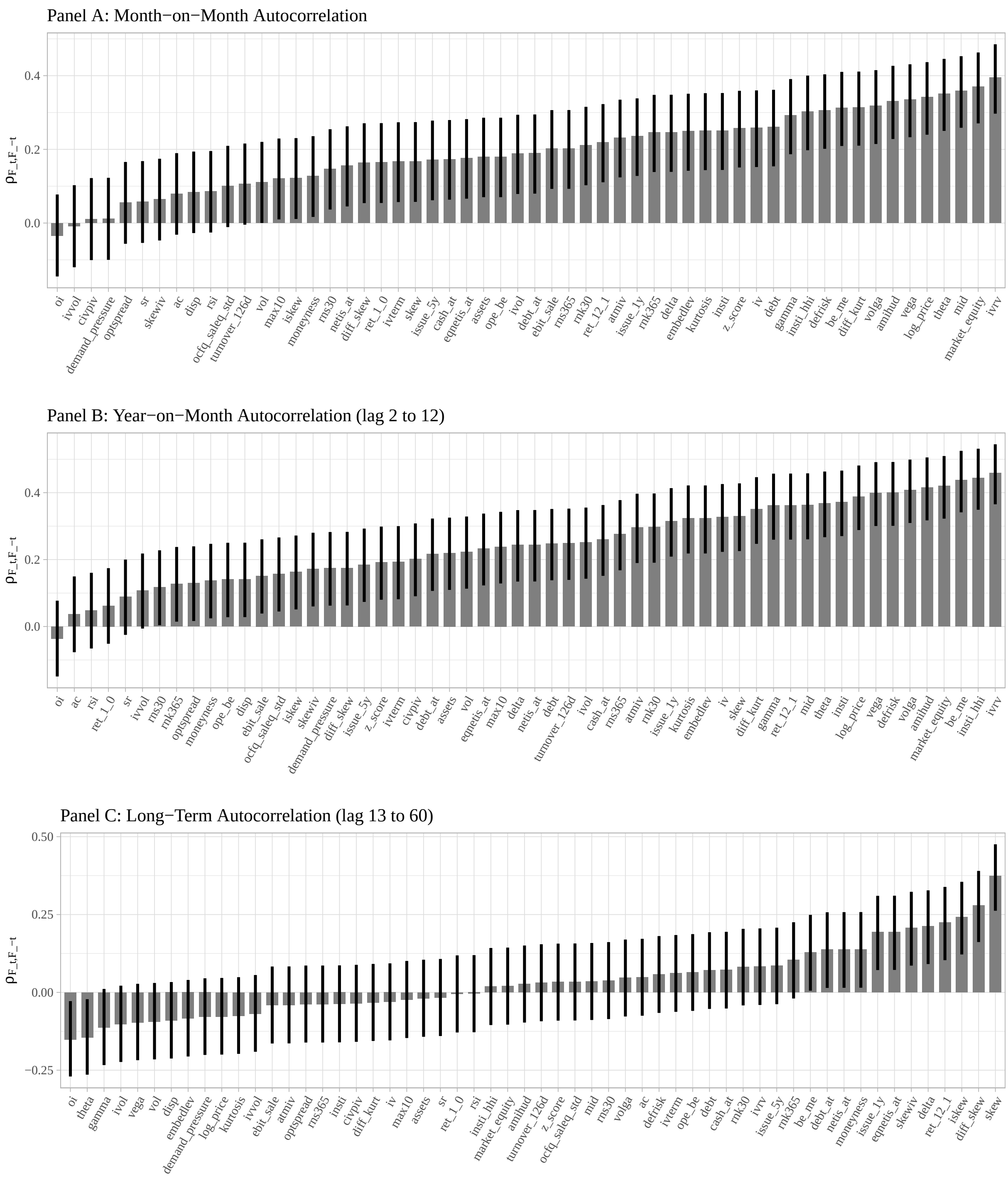


Fig. 1. **Autocorrelation of individual factor returns.**

Notes: This figure shows autocorrelation coefficients (grey bars) between factor returns and their own past returns over various formation periods. 95% confidence intervals are depicted by the black lines and estimated via bootstrapping. The sample period is from February 1996 to December 2021. Detailed descriptions of the characteristics used for factor construction are documented in Appendix A.

Mathematically, the return of the time-series strategy in month t with the formation period $-t$ is defined as

$$R_t^{TSFM} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(F_{i,-t}) F_{i,t}. \tag{3}$$

For the cross-sectional strategy, the return is given by

$$R_t^{CSFM} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(F_{i,-t} - \tilde{F}_{i,-t}) F_{i,t}, \tag{4}$$

where $\tilde{F}_{i,-t}$ is the median formation period return. These strategies and formation periods are standard in the literature (see, e.g., Gupta & Kelly, 2019). We consider both strategies because time-series momentum strategies rely on factors exhibiting performance continuation, while cross-sectional strategies additionally bet on the continuation of relative performance between factors. Note that there are always $N/2$ factors in the long and in the short portfolios for the cross-sectional strategy. In the time-series strategy, there are most often more factors with positive weight than negative. TSFM long and short legs are especially imbalanced for longer formation periods, as by construction, all factors exhibit positive unconditional mean returns.

We report annualized mean returns and Sharpe ratios for both TSFM and CSFM in Table 3.[5] All standard errors are robust to heteroskedasticity and autocorrelation in residuals up to the fourth lag following Newey & West (1987). We rely on GMM and the Delta Method to estimate the standard errors of the Sharpe ratios.

For TSFM, annualized mean returns are all positive and significant, ranging from 9.39% (t-stat: 7.00) for the 1-month formation period to 13.62% (t-stat: 9.87) for the 12-month formation period. Sharpe ratios are exceptionally high and range from 1.96 to 3.16. This result is not surprising since some individual option factors achieve high Sharpe ratios, and the equally-weighted factor portfolio earns an annualized Sharpe ratio of 2.51. For CSFM, the results are similar. Annualized mean returns range from 4.59% (t-stat: 8.80) for the 5-year excluding the most recent year formation period to 8.48% (t-stat: 9.36) for the 12-month formation period. Sharpe ratios range from 1.73 to 3.13. Returns

[5]We additionally report our main results for an alternative return definition for daily-delta hedged call positions in Appendix B.2. The alternative return definition incorporates margin requirements and is outlined in Appendix B.1. Results are robust and very similar to those presented in the main body.

Table 3: **Option factor momentum profitability.**

This table reports performance measures of both time series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) strategies based on eight formation periods. All strategies are built from a set of 56 option factors with monthly returns from February 1996 to December 2021. TSFM strategies go long (short) in factors with positive (negative) formation period returns. CSFM strategies go long (short) in factors with an above (below) median return in the formation period. The strategies are rebalanced monthly, and the sum of absolute factor weights in both TSFM and CSFM strategies sum to two. Mean returns of TSFM, CSFM, and their respective long and short portfolios are annualized and given in percent. Sharpe ratios are also annualized by multiplying by $\sqrt{12}$. ρ denotes the Pearson correlation coefficients. All t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	t-1	t-3	t-6	t-12	t-36	t-60	t-2 - t-12	t-13 - t-60
Panel A: Time-series factor momentum								
$TSFM$	9.39	11.66	13.18	13.62	12.92	11.65	13.21	10.52
	(7.00)	(8.66)	(10.01)	(9.87)	(8.90)	(8.65)	(9.73)	(8.94)
Sharpe Ratio	1.96	2.71	3.08	3.16	2.90	2.75	3.09	2.63
	(9.75)	(11.64)	(14.13)	(13.57)	(13.89)	(11.03)	(13.31)	(9.66)
$Long$	8.17	8.45	8.67	8.37	7.74	6.94	8.28	6.80
	(10.40)	(10.77)	(10.89)	(10.31)	(8.98)	(8.71)	(10.12)	(8.61)
$Short$	2.30	0.45	-0.14	-0.73	-0.68	0.25	-0.37	1.58
	(3.98)	(0.78)	(-0.26)	(-1.05)	(-0.94)	(0.46)	(-0.55)	(2.29)
$\rho_{TSFM,Long}$	0.74	0.80	0.85	0.91	0.96	0.98	0.91	0.98
$\rho_{TSFM,Short}$	-0.42	-0.12	-0.05	0.05	0.27	0.25	0.10	0.26
Panel B: Cross-sectional factor momentum								
$CSFM$	5.56	7.34	8.21	8.48	7.46	5.58	8.06	4.59
	(6.42)	(8.71)	(10.19)	(9.36)	(8.52)	(9.35)	(9.20)	(8.80)
Sharpe Ratio	1.73	2.56	3.01	3.13	3.06	2.82	3.08	2.31
	(9.36)	(12.27)	(14.87)	(14.48)	(13.16)	(8.78)	(13.53)	(5.95)
$Long$	9.33	10.17	10.69	10.76	10.06	8.67	10.55	8.17
	(9.62)	(10.30)	(10.73)	(10.34)	(9.39)	(9.19)	(10.28)	(9.17)
$Short$	3.77	2.83	2.48	2.28	2.60	3.09	2.49	3.59
	(5.84)	(4.62)	(4.26)	(3.75)	(4.04)	(5.64)	(4.07)	(6.02)
$\rho_{CSFM,Long}$	0.60	0.64	0.64	0.68	0.73	0.79	0.68	0.78
$\rho_{CSFM,Short}$	-0.44	-0.29	-0.24	-0.16	0.02	0.22	-0.14	0.21

are lower for the CFSM strategies as they have net zero weight in factors earning positive returns by construction. On the other hand, for TSFM, more factors are in the long leg than in the short leg. This fact holds particularly true for longer formation periods, where the formation returns are more likely to resemble the fact that all factors yield positive mean returns in the full sample. For instance, taking the 5-year formation strategy as an example, there are, on average, 39 factors in the long leg but only 17 in the short leg. This stylized fact is also inherent in the returns of the long and short legs. While CFSM returns are equal to the spread between the long and short-leg returns, returns of TSFM strategies are much closer to the returns of the long leg, with correlations of up to 98%

for the longer formation periods. Even for CSFM, correlations between the long leg and the strategies are high, and up to 79% for the 5-year formation period.

For readability, we continue with only four of the eight formation periods, namely the last month, the last six months, the last twelve months excluding the most recent month, and the last five years excluding the most recent year. However, results are similar for the other strategies.

Especially because of the long-factor bias in the TSFM strategies, returns may likely be similar to a static factor investing strategy, BM, that equally weighs all 56 factors such that

$$R_t^{BM} = \frac{1}{N}\sum_{i=1}^{N} F_{i,t} \tag{5}$$

We test this by running the following regression for both the four TSFM and the four CSFM strategies:

$$R_t^{FM} = \alpha + \beta R_t^{BM} + \varepsilon_t \tag{6}$$

Additionally, we control for factors used by Horenstein et al. (2020) (HVX factors in the following) to describe the cross-section of delta-hedged option returns. These factors include the returns on a daily delta-hedged at-the-money S&P 500 call position to capture market-wide volatility risk (*SPX DHC*) as well as three factors of our factor sample: namely the factors sorted on the idiosyncratic volatility of the underlying stock (*ivol*), on the underlyings' total market equity (*market equity*), and on the difference between implied volatility and realized volatility (*ivrv*).

