# A New Option Momentum: Compensation for Risk *

Heiner Beckmeyer† Ilias Filippou‡ Guofu Zhou§

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In this paper, we propose a cross-sectional option momentum strategy that is based on the risk component of delta-hedged option returns. We find strong evidence of risk continuation in option returns. Specifically, options with a high risk component significantly outperform those with a low risk component. The risk-based option momentum strategy is highly profitable for different formation and holding periods, and it is more profitable than the recently discovered option momentum strategy of Heston, Jones, Khorram, Li, and Mo (2023). We show that risk-based option momentum is unrelated to their return-based option momentum and fully subsumes its performance. The strategy is not subject