As reported in Table 4, all but one TSFM and CSFM strategies produce positive and statistically significant profits at the 1%-level after controlling for the equally-weighted factor portfolio. Even though alphas decrease relative to mean returns, high annualized information ratios (IR) provide evidence that option factor momentum increases the investment opportunity set as these ratios are equal to Sharpe ratios after orthogonalizing TSFM and CSFM returns to the control factors (Haddad et al., 2020).

In line with Table 3, we find that the TSFM strategies converge to static factor investing the longer the formation period with a high R^2 of 0.68 for the $t-2$ to $t-12$ strategy and 0.89 for the $t-13$ to $t-60$ strategy. This is not the case for CSFM with R^2

Table 4: **Benchmarking and risk-adjusting option factor momentum.**
Panel A of this table reports the results of regressing both TSFM and CSFM strategies against an equally-weighted portfolio of 56 option factors with monthly rebalancing from February 1996 to December 2021. Panel B reports results of regressing TSFM and CSFM on the factors presented in Horenstein et al. (2020) (HVX): the returns of a daily delta-hedged at-the-money call position on the S&P 500 (SPX DHC) and three factors constructed from characteristic sorts in the same way as our option factors. The characteristics are the idiosyncratic volatility of the underlying (ivol), the underlyings' total market equity (market equity), and the difference between implied volatility and realized volatility (ivrv). Regression intercepts (α) are annualized and given in percent. Information ratios (IR) are the ratio of α and the standard deviation of regression residuals. IRs are annualized by multiplying by $\sqrt{12}$. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series factor momentum				Cross-sectional factor momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Factor momentum vs. equally-weighted factor portfolio								
α	4.63	5.53	4.49	1.11	4.48	6.27	5.67	1.65
	(2.13)	(3.50)	(3.82)	(2.44)	(2.56)	(4.49)	(4.23)	(2.39)
$EW Factors$	0.73	1.16	1.34	1.60	0.16	0.29	0.37	0.50
	(2.61)	(5.38)	(8.91)	(19.34)	(0.86)	(1.90)	(2.77)	(5.64)
R^2	0.16	0.50	0.68	0.89	0.02	0.08	0.14	0.35
IR	1.05	1.83	1.86	0.84	1.41	2.40	2.33	1.03
Panel B: Factor momentum vs. HVX factors								
α	2.32	4.97	4.92	2.07	2.09	4.81	4.48	1.37
	(2.62)	(6.57)	(8.02)	(3.53)	(3.12)	(7.15)	(8.28)	(2.34)
SPX DHC	0.06	0.12	0.10	0.07	0.01	0.06	0.05	-0.01
	(0.86)	(2.81)	(3.90)	(1.10)	(0.12)	(2.03)	(1.74)	(-0.09)
ivol	0.12	0.30	0.36	0.65	-0.08	-0.04	-0.02	0.27
	(1.45)	(4.39)	(7.99)	(12.75)	(-1.12)	(-0.79)	(-0.59)	(4.79)
market equity	0.15	0.17	0.21	-0.06	0.11	0.16	0.18	-0.13
	(2.19)	(4.61)	(4.59)	(-1.09)	(2.45)	(3.19)	(3.97)	(-2.54)
ivrv	0.43	0.39	0.33	0.32	0.28	0.23	0.22	0.14
	(5.48)	(8.00)	(8.17)	(6.67)	(5.60)	(6.55)	(6.62)	(2.76)
R^2	0.33	0.57	0.67	0.79	0.32	0.41	0.48	0.37
IR	0.59	1.77	2.01	1.14	0.79	2.30	2.37	0.86

ranging from 0.02 to 0.35. The β-coefficient on the static factor portfolio is insignificant for the 1-month formation period CSFM strategy.

In addition, when controlling for the HVX factors, alphas are positive and statistically significant with t-statistics ranging from 2.34 to 8.24. Especially the medium formation period strategies yield high annualized information ratios: 2.01 and 2.37 for the $t-2$ to $t-12$ TSFM and CSFM strategies, respectively. TSFM strategies load highly and positively on the *ivol* and *ivrv* factors. This explanatory power is due to the fact that the two factors yield on average 0.71% and 0.97% per month and are assigned a long position for the $t-2$ to $t-12$ strategy in 89% and 95% of months. The HVX factors better explain variation in CSFM strategies relative to the equally-weighted factor portfolio (R^2 ranging from 0.32 to 0.48) and perform similarly for the TSFM strategies (R^2 ranging from 0.33 to 0.79).

Overall, both TSFM and CSFM strategies yield positive and statistically significant returns and present novel investment opportunities that expand upon a static, equally-weighted option factor portfolio and the HVX factors.

4.3. Difference between TSFM and CSFM

Next, we compare the performance of our TSFM and CSFM strategies by regressing one on the other. Time-series momentum was proposed by Moskowitz et al. (2012) as a purer bet on assets' autocorrelation compared to cross-sectional momentum. Overcoming negative cross-serial correlation, Moskowitz et al. (2012) find that time-series momentum yields higher returns than cross-sectional momentum. In addition, while cross-sectional momentum cannot fully explain time-series momentum, no alphas remain for cross-sectional momentum after controlling for time-series momentum. However, Goyal & Jegadeesh (2018) argue that time-series momentum exhibits a positive average net position in risky assets, while cross-sectional momentum is a zero-cost strategy. Following Leippold & Yang (2021), we treat both our TSFM and CSFM as zero-cost strategies because the underlying high-minus-low factors are by construction zero-cost strategies. Thus, we do not enhance the CSFM strategies with a time-varying position in an equally-weighted market portfolio with a weight equal to the net-long position of the TSFM.

For factor momentum in stocks, Arnott et al. (2023) show that their CSFM strategy is distinct from the TSFM strategy of Ehsani & Linnainmaa (2022). Both strategies yield robust alphas after controlling for the profits of the other. However, the TSFM strategy is based on a 1-year formation period, while the CSFM strategy is based on a 1-month formation period. Instead, we compare strategies with identical formation periods to compare the performance more fairly.

Results of pairwise regressions are listed in Table 5, with TSFM returns being the dependent variable on the left-hand panel. Our strategies are strongly related, as indicated by high t-statistics on the slope coefficients and high R^2 of up to 0.77 for the 1-month formation period strategies. Nevertheless, six out of eight strategies produce positive alphas at the 1% significance level, providing evidence that TSFM and CSFM are partly distinct phenomena in the options market. Only the 1-month and the long-term CSFM strategies are fully subsumed by their TSFM counterparts, but not vice versa. Especially

Table 5: **Time-series vs. cross-sectional factor momentum.**
This table reports the results of regressing TSFM and CSFM strategies with identical formation periods against each other. TSFM strategy returns are the dependent variable on the left-hand side of the table. Regression intercepts (α) are annualized and given in percent. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series factor momentum				Cross-sectional factor momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
α	2.14	3.23	3.75	3.39	0.05	1.75	2.24	0.54
	(3.97)	(3.20)	(3.88)	(3.67)	(0.17)	(2.95)	(2.52)	(0.91)
CSFM	1.30	1.21	1.17	1.55				
	(14.22)	(7.26)	(6.58)	(10.21)				
TSFM					0.59	0.49	0.44	0.38
					(12.09)	(16.86)	(10.57)	(9.01)
R^2	0.77	0.59	0.52	0.60	0.77	0.59	0.52	0.60

for the 1-month formation period, there might be a strong common driver between the two strategies – the factors' autocorrelation – which is more purely captured by TSFM strategies. We next dissect both strategies to more clearly understand the drivers of both TSFM and CSFM.

4.4. Decomposing option factor momentum

Conrad & Kaul (1998) stress that profitable momentum strategies do not solely stem from serial correlation in asset returns but also from variation across unconditional mean returns of individual assets. The authors argue that differences in mean returns result in momentum profitability as the purchase of high-mean assets and the sale of low-mean assets is equivalent to purchasing permanent winners and selling permanent losers. Whereas the arguments by Conrad & Kaul (1998) focus on cross-sectional momentum strategies, the role of mean returns in time-series momentum strategies slightly differs. Here, consistently low or high returns on individual factors can drive momentum profits. These high absolute mean returns are a source of time-series momentum as such strategies will be long (short) in assets that were profitable (non-profitable) in the past and will continue to do so in the future.

Despite evidence of considerable autocorrelation in option factors as depicted in Figure 1, our results so far indicate that mean returns play an important role in explaining option factor momentum profitability. First, the high absolute mean returns of individual factors in Table 2 is a likely source of TSFM. At the same time, cross-sectional variation in mean factor returns could drive CSFM. Moreover, if persistently high and above-median factor returns drive momentum profitability in option factors, select factors can themselves explain momentum. In this context, individual factors with (without) these properties are permanent constituents of the long (short) leg of our factor momentum strategies. Hence, the returns on these factors are positively correlated with factor momentum returns. This effect is evident in Table 4. Although individual factors such as *ivrv* cannot fully subsume the profitability of our momentum strategies, their inclusion in a factor risk model significantly reduces the strategies' alphas compared to our baseline results in Table 3. In particular, using the formation period of one year and omitting the most recent month, *ivrv* is an example of a consistently well-performing factor that exhibits for 285 out of 299 formation periods a positive return and for 187 formation periods an above the cross-sectional median return. Consequently, Table 4 already provides tentative evidence of unconditional factor mean returns driving factor momentum strategies.

To formally examine the extent to which option factor momentum is driven by serial correlation and factor premia, we employ several momentum return decompositions that have been proposed in the literature. First, Lo & MacKinlay (1990) introduce a decomposition of a cross-sectional momentum strategy that can be defined as

$$R_t^{LM} = \frac{1}{N}\sum_{i=1}^{N}(F_{i,-t} - \bar{F}_{-t})F_{i,t}. \tag{7}$$

For this strategy, at the end of each month t, we weigh individual factor returns $F_{i,t}$ by the difference between the respective factor's return during the formation period $-t$ and the cross-sectional mean factor return $\bar{F}_{-t}$ in $-t$. Note that this strategy does not correspond to our CSFM strategy defined in equation (4). We solely consider the LM strategy from equation (7) to apply the corresponding Lo-MacKinlay return decomposition.

Taking the expectation of the LM strategy in (7), Lo & MacKinlay (1990) show that the following equation holds

$$\mathrm{E}[R_t^{LM}] = \underbrace{\frac{N-1}{N}\mathrm{Tr}(\Omega)}_{\text{Autocovariance}} - \underbrace{\frac{1}{N^2}(\vec{1}'\Omega\vec{1} - \mathrm{Tr}(\Omega))}_{\text{Cross-serial covariance}} + \underbrace{\mathrm{Var}[\mu^F]}_{\substack{\text{Variation} \\ \text{in means}}}, \tag{8}$$

where μ^F is the vector of unconditional factor mean returns, $\mathrm{Var}[\mu^F]$ is the cross-sectional variance of mean returns, $\Omega = \mathrm{E}[(F_{i,t} - \mu^F)'(F_{i,t} - \mu^F)]$ is the autocovariance matrix of option factor returns, and $\mathrm{Tr}(\Omega)$ is the trace of Ω. As highlighted in (8), the Lo-MacKinlay decomposition splits the expected return of the LM strategy into three distinct components:

1. Autocovariance: Positive autocovariance in individual factor returns indicates a high (low) return following a positive (negative) past return signal.
2. Cross-serial covariance: Negative cross-serial correlations between different factor returns positively contribute to momentum profits as a positive (negative) past return on one factor signals low (high) returns on other factors.
3. Cross-sectional variance of mean factor returns: Some factors with high (low) expected returns persistently earn higher (lower) returns than other factors.

The Lo-MacKinlay decomposition above considers the expected return of a cross-sectional momentum strategy. Analogously, Moskowitz et al. (2012) propose a decomposition of a time-series momentum strategy that linearly weighs individual asset returns by their average return over the formation period,

$$R_t^{MOP} = \frac{1}{N} \sum_{i=1}^{N} F_{i,-t} F_{i,t}. \tag{9}$$

This time-series momentum strategy is also not equivalent to our baseline TSFM case in equation (3) and therefore only relevant to assess the influence of serial correlation and factor mean returns for time-series momentum strategies. After taking expectations, Moskowitz et al. (2012) decompose the strategy in equation (9) into

$$\mathrm{E}[R_t^{MOP}] = \underbrace{\frac{\mathrm{Tr}(\Omega)}{N}}_{\text{Autocovariance}} + \underbrace{\frac{\mu^{F\prime}\mu^F}{N}}_{\substack{\text{Sum of squared} \\ \text{mean returns}}}. \tag{10}$$

The MOP strategy decomposes into two parts. The first term again captures the autocorrelation inherent in individual factors. The second term represents the dependency of the time-series momentum strategy on mean returns. If absolute factor returns are persistently high, time-series momentum is profitable as the long (short) positions in the strategy tend to be invested long (short) in factors with persistently high (low) returns.

For our empirical implementation of both decompositions above, we follow Arnott et al. (2023) in computing Ω from our full sample of factor returns and computing the terms $\mathrm{Var}[\mu^F]$ and $\frac{\mu^{F\prime}\mu^F}{N}$ by subtracting the other decomposition terms from the total strategy returns in (7) and (9). To estimate standard errors for the three decomposition terms, we bootstrap our factor returns by month. We apply block bootstrapping with blocks of

Table 6: **Decompositions of option factor momentum strategies.**
This table reports empirical estimates for the cross-sectional and time-series momentum decompositions as proposed by Lo & MacKinlay (1990) and Moskowitz et al. (2012). The cross-sectional LM decomposition in Panel A is given by

$$\mathrm{E}[R_t^{LM}] = \underbrace{\frac{N-1}{N}\mathrm{Tr}(\Omega)}_{\text{Autocovariance}} - \underbrace{\frac{1}{N^2}(\vec{1}'\Omega\vec{1} - \mathrm{Tr}(\Omega))}_{\text{Cross-serial covari-ance}} + \underbrace{\mathrm{Var}[\mu^F]}_{\text{Variation in means}}.$$

The time-series MOP decomposition is given by

$$\mathrm{E}[R_t^{MOP}] = \underbrace{\frac{\mathrm{Tr}(\Omega)}{N}}_{\text{Autocovariance}} + \underbrace{\frac{\mu^{F'}\mu^F}{N}}_{\text{Sum of squared mean returns}}.$$

We compute the autocovariance matrix Ω from our full sample of factor returns and compute the terms $\mathrm{Var}[\mu^F]$ and $\mu^{F'}\mu^F/N$ by subtracting the other decomposition terms from the total strategy returns in (7) and (9). We bootstrap factor returns by month (2,000 draws) to estimate standard errors of decomposition components. Block bootstrapping with a block length of 4 mimics the autocorrelation-robust Newey-West standard errors with 4 lags. The sample period is from February 1996 to December 2021. All returns are annualized and in percent.

	t-1	t-6	t-2 – t-12	t-13 – t-60
Panel A: Cross-sectional factor momentum				
Autocovariance	6.37	10.68	9.95	1.07
	(3.52)	(4.77)	(4.90)	(0.96)
− Cross-serial covariance	-2.08	-3.07	-3.06	0.52
	(-2.44)	(-2.65)	(-2.52)	(0.81)
+ Variation in mean returns	2.15	3.48	4.88	8.79
	(1.79)	(2.36)	(3.81)	(10.45)
= Cross-section option factor momentum (LM)	6.44	11.09	11.76	10.37
	(4.72)	(6.39)	(6.04)	(7.89)
Panel B: Time-series factor momentum				
Autocovariance	3.54	5.19	4.47	0.44
	(3.52)	(4.77)	(4.90)	(0.96)
+ Sum of squared mean returns	3.42	5.55	6.30	10.79
	(3.40)	(5.10)	(6.90)	(23.84)
= Time-series option factor momentum (MOP)	6.96	10.74	10.77	11.23
	(4.94)	(5.81)	(5.73)	(8.71)

length 4 to mimic the autocorrelation-robust Newey-West standard errors. Again following Arnott et al. (2023), to make strategies across different formation periods comparable, we scale the decomposition components and total strategy returns so that the strategy's annualized volatility is 5% for each formation period. 5% is in the general vicinity of the annualized volatility exhibited by our baseline results in section 4.2.

Table 6 depicts the results of the decompositions proposed by Lo & MacKinlay (1990) and Moskowitz et al. (2012). In line with Ehsani & Linnainmaa (2022) and Arnott et al. (2023) for stock factor momentum, we observe positive cross-serial covariance terms that *negatively* influence cross-sectional option factor momentum. For the LM cross-sectional strategy in Panel A, the t-stats of the autocovariance estimates range between 3.48 and 4.68 for the formation periods up to one year. For the MOP time-series strategy in Panel B, the t-stats range between 3.48 and 4.68. Interestingly, the autocovariance in both the LM and MOP strategy is slightly less significant for the 1-month formation period compared to the $t-6$ and $t-2$ to $t-12$ periods. The autocovariance term is no significant contributor to momentum profitability in both strategies for the long-term horizon of $t-13$ to $t-60$.

More crucially, mean factor returns are a key component of momentum strategies next to the autocovariance in factor returns. The variation and sum of squared returns increase in statistical significance the longer the formation period. This observation is unsurprising, considering that the formation period returns more closely resemble the respective unconditional means for longer periods. However, the decomposition terms related to mean factor returns also significantly contribute to momentum strategies for short-term formation periods. Only the estimate of variation in mean returns for the $t-1$ LM strategy exhibits a t-stat below 2. Also, mean returns are generally a stronger contributor to momentum for the time-series MOP strategies where their significance is at least as high as for the autocovariance term. In summary, especially for MOP, the results for the factor momentum decompositions in Table 6 indicate a considerable role of factor mean returns in explaining option factor momentum. Although the LM and MOP momentum strategies are not equivalent to our baseline strategies introduced in section 4.2, we still consider these results as strong evidence that, generally, option factor momentum strategies are to a large part driven by strong variation in means returns and high absolute factor returns.

As time-series MOP strategies appear more susceptible to the impact of factor premia, we will focus on time-series momentum in the following paragraphs. Despite their frequent use in momentum-related literature, the MOP decomposition introduced has its downsides. As already mentioned, the MOP strategy in equation (9) does not correspond to our baseline time-series strategy that we implement in this paper. Moreover, Leippold & Yang (2021) points out that this strategy underestimates the true impact of mean factor returns. To show this, the authors derive a decomposition of the baseline TSFM strategy into a factor timing (FT),

$$R_t^{FT} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(F_{i,-t} - \bar{F}_i) F_{i,t}, \tag{11}$$

and a buy-and-hold (BH) strategy,

$$R_t^{BH} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(\bar{F}_i) F_{i,t}, \tag{12}$$

where $\bar{F}_i$ is the prevailing historical factor mean return up to month $t-1$. FT is long (short) in factors that outperform (underperform) their prevailing mean return during the formation period. BH is long (short) in factors that have a positive (negative) prevailing mean return. Notably, BH tends to perform well if factor returns are persistently positive or negative corresponding to large absolute factor mean returns. In this sense, BH is strongly related to the second term of the MOP decomposition in (10). In contrast, FT represents predictability in individual factor returns and is, therefore, conceptually more closely related to the autocovariance term in equation (10).

Leippold & Yang (2021) show that time-series momentum returns of *individual factors*, as in equation (3), can be expressed as a linear combination of individual FT and BH returns (i.e., the terms within the summations for factor i). Moreover, they demonstrate that the MOP time-series strategy can be similarly constructed as a linear combination. However, the weight on BH is smaller for the MOP strategy than the baseline time-series strategy in equation (3). Consequently, the MOP decomposition even underestimates the already considerable contribution by mean factor returns to the baseline TSFM strategy.

In Panel A of Table 7, we depict the returns and Sharpe ratios of the BH and FT strategies over different formation periods. Although BH considers the prevailing unconditional mean return, note that it varies across formation periods as we only consider factor returns for BH that are also included in the corresponding time-series momentum strategy. Consequently, as it only includes return periods after five years, the long-term BH strategy differs most noticeably from the other three. Nonetheless, the annualized mean returns of the BH strategy are consistently positive across formation periods ranging from 12.63% (t-stat: 8.75) to 10.58% (t-stat: 7.29). On the other hand, the FT strategies based on formation periods up to one year display mean returns ranging from 2.92% to 3.86% with t-stats around 2. In addition, FT for the formation period $t-13$ to $t-60$ even yields a negative mean return.

Table 7: **Buy-and-hold and factor timing strategies with option factors**
Panel A of this table reports mean and Sharpe ratios (SR) for buy-and-hold (BH) and factor timing (FT) strategies over different formation periods using option factors. BH is the return of a strategy that is long (short) in factors with a positive (negative) prevailing mean return (equation 5. We start computing BH returns for starting with the month in which we can observe a full formation period. FT is a strategy that is long (short) in factors that have outperformed their prevailing mean return up to $t-1$ during the respective formation period. We perform pairwise spanning tests in Panel B and C by regressing TSFM returns on either BH or FT returns (as denoted by the superscript k) or the other way around. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987). We estimate SR standard errors using GMM. All returns are annualized and in percent.

	$k = BH$ (buy-and-hold)				$k = FT$ (factor timing)			
	t-1	t-6	t-2 – t-12	t-13 – t-60	t-1	t-6	t-2 – t-12	t-13 – t-60
Panel A: Summary								
$E[R^k]$	12.63	12.72	12.60	10.58	2.93	3.86	2.92	-2.17
	(8.75)	(8.69)	(8.47)	(7.29)	(2.35)	(2.58)	(1.91)	(-2.66)
SR	2.56	2.58	2.54	2.30	0.60	0.81	0.64	-0.72
	(10.62)	(10.50)	(10.37)	(9.11)	(2.85)	(3.12)	(2.28)	(-2.59)
Panel B: Regression $R_t^{TSFM} = \alpha + \beta R_t^k + \varepsilon_t$								
Alpha	3.32	4.97	4.13	2.02	7.01	11.24	11.88	10.58
	(2.29)	(3.81)	(3.88)	(4.11)	(12.07)	(14.06)	(12.57)	(8.05)
Beta	0.48	0.65	0.72	0.80	0.81	0.50	0.45	0.03
	(4.78)	(6.94)	(10.07)	(16.78)	(24.61)	(5.66)	(3.99)	(0.12)
R^2	0.24	0.55	0.70	0.86	0.69	0.31	0.23	0.00
Panel C: Regression $R_t^k = \alpha + \beta R_t^{TSFM} + \varepsilon_t$								
Alpha	7.86	1.43	-0.25	-0.65	-5.08	-4.36	-3.93	-2.34
	(6.37)	(1.22)	(-0.37)	(-0.93)	(-9.44)	(-3.10)	(-2.62)	(-1.57)
Beta	0.51	0.86	0.97	1.07	0.85	0.62	0.52	0.02
	(4.00)	(9.03)	(21.89)	(13.37)	(0.85)	(0.62)	(0.52)	(0.02)
R^2	0.24	0.55	0.70	0.86	0.69	0.31	0.23	0.00

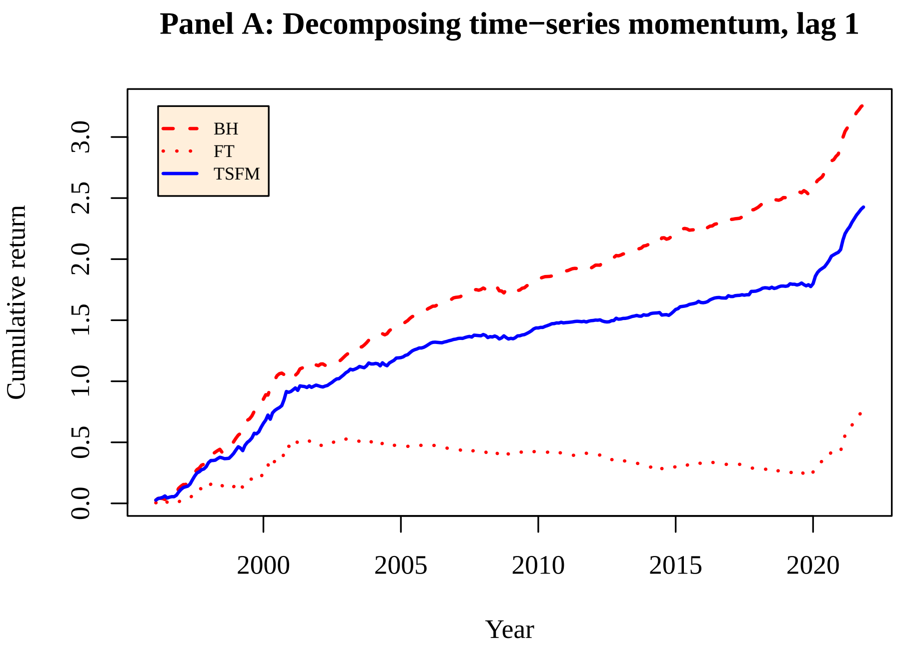
In this context, Figure 2 presents further evidence of the contribution of BH to time-series momentum in option factors. The figure shows the cumulative return, defined as the cumulative sum of strategy returns, of BH, FT, and TSFM with formation period lags of one month or one year (with the omission of the most recent month). In Panel A, for the 1-month formation period, the time-series momentum is visibly more correlated with BH than FT. This observation is even more evident for the formation period of one year. Here, the time-series factor momentum is almost identical in terms of cumulative return to the BH strategy. Whereas both BH and TSFM exhibit an impressive performance over the sample period from 1996 to 2021, FT is relatively flat during this period. Overall, the high contribution by BH to time-series momentum underlines the significance of persistently positive or negative factor returns. This return persistency relates to the driving force behind option factor momentum strategies: factor premia.

Next, to complement our illustrative evidence from Figure 2, we follow Leippold & Yang (2021) in performing spanning tests for TSFM, BH, and FT strategies. To do so, we first regress our baseline TSFM returns on either BH or FT returns. Panel B of Table 7 summarizes the results. Judging by the significance of the regression alphas, we find that option factor momentum using a time-series strategy is largely explained by BH. The alpha coefficient remains statistically significant, however, it decreases noticeably in terms of economic magnitude and statistical significance compared to the strategy's mean returns presented in Table 3. On the other hand, alphas remain higher after regressing on FT returns and significance levels even increase compared to our baseline results. Turning to the reported R^2 values, we find that BH accounts for large parts of the variation in R^{FM} for longer formation periods, and FT accounts for most of the variation in the 1-month formation period. This result is not surprising considering how closely the option factor momentum return series resembles the returns of the BH strategy in Figure 2. However, it is interesting to point out that FT explains much less of the time variation in option factor momentum ($R^2 = 0.23$, 1-year lag) than in the analogous analysis by Leippold & Yang (2021) for stock factor momentum with an R^2 of 0.96. Once more, for formation periods longer than one month, this insight indicates a relatively minor contribution by FT to times-series factor momentum compared to BH. Similarly, considering again the 1-year formation period, the beta coefficient on R^{FT} with 0.45 (*t*-stat: 3.99) is smaller in terms of magnitude and statistical significance compared to the coefficient on R^{BH} (0.72, *t*-stat: 10.07). When regressing either BH or FT on TSFM in Panel B, we find that, except for the 1-month formation period, the BH alpha turns insignificant. Thus, option factor momentum has the tendency to subsume BH returns. This result is another deviation from the stock factor-level analyses by Leippold & Yang (2021) where BH subsumes factor momentum. Controlling FT returns for option factor momentum yields negatively significant or insignificant FT alphas.

In conclusion, the results in Table 7 point again at TSFM being largely but not exclusively driven by factor mean returns (as represented by BH) rather than serial correlation and predictability in factor returns (as represented by FT).

4.5. Principal component momentum

A common theme in the factor momentum literature (e.g., Arnott et al., 2023; Ehsani & Linnainmaa, 2022) is the focus on momentum in the factors' largest principal compo-



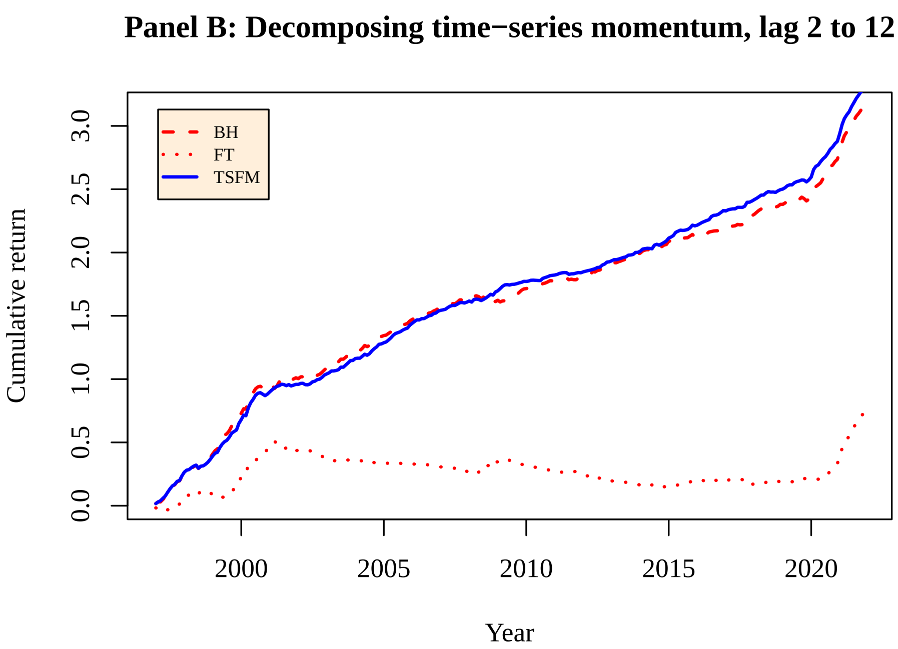


Fig. 2. **Cumulative returns of buy-and-hold and factor timing strategies.**

Notes: This figure shows cumulative return series by summing up the monthly returns of TSFM (blue line), buy-and-hold (BH, red dashed line), and factor timing (FT, red dotted line) strategies using option factors. BH is the return of a strategy that is long (short) in factors with a positive (negative) prevailing mean return (equation 5). We compute BH returns starting with the month for which we can observe a full formation period. FT strategies are long (short) in factors that have outperformed their prevailing mean return up to $t-1$ during the respective formation period. Panel A depicts the formation period of 1-month, and Panel B depicts the formation period of one year with the omission of the most recent month's return.

nents. Following a model by Kozak et al. (2018), Ehsani & Linnainmaa (2022) show that sentiment-driven excess demand of investors can lead to autocovariance in factor returns as long as the demand is sufficiently persistent. Transitioning from the space of factors to their principal components, the authors argue that in the absence of no near arbitrage, rational arbitrageurs will only trade against sentiment demand in low eigenvalue PCs, as trading in high eigenvalue PCs carries high systematic risks. Therefore, persistence and profitable momentum effects should only remain in high-eigenvalue PCs. In line with the model, Ehsani & Linnainmaa (2022) find that a TSFM strategy trading the factors' largest 10 PCs ordered by eigenvalues subsumes most momentum in the other subset of PCs and can explain cross-sectional momentum in stocks. Further, Arnott et al. (2023) also find that a CSFM strategy trading their factors' largest 5 PCs subsumes momentum in all other subsets of PCs and explains industry momentum.

We extend these tests to our option factor sample. We largely follow Ehsani & Linnainmaa (2022) to construct out-of-sample momentum returns on principal components. To do so, we follow three steps for each month t:

1. We calculate eigenvectors from the covariance matrix of demeaned monthly factor returns up to month $t-1$. The first PC analysis takes 120 months of factor returns as input. The principal component returns up to month t are the product of eigenvectors and raw factor returns.
2. We scale the principal components such that their standard deviation up to month $t-1$ equals the median factor standard deviation over the same time period.
3. Using the re-scaled principal component returns, we construct both time-series and cross-sectional momentum strategies using our standard lock-back periods following equations (3) and (4). We store the profits of these strategies for month t.

In Panel A of Table 8, we report the mean returns of both the TSFM and the CSFM strategies based on all PCs and subsets of 10 PCs. In line with the findings for equity market factors, profits are the highest and the most statistically significant in the ten largest PCs, with t-stats ranging from 6.58 to 10.17. Nevertheless, all other subsets also yield positive and significant momentum profits for most or all formation periods. This result does not immediately contradict the results of Ehsani & Linnainmaa (2022) and Arnott et al. (2023), who find momentum in lower-eigenvalue PCs as well. However, momentum in high-eigenvalue PCs fully explains lower-eigenvalue PC momentum in these studies. We test for this by regressing each TSFM and CSFM strategy return series against the respective PC_{1-10} counterpart. Alphas are reported in Panel B of Table 8. Positive and

Table 8: **Momentum in option factors' principal components.**
This table reports the mean returns of TSFM and CSFM strategies based on the principal components (PCs) of 56 option factors. For each month t, we compute the PC momentum returns in three steps. First, we compute eigenvectors from the covariance matrix of demeaned factor returns up to month $t-1$. The PC returns are then the product of these eigenvectors and the raw option factor returns. Second, we scale PCs to have the same standard deviation as the median factor up to month $t-1$. Third, we construct TSFM and CSFM strategies using all PCs and subsets of 10 PCs and save the profits for month t. We take 120 months of factor returns to perform the first PC analysis. Therefore, the PC momentum returns range from February 2006 to December 2021. In Panel A, we report annualized mean returns in percent for different subsets of PCs. For example, PC_{1-10} denotes the subset of the largest ten PCs ordered by eigenvalue. In Panel B, we report the annualized alphas after controlling for the returns of the PC_{1-10} subset with the identical formation period. t-stats of mean returns and alphas account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series factor momentum				Cross-sectional factor momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Mean PC momentum returns								
PC_{1-56}	4.19	7.25	6.38	6.69	4.13	6.86	6.41	6.59
	(6.44)	(10.53)	(11.46)	(12.52)	(6.33)	(9.90)	(11.01)	(12.88)
PC_{1-10}	7.34	11.42	11.49	9.29	6.58	9.94	10.37	9.17
	(7.59)	(10.17)	(9.97)	(9.45)	(6.58)	(8.19)	(9.45)	(9.27)
PC_{11-20}	4.62	8.45	7.21	7.76	3.96	6.80	7.52	7.99
	(4.88)	(7.30)	(6.14)	(8.32)	(4.45)	(6.48)	(6.33)	(6.83)
PC_{21-30}	0.98	5.62	4.77	5.37	0.78	4.55	4.46	5.14
	(1.00)	(5.64)	(5.23)	(6.34)	(0.80)	(4.91)	(4.47)	(6.05)
PC_{31-40}	2.63	3.81	2.96	3.94	2.61	3.31	3.77	2.20
	(2.30)	(3.42)	(2.54)	(3.34)	(2.39)	(2.53)	(3.23)	(2.09)
PC_{41-50}	4.88	5.04	2.76	4.02	3.90	6.25	3.76	3.39
	(3.52)	(3.25)	(2.32)	(3.24)	(2.61)	(4.16)	(2.92)	(2.88)
Panel B: Alphas after adjusting for PC_{1-10} momentum								
PC_{1-56}	2.67	3.13	2.94	3.79	2.75	3.57	3.43	4.13
	(5.04)	(4.06)	(6.05)	(4.40)	(4.10)	(4.85)	(6.18)	(4.85)
PC_{11-20}	2.78	5.45	5.09	7.24	2.59	4.41	5.72	7.70
	(3.01)	(4.32)	(3.89)	(5.62)	(2.74)	(4.18)	(5.11)	(5.68)
PC_{21-30}	1.09	4.82	3.93	3.65	1.36	3.70	1.92	4.37
	(1.07)	(3.13)	(3.51)	(3.03)	(1.41)	(3.11)	(1.62)	(3.56)
PC_{31-40}	2.01	-0.49	0.20	-0.46	1.29	-0.36	1.56	0.88
	(1.39)	(-0.29)	(0.13)	(-0.34)	(1.07)	(-0.23)	(0.96)	(0.69)
PC_{41-50}	4.97	2.21	0.41	4.67	3.07	4.05	0.21	2.81
	(3.21)	(1.19)	(0.32)	(1.95)	(1.72)	(2.17)	(0.13)	(1.70)

significant returns remain for the full PC sample strategies. This suggests that there are momentum effects in lower eigenvalue PCs, which are distinct from momentum effects inhibited by the largest ten PCs. These effects seem to mainly arise from the groups of PCs with the next largest eigenvalues, namely PC_{11-20} and PC_{21-30}. Almost all of their profitable TSFM and CSFM strategies remain robust after controlling for the PC_{1-10}

counterparts. Nevertheless, for the PC_{31-40} subset, all 8 strategies, and for the PC_{41-50}, 6 out of 8 strategies do not yield returns distinct from the PC_{1-10} subset at the 5% significance level.

Overall, our results suggest that the highest-eigenvalue PCs exhibit the strongest momentum. However, the results are not as unambiguous as those found for stock factor momentum. We believe that two effects explain the difference. First, as shown in section 4.4, option factor momentum is largely driven by persistent differences in expected factor returns. As we do not demean PC returns, these differences might transmit from factors to PCs. Because large PCs do not necessarily load more on factors with high mean returns, there can be PCs with persistently different expected returns in all subsets of PCs, leading to PC momentum. Second, as derived by Haddad et al. (2020), the number of predictable PCs increases in the maximum squared Sharpe ratio under the no near-arbitrage argument. Since the squared Sharpe ratio is much higher in the optimal option factor portfolio than in the optimal equity factor portfolio, the predictability in the option factors might stretch to more PCs than in the stock factors, as indicated by robust momentum profits in the PC_{11-20} and PC_{21-30} subsets.

4.6. Option momentum and momentum in option factors

After discussing the properties of our option factor momentum strategies in detail, we next turn to two further questions: first, is there also momentum in underlying delta-hedged options? And second, does option factor momentum explain this momentum at the option level? To answer these questions, we first consider the daily delta-hedged option returns underlying our set of option factors and define option momentum strategies analogous to our baseline strategies outlined in equations (3) and (4). Recall that for each stock identifier with options data in our sample, we consider the monthly return of the call contract closest to being ATM if the contract fulfills the filter criteria described in section 3. Using delta-hedged call returns instead of straddles is a deviation from the construction of option momentum in Heston et al. (2022). However, we do not expect a vastly different return behavior, as both straddles and delta-hedged calls are roughly delta-neutral and a bet on realized versus implied volatility of the underlying. In contrast to the set of factor returns and due to the strict filters at the company and option level, we do not obtain a complete time series of option returns for every company during our sample period. Following Heston et al. (2022), we require return observations for two-thirds of months during a formation period to include an option in winner or loser

Table 9: **Option momentum profitability.**

This table reports performance measures of both time series momentum (TSM) and cross-sectional momentum (CSM) strategies based on eight formation periods. All strategies are built from daily delta-hedged call option returns from February 1996 to December 2021. TSM strategies go long (short) in factors with positive (negative) formation period returns. CSM strategies go long (short) in factors with an above (below) median return in the formation period. For each underlying company, we require return observations for at least two-thirds of the months of the formation period. Panel A provides a summary of option momentum strategies. Panel B reports results of regressing TSM and CSM on the factors presented in Horenstein et al. (2020) (HVX): the returns of a daily delta-hedged at-the-money call position on the S&P 500 (SPX DHC) and three factors constructed from characteristic sorts in the same way as our option factors. The characteristics are the idiosyncratic volatility of the underlying (ivol), the underlyings' total market equity (market equity), and the difference between implied volatility and realized volatility (ivrv). Mean returns, Sharpe ratios, and regression alphas are annualized and given in percent. All t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Panel A: Time-series momentum				Panel B: Cross-sectional momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Option momentum								
Mean Return	6.02	5.44	5.43	0.86	2.96	4.64	5.01	2.54
	(4.50)	(4.93)	(4.17)	(0.80)	(4.04)	(6.44)	(6.90)	(3.64)
Sharpe Ratio	0.93	1.02	0.98	0.18	1.03	1.48	1.60	0.77
	(5.94)	(5.12)	(4.57)	(0.78)	(4.49)	(8.56)	(8.56)	(2.36)
Panel B: Controlling for HVX factors								
α	-0.89	3.15	5.92	1.45	0.44	3.18	3.29	4.09
	(-0.58)	(2.33)	(3.89)	(0.89)	(0.69)	(4.74)	(4.56)	(3.11)
SPX DHC	0.33	0.03	-0.13	-0.12	-0.01	0.05	0.05	0.03
	(1.67)	(0.25)	(-1.32)	(-1.04)	(-0.39)	(0.95)	(1.29)	(0.59)
ivol	0.14	-0.24	-0.46	-0.01	-0.12	-0.19	-0.12	-0.19
	(1.12)	(-2.19)	(-3.57)	(-0.07)	(-2.41)	(-3.05)	(-1.63)	(-1.17)
market equity	-0.16	0.21	0.31	-0.20	0.09	0.12	0.04	0.08
	(-1.77)	(2.04)	(2.81)	(-1.81)	(1.85)	(2.55)	(0.69)	(0.55)
ivrv	0.61	0.25	0.11	0.01	0.26	0.20	0.22	-0.01
	(5.95)	(3.09)	(1.32)	(0.17)	(5.60)	(4.01)	(4.20)	(-0.13)
R^2	0.27	0.18	0.24	0.05	0.33	0.30	0.22	0.07

portfolios.

Panel A of Table 9 summarizes the performance of option momentum in daily delta-hedged call positions. Except for the long-term horizon time-series strategy, both times-series option momentum (TSM) and cross-sectional option momentum (CSM) strategies yield, on average, positive returns, albeit smaller in economic magnitude and statistical significance than our factor momentum strategies. We obtain insignificant mean returns for 1-month formation periods when performing a risk adjustment using the HVX factor model in Panel B. However, despite decreases in magnitude and significance, the alphas of strategies with the formation periods of six and twelve months remain positive and highly statistically significant. t-stats of alphas range from 2.33 for the 6-month formation period TSM strategy to 4.74 for the 6-month formation period CSM strategy. Especially for the 1-month formation periods, the HVX factors offer high explanatory power, with R^2 of 0.27 for TSM and 0.33 for CSM.

In search for drivers of their profitable straddle momentum strategies, Heston et al. (2022) also turn to option factor momentum. To explain the returns of their cross-sectional straddle momentum strategies, they rely on a time-series momentum strategy built from a set of just seven option straddle factors.

In Panel A of Table 10, we regress option momentum returns on the corresponding option factor momentum returns. All regression alphas are negative, except for cross-sectional momentum with the formation period from $t-13$ to $t-60$. On the other hand, when controlling for option momentum in Panel D, option factor momentum alphas remain significantly positive at high confidence levels. Contrary to Heston et al. (2022) but in line with findings of Ehsani & Linnainmaa (2022) for the stock market, we show that factor momentum based on our 56 option factors subsumes option momentum.

We also follow tests of Ehsani & Linnainmaa (2022), which show that the momentum found in stock factors' largest 10 PCs subsumes stock momentum. We regress option momentum returns on the returns of momentum strategies built from the largest 10 PCs of our option factor set. We show results in Panel C and D of Table 10. For time-series strategies, large PC momentum subsumes option momentum. All option momentum alphas turn insignificant, and R^2 are even higher than for the regressions on factor momentum, going up to 0.3 for the 1-month formation period. On the other hand, time-series PC momentum remains highly positive and statistically significant after controlling for option momentum. Cross-sectional option momentum, however, yields significant alphas after controlling for large PC momentum. Nevertheless, alphas are lower than mean returns and t-stats are barely above 2 for all formation periods, indicating that momentum in large PCs is at least a partial driver of cross-sectional option momentum.

Finally, we test for the significance of momentum effects in high eigenvalue PCs relative to low eigenvalue PCs for explaining option momentum. To do so, we follow Arnott et al. (2023) and construct time-series and cross-sectional PC momentum strategies, first built from only two PCs and then adding PCs until the full sample of 56 PCs is reached. We then regress option momentum returns on these various PC momentum strategies and report t-stats of the regression intercepts in Figure 3. We step-wise add PCs in two ways. For the black lines, we start constructing momentum strategies with the two highest eigenvalue PCs and consequentially add further PCs ordered from high to low

Table 10: **Option momentum vs. option factor momentum.**
Panel A and Panel B of this table report the results of pairwise regression tests between option factor momentum (FM) and option momentum (OM) strategy returns with identical formation periods. Panel C and Panel D report results of identical regressions but momentum strategies (PCM) built from the factors' 10 largest PCs replace the FM strategies. The respective regression equations are stated above the results. The sample period for Panel A and Panel B ranges from February 1996 to December 2021 and is 10 years longer than for Panel C and D because PCs are at first estimated from 10 years of factor return data. Regression intercepts (α) are annualized and given in percent. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series momentum				Cross-sectional momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Regression $R_t^{OM} = \alpha + \beta R_t^{FM} + \varepsilon_t$								
α	-0.59	-0.22	3.42	1.88	0.50	0.36	1.16	2.40
	(-0.43)	(-0.15)	(1.54)	(0.99)	(0.87)	(0.51)	(1.69)	(3.31)
FM	0.70	0.43	0.15	-0.10	0.44	0.52	0.48	0.03
	(5.49)	(4.47)	(1.27)	(-0.71)	(9.80)	(5.13)	(5.84)	(0.20)
R^2	0.27	0.12	0.01	0.01	0.24	0.21	0.16	0.00
Panel B: Regression $R_t^{FM} = \alpha + \beta R_t^{OM} + \varepsilon_t$								
α	7.06	11.68	12.71	10.58	3.94	6.38	6.40	4.56
	(6.74)	(9.63)	(9.01)	(8.84)	(6.49)	(10.99)	(9.43)	(8.92)
OM	0.39	0.28	0.09	-0.07	0.55	0.40	0.33	0.01
	(5.11)	(4.53)	(1.16)	(-0.72)	(5.02)	(6.38)	(5.27)	(0.19)
R^2	0.27	0.12	0.01	0.01	0.24	0.21	0.16	0.00
Panel C: Regression $R_t^{OM} = \alpha + \beta R_t^{PCM} + \varepsilon_t$								
α	-1.67	-1.56	2.60	-1.05	1.54	1.67	2.17	2.12
	(-0.74)	(-0.84)	(1.11)	(-0.62)	(2.10)	(2.16)	(2.35)	(2.39)
PCM	1.04	0.53	0.06	0.26	0.06	0.19	0.18	0.03
	(2.75)	(4.01)	(0.33)	(1.86)	(0.69)	(2.49)	(2.31)	(0.29)
R^2	0.30	0.15	0.00	0.05	0.01	0.08	0.06	0.00
Panel D: Regression $R_t^{PCM} = \alpha + \beta R_t^{OM} + \varepsilon_t$								
α	5.63	10.14	11.36	9.04	6.38	8.45	9.10	9.08
	(7.39)	(11.16)	(8.98)	(8.88)	(6.46)	(7.97)	(10.07)	(9.10)
OM	0.29	0.29	0.04	0.18	0.10	0.42	0.32	0.03
	(8.44)	(4.45)	(0.35)	(2.36)	(0.62)	(2.55)	(2.32)	(0.25)
R^2	0.30	0.15	0.00	0.05	0.01	0.08	0.06	0.00

based on eigenvalues. For the red lines, we start with the two lowest eigenvalue PCs. We show t-stats of time-series and cross-sectional option momentum alphas for two formation periods: one month and one year, excluding the most recent month. However, results are similar for the two other formation periods. Generally, we see that t-stats decrease much faster when starting with the highest eigenvalue PCs. The red lines show that t-stats decrease very little when controlling for momentum effects in the lowest eigenvalue PCs. This observation provides evidence that momentum effects in PCs, which are able

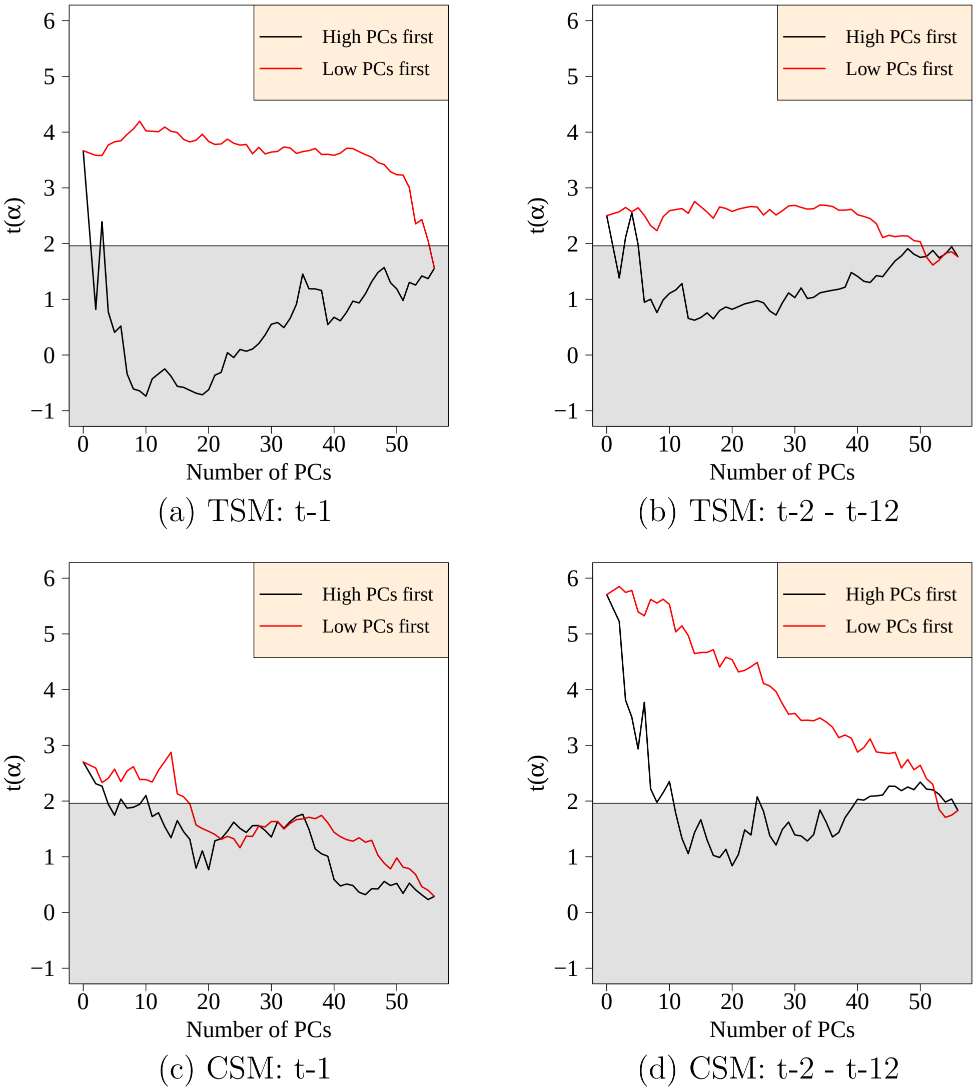


Fig. 3. **Significance of option momentum after controlling for PC momentum.**

Notes: This figure shows t-stats of regression alphas estimated from regressing time-series (TSM) and cross-sectional (CSM) option momentum returns on the returns of PC momentum strategies. For the black lines, we construct PC momentum strategies from the highest-eigenvalue PCs of our set of 56 option factors and add lower-eigenvalue PCs going from left to right. For the red lines, we start with the lowest-eigenvalue PCs. The number of PCs from which the PC momentum strategies are built is shown on the x-axis. For 0, we depict t-stats of the raw mean option momentum returns. All t-stats account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

to explain option momentum, lie in high eigenvalue rather than low eigenvalue PCs. In fact, the black lines inhibit a U-shape, indicating that adding further low eigenvalue PCs only adds noise to the PC momentum strategies and dilutes the explanatory power of high eigenvalue PCs. Overall, our results are in line with Ehsani & Linnainmaa (2022). Both option factor momentum and momentum in the factors' largest PCs subsume option momentum, but not vice versa.

5. Conclusion

Factors that describe the cross-section of stock returns exhibit momentum, and through stocks' and industries' factor exposure, this momentum causes stock and industry momentum (Ehsani & Linnainmaa, 2022; Arnott et al., 2023). In this paper, we extend tests for factor momentum to the options markets, relying on a novel set of 56 factors based on sorts of daily delta-hedged call options. We find corroborating evidence for both the existence of factor momentum and its explanatory power for momentum in the factors' underlying assets: First, time-series and cross-sectional factor momentum strategies are profitable. Their returns are distinct from returns of an equally-weighted factor portfolio and robust to the factor model of Horenstein et al. (2020). Second, strategies relying on a one-month formation period are largely driven by factor autocorrelation. However, the longer the formation period, the more important are high mean factor returns and their persistent variation as momentum drivers. Third, as in Ehsani & Linnainmaa (2022) and Arnott et al. (2023), momentum effects are the strongest in the option factors' largest eigenvalue principal components. Fourth, and extending the findings in Heston et al. (2022) to single option returns, we find momentum at the option level. Spanning tests suggest that option factor momentum subsumes option momentum and not vice versa. While our results are similar to studies focusing on the equity market, there are some remarkable differences. Although autocorrelation is high in option factors, some also exhibit extraordinary mean returns and Sharpe ratios driving factor momentum. We suggest future research to analyze the implications for optimal option portfolios.

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Appendix A. List of characteristics

A.1. Option contract characteristics

1. Delta (*delta*): The delta of the option contract.
2. Embedded leverage (*embedlev*): The embedded leverage of the option contract following Frazzini & Pedersen (2022).
3. Gamma (*gamma*): The gamma of the option contract.
4. Implied volatility (*iv*): The implied volatility of the option contract.
5. Moneyness (*moneyness*): Moneyness defined as the ratio of the strike price to the underlying price.
6. Open interest (*oi*): The open interest of the option contract.
7. Option bid-ask spread (*optspread*): The bid-ask spread of the option contract.
8. Option mid price (*mid*): The mid price of the option contract.
9. Theta (*theta*): The theta of the option contract.
10. Vega (*vega*): The vega of the option contract.
11. Volga (*volga*): The volga of the option contract.

A.2. Stock-level characteristics

A.2.1. Derived from options data

12. At-the-money implied volatility (*atmiv*): The average of put and call implied volatility with an absolute delta of 0.5 following Goyal & Saretto (2022). We use the 30-day implied volatility surface of OptionMetrics.
13. Call-put implied volatility spread (*civpiv*): Call minus put at-the-money implied volatility as in Bali & Hovakimian (2009).
14. Demand pressure (*demand_pressure*): The ratio of option market value (total option open interest times mid price of the contract) and market capitalization for the underlying stock following Zhan et al. (2022).
15. Implied volatility skew (*skewiv*): Following Xing, Zhang, & Zhao (2010), an implied volatility smirk measure as the difference between the implied volatilities of out-of-the-money puts and at-the-money calls.
16. Implied volatility term structure (*ivterm*): The difference between 365 and 30-days to expiration at-the-money implied volatility following Goyal & Saretto (2022). At-the-money implied volatility is the average of put and call implied volatility with

an absolute delta of 0.5. We use the 30 and 365-day implied volatility surface of OptionMetrics.

17. Risk-neutral kurtosis with 30-days to expiration (*rnk30*): Model-free implied kurtosis constructed from 30 days out-of-the-money call and out-of-the-money put option prices as in Bakshi et al. (2003). We use the 30-day implied volatility surface of OptionMetrics. Code is taken from Grigory Vilkov's website.
18. Risk-neutral kurtosis with 365-days to expiration (*rnk365*): Model-free implied kurtosis constructed from 365 days out-of-the-money call and out-of-the-money put option prices. We use the 365-day implied volatility surface of OptionMetrics. Code is taken from Grigory Vilkov's website.
19. Risk-neutral skewness with 30-days to expiration (*rns30*): Model-free implied skewness constructed from 30 days out-of-the-money call and out-of-the-money put option prices as in Bakshi et al. (2003). We use the 30-day implied volatility surface of OptionMetrics. Code is taken from Grigory Vilkov's website.[6]
20. Risk-neutral skewness with 365-days to expiration (*rns365*): Model-free implied skewness constructed from 365 days out-of-the-money call and out-of-the-money put option prices. We use the 365-day implied volatility surface of OptionMetrics. Code is taken from Grigory Vilkov's website.
21. Stochastic volatility risk (*sr*): The standard deviation of log changes in at-the-money implied volatility following Tian & Wu (2023). At-the-money implied volatility is the average of put and call implied volatility with an absolute delta of 0.5 and 91 days to expiration. We use the 91-day implied volatility surface of OptionMetrics. A minimum of 15 days over the last month is required.
22. Volatility of implied volatility (*ivvol*): Following Baltussen, van Bekkum, & van der Grient (2018), volatility of atm implied volatility scaled by average implied volatility.

A.2.2. Derived from stock price and accounting data

23. 1-year new stock issues (*issue_1y*): The one-year change in log of number of shares outstanding as in Pontiff & Woodgate (2008). Data is taken from Jensen, Kelly, & Pedersen (2022).
24. 5-year new stock issues(*issue_5y*): The five-year change in the log of number of shares outstanding as in Daniel & Titman (2006).

[6] `https://www.vilkov.net/index.html`

25. Altman Z-score (*z_score*): The Altman Z-score as in Dichev (1998). Data is taken from Jensen et al. (2022).
26. Analyst dispersion (*disp*): Analyst earnings forecast dispersion computed as the standard deviation of analysts' annual earnings-per-share forecasts over the absolute value of the average forecast (Diether, Malloy, & Scherbina, 2002). Data is constructed using the replication code of Green, Hand, & Zhang (2017).[7]
27. Autocorrelation (*ac*): The autocorrelation of daily returns over the last 6 months requiring at least 100 observations (Goyal & Saretto, 2022; Jeon, Kan, & Li, 2019).
28. Average of 10 highest past returns (*max10*): The average of the 10 highest daily returns over the last 3 months following Bali, Cakici, & Whitelaw (2011).
29. Book to market equity (*be_me*): The book-to-market ratio as in Rosenberg, Reid, & Lanstein (1998). Data is taken from Jensen et al. (2022) using *debt_at* and *asset*.
30. Cash-to-assets ratio (*cash_at*): The corporate cash holdings over total assets as in Palazzo (2012). Data is taken from Jensen et al. (2022).
31. Cash flow volatility (*ocfq_saleq_std*): The standard deviation quarterly reported operating cash flows over quarterly sales as in Huang (2009). Data is taken from Jensen et al. (2022).
32. Debt to total assets (*debt_at*): The firm's leverage defined as total debt over total assets. Data is taken from Jensen et al. (2022).
33. Default risk (*defrisk*): Following Vasquez & Xiao (2020), we calculate the default probability of the underlying stock as in Bharath & Shumway (2008).
34. Financial debt (*debt*): The firm's total book value of debt. Data is taken from Jensen et al. (2022) using *debt_at* and *asset*.
35. Idiosyncratic skewness (*iskew*): The third moment of the residuals from regressing the stock returns on the market return and its square following Byun & Kim (2016).
36. Idiosyncratic volatility (*ivol*): The idiosyncratic volatility of the underlying with respect to the Fama & French (1993) 3-factor model over the past month. The construction follows Goyal & Saretto (2022).
37. Implied volatility minus realized volatility (*ivrv*: The difference between *iv* and *vol* as in Goyal & Saretto (2009).
38. Institutional ownership (*insti*): The institutional ownership in percentage derived from Thomson Reuters 13f holdings (Goyal & Saretto, 2022).
39. Institutional ownership concentration (*insti_hhi*): The concentration of institutional ownership constructed as Herfindahl–Hirschman index.

[7] `https://sites.google.com/site/jeremiahrgreenacctg/home`

40. Market equity (*market_equity*): The total market value of equity as in Banz (1981). Data is taken from Jensen et al. (2022).
41. Net equity issuance (*eqnetis_at*): Net equity issuance defined as total share issuance minus cash dividend payments as in Bradshaw, Richardson, & Sloan (2006). Data is taken from Jensen et al. (2022).
42. Net total issuance (*netis_at*): Net total issuance defined as total share and debt issuance minus cash dividend payments as in Bradshaw et al. (2006). Data is taken from Jensen et al. (2022).
43. Operating profits-to-book equity (*ope_be*): The Operating profits-to-book equity ratio as in Fama & French (2015). Data is taken from Jensen et al. (2022).
44. Profit margin (*ebit_sale*): The profit margin defined as EBIT over total sales as in Soliman (2008). Data is taken from Jensen et al. (2022).
45. Realized kurtosis (*kurtosis*): The kurtosis of daily log returns over the last 12 months requiring at least 150 observations (Goyal & Saretto, 2022).
46. Realized kurtosis minus risk-neutral kurtosis (*diff_kurtosis*): The difference between *kurtosis* and *rnk30* following Goyal & Saretto (2022).
47. Realized skewness minus risk-neutral skewness (*diff_skew*): The difference between *skew* and *rns30* following Goyal & Saretto (2022).
48. Realized skewness (*skew*): The skewness of daily log returns over the last 12 months requiring at least 150 observations (Goyal & Saretto, 2022).
49. Realized volatility (*vol*): The volatility of daily log returns over the last 12 months requiring at least 150 observations (Goyal & Saretto, 2022).
50. Share turnover (*turnover_126d*): The total share turnover rate (trading volume over shares outstanding) over the past 126 trading days (6 months) as in Datar, Naik, & Radcliffe (1998). Data is taken from Jensen et al. (2022).
51. Short-term stock return reversal (*ret_1_0*): The short-term stock return reversal measured as the return in month $t-1$ as in Jegadeesh (1990). Data is taken from Jensen et al. (2022).
52. Short interest (*rsi*): The ratio between short interest (taken from Compustat's Supplemental Short Interest File (*shortintadj*)) and the total shares outstanding (Ramachandran & Tayal, 2021).
53. Stock illiquidity (*amihud*): The Amihud (2002) illiquidity measure over the past month.
54. Stock price (*log_price*): The log of the underlying stock's close price as in Blume & Husic (1973).

55. Stock return momentum (*ret_12_1*): Stock price momentum measured as return from month $t-12$ to $t-1$ as in Jegadeesh & Titman (1993). Data is taken from Jensen et al. (2022).
56. Total assets (*asset*): The firm's total book value of assets. Data is taken from Jensen et al. (2022).

Appendix B. Margin-adjusted Returns

B.1. Definition of margin-adjusted returns

In the main analyses, we scale the delta-hedged portfolio gain by the cash requirement to enter into a delta-hedged option position. In the following, we change the return definition to incorporate margin requirements. Precisely, we change Equation 2 to

$$r_{t,t+\tau} = \frac{\Pi(t, t+\tau)}{M_t}, \tag{B1}$$

where $M_t > 0$ denotes the margin requirement for sustaining a delta-hedged option position from t to $t+\tau$. For the exact margin requirements, we adopt the CBOE minimum margin for customer accounts.[8] Also assuming a 50% margin requirement for long and short positions in the underlying stock, the margin requirement is given as

$$M_t = \begin{cases} V_t + 0.5|\Delta_t|S_t, & \text{for hedged long positions} \\ V_t + \max(0.1S_t, 0.2S_t - \max(0, K - S_t)) + 0.5|\Delta_t|S_t, & \text{for hedged short calls} \\ 0.1K + 0.5|\Delta_t|S_t, & \text{for hedged short puts} \end{cases} \tag{B2}$$

where K denotes the strike price, V_t the option price, and S_t is the price of the underlying stock.

[8]See `https://www.cboe.com/us/options/strategy_based_margin`.

B.2. Main results for margin-adjusted returns

Table B1: **Option factor momentum profitability – margin-adjusted returns.** This table reports performance measures of both time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) strategies based on eight formation periods. All strategies are built from 56 option factors with monthly returns from February 1996 to December 2021. Factor returns are based on the margin-adjusted returns of delta-hedged call options as outlined in B.1. TSFM strategies go long (short) in factors with positive (negative) formation period returns. CSFM strategies go long (short) in factors with an above (below) median return in the formation period. The strategies are rebalanced monthly, and the sum of absolute factor weights in both TSFM and CSFM strategies sum to two. Mean returns of TSFM, CSFM, and their respective long and short portfolios are annualized and given in percent. Sharpe ratios are also annualized by multiplying by $\sqrt{12}$. ρ denotes the Pearson correlation coefficients. All t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	t-1	t-3	t-6	t-12	t-36	t-60	t-2 - t-12	t-13 - t-60
Panel A: Time-series factor momentum								
$TSFM$	9.72	12.14	13.61	13.99	13.00	11.19	13.56	10.14
	(7.41)	(10.34)	(11.31)	(11.11)	(9.67)	(9.31)	(11.43)	(8.45)
Sharpe ratio	1.96	2.81	3.17	3.26	2.83	2.57	3.49	2.33
	(7.76)	(8.39)	(9.65)	(8.51)	(7.03)	(5.86)	(13.28)	(5.67)
Long	8.57	8.95	9.01	8.72	7.80	6.95	8.66	6.76
	(10.65)	(11.62)	(11.53)	(11.06)	(9.72)	(8.98)	(10.98)	(8.66)
Short	2.18	0.10	-0.63	-0.99	-1.26	-0.05	-0.65	1.17
	(3.74)	(0.16)	(-1.09)	(-1.39)	(-1.88)	(-0.09)	(-0.93)	(1.68)
$\rho_{TSFM,Long}$	0.87	0.85	0.89	0.92	0.96	0.98	0.88	0.97
$\rho_{TSFM,Short}$	-0.22	-0.09	0.01	0.09	0.17	0.20	0.09	0.15
Panel B: Cross-sectional factor momentum								
$CSFM$	6.25	8.18	8.66	9.17	8.10	5.99	8.87	5.28
	(7.16)	(9.70)	(11.03)	(10.73)	(9.89)	(9.99)	(10.52)	(8.67)
Sharpe ratio	1.84	2.64	2.97	3.19	3.09	2.52	3.18	2.21
	(8.76)	(11.01)	(13.53)	(12.42)	(11.90)	(7.42)	(12.88)	(7.06)
Long	9.71	10.62	10.94	11.15	10.17	8.50	11.00	8.15
	(9.72)	(10.87)	(11.40)	(11.21)	(10.31)	(10.20)	(11.24)	(9.67)
Short	3.46	2.44	2.28	1.98	2.06	2.51	2.13	2.87
	(6.18)	(4.16)	(3.92)	(3.31)	(3.24)	(4.12)	(3.47)	(4.77)
$\rho_{CSFM,Long}$	0.75	0.73	0.70	0.70	0.72	0.68	0.65	0.70
$\rho_{CSFM,Short}$	-0.24	-0.18	-0.19	-0.16	-0.05	-0.08	-0.22	-0.06

Table B2: **Benchmarking and risk-adjusting option factor momentum – margin-adjusted returns.**

Panel A of this table reports the results of regressing both TSFM and CSFM strategies against an equally-weighted portfolio of 56 option factors with monthly rebalancing from February 1996 to December 2021. Factor returns are based on the margin-adjusted returns of delta-hedged call options as outlined in B.1. Panel B reports results of regressing TSFM and CSFM on the factors presented in Horenstein et al. (2020) (HVX): the returns of a daily delta-hedged at-the-money call position on the S&P 500 (SPX DHC) and three factors constructed from characteristic sorts in the same way as our option factors: the characteristics are the idiosyncratic volatility of the underlying (ivol), the underlyings' total market equity (market equity), and the difference between implied volatility and realized volatility (ivrv). Regression intercepts (α) are annualized and given in percent. Information ratios (IR) are the ratio of α and the standard deviation of regression residuals. IRs are annualized by multiplying by $\sqrt{12}$. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series factor momentum				Cross-sectional factor momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Factor momentum vs. equally-weighted factor portfolio								
α	1.47	5.55	6.20	1.47	2.86	6.07	6.84	3.13
	(0.88)	(4.86)	(7.51)	(2.43)	(2.16)	(5.68)	(7.30)	(4.73)
$EW Factors$	1.25	1.22	1.12	1.57	0.52	0.39	0.31	0.39
	(5.64)	(8.71)	(11.71)	(11.94)	(3.41)	(3.37)	(3.69)	(3.13)
R^2	0.46	0.58	0.61	0.85	0.17	0.13	0.09	0.17
IR	0.40	2.00	2.55	0.86	0.92	2.23	2.57	1.44
Panel B: Factor momentum vs. HVX Factors								
α	2.16	7.01	7.20	3.29	2.20	5.78	6.58	2.17
	(1.98)	(8.74)	(9.71)	(4.34)	(2.60)	(8.64)	(9.32)	(2.61)
SPX DHC	0.37	0.38	0.27	0.53	0.11	0.13	0.10	0.08
	(2.72)	(5.75)	(8.24)	(7.64)	(1.28)	(2.66)	(2.49)	(1.08)
ivol	0.25	0.20	0.22	0.59	0.03	-0.05	-0.08	0.29
	(2.65)	(4.15)	(6.27)	(10.67)	(0.39)	(-1.10)	(-2.27)	(4.08)
market equity	-0.01	0.09	0.14	-0.29	-0.01	0.07	0.11	-0.27
	(-0.15)	(1.84)	(2.57)	(-4.69)	(-0.15)	(1.41)	(2.05)	(-4.14)
ivrv	0.50	0.39	0.33	0.30	0.34	0.25	0.20	0.16
	(6.58)	(7.59)	(7.94)	(4.63)	(6.55)	(7.01)	(5.85)	(2.75)
R^2	0.45	0.54	0.55	0.71	0.29	0.33	0.31	0.28
IR	0.59	2.40	2.77	1.40	0.77	2.42	2.84	1.07

Table B3: **Option momentum profitability – margin-adjusted returns.** This table reports performance measures of both time-series momentum (TSM) and cross-sectional momentum (CSM) strategies based on eight formation periods. All strategies are built from the margin-adjusted returns of daily delta-hedged call options as outlined in B.1 for the period from February 1996 to December 2021. TSM strategies go long (short) in factors with positive (negative) formation period returns. CSM strategies go long (short) in factors with an above (below) median return in the formation period. For each underlying company, we require return observations for at least two-thirds of the months of the formation period. Panel A provides a summary of option momentum strategies. Panel B reports results of regressing TSM and CSM on the factors presented in Horenstein et al. (2020) (HVX): the returns of a daily delta-hedged at-the-money call position on the S&P 500 (SPX DHC) and three factors constructed from characteristic sorts in the same way as our option factors. The characteristics are the idiosyncratic volatility of the underlying (ivol), the underlyings' total market equity (market equity), and the difference between implied volatility and realized volatility (ivrv). Mean returns, Sharpe ratios, and regression alphas are annualized and given in percent. All t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Panel A: Time-series momentum				Panel B: Cross-sectional momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Option momentum								
Mean Return	6.02	5.44	5.43	0.86	2.96	4.64	5.01	2.54
	(4.50)	(4.93)	(4.17)	(0.80)	(4.04)	(6.44)	(6.90)	(3.64)
Sharpe Ratio	0.93	1.02	0.98	0.18	1.03	1.48	1.60	0.77
	(5.94)	(5.12)	(4.57)	(0.78)	(4.49)	(8.56)	(8.56)	(2.36)
Panel B: Controlling for HVX factors								
α	-0.89	3.15	5.92	1.45	0.44	3.18	3.29	4.09
	(-0.58)	(2.33)	(3.89)	(0.89)	(0.69)	(4.74)	(4.56)	(3.11)
SPX DHC	0.33	0.03	-0.13	-0.12	-0.01	0.05	0.05	0.03
	(1.67)	(0.25)	(-1.32)	(-1.04)	(-0.39)	(0.95)	(1.29)	(0.59)
ivol	0.14	-0.24	-0.46	-0.01	-0.12	-0.19	-0.12	-0.19
	(1.12)	(-2.19)	(-3.57)	(-0.07)	(-2.41)	(-3.05)	(-1.63)	(-1.17)
market equity	-0.16	0.21	0.31	-0.20	0.09	0.12	0.04	0.08
	(-1.77)	(2.04)	(2.81)	(-1.81)	(1.85)	(2.55)	(0.69)	(0.55)
ivrv	0.61	0.25	0.11	0.01	0.26	0.20	0.22	-0.01
	(5.95)	(3.09)	(1.32)	(0.17)	(5.60)	(4.01)	(4.20)	(-0.13)
R^2	0.27	0.18	0.24	0.05	0.33	0.30	0.22	0.07

Table B4: **Option momentum and option factor momentum – margin-adjusted returns.**

Panel A and Panel B of this table report the results of pairwise regression tests between option factor momentum (FM) and option momentum (OM) strategy returns with identical formation periods. The underlying daily delta-hedged call option returns are margin-adjusted as outlined in B.1. Panel C and Panel D report results of identical regressions but momentum strategies (PCM) built from the factors' 10 largest PCs replace the FM strategies. The respective regression equations are stated above the results. The sample period for Panel A and Panel B ranges from February 1996 to December 2021 and is 10 years longer than for Panel C and D because PCs are at first estimated from 10 years of factor return data. Regression intercepts (α) are annualized and given in percent. t-stats (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag four, following Newey & West (1987).

	Time-series momentum				Cross-sectional momentum			
	t-1	t-6	t-2 - t-12	t-13 - t-60	t-1	t-6	t-2 - t-12	t-13 - t-60
Panel A: Regression $R_t^{OM} = \alpha + \beta R_t^{FM} + \varepsilon_t$								
α	-1.81	-0.04	2.06	1.37	0.69	0.93	1.21	1.88
	(-1.34)	(-0.03)	(0.89)	(1.27)	(1.22)	(1.20)	(1.69)	(2.82)
FM	0.81	0.40	0.25	-0.05	0.36	0.43	0.43	0.12
	(6.67)	(3.96)	(1.73)	(-0.86)	(5.32)	(3.91)	(5.64)	(1.10)
R^2	0.38	0.10	0.03	0.00	0.18	0.16	0.15	0.01
Panel B: Regression $R_t^{FM} = \alpha + \beta R_t^{OM} + \varepsilon_t$								
α	6.86	12.21	12.89	10.18	4.77	6.94	7.17	5.12
	(7.05)	(11.08)	(10.60)	(8.38)	(6.84)	(10.82)	(10.49)	(8.35)
OM	0.47	0.26	0.12	-0.04	0.50	0.37	0.34	0.06
	(4.47)	(5.81)	(1.78)	(-0.81)	(4.80)	(5.82)	(4.70)	(0.76)
R^2	0.38	0.10	0.03	0.00	0.18	0.16	0.15	0.01
Panel C: Regression $R_t^{OM} = \alpha + \beta R_t^{PCM} + \varepsilon_t$								
α	0.25	0.13	1.67	0.59	1.23	1.44	1.25	1.83
	(0.16)	(0.10)	(0.78)	(0.35)	(1.92)	(2.01)	(1.48)	(1.88)
PCM	1.05	0.43	0.16	0.08	0.12	0.22	0.28	0.07
	(3.76)	(3.70)	(0.92)	(0.69)	(2.15)	(2.74)	(3.36)	(0.99)
R^2	0.35	0.10	0.02	0.01	0.04	0.11	0.13	0.00
Panel D: Regression $R_t^{PCM} = \alpha + \beta R_t^{OM} + \varepsilon_t$								
α	3.44	9.04	10.08	9.21	5.10	7.88	8.03	8.04
	(4.87)	(8.33)	(8.35)	(8.58)	(4.58)	(8.38)	(7.95)	(9.91)
OM	0.34	0.25	0.10	0.07	0.33	0.49	0.47	0.06
	(3.55)	(3.18)	(0.99)	(0.80)	(1.52)	(4.29)	(3.05)	(0.81)
R^2	0.35	0.10	0.02	0.01	0.04	0.11	0.13	0.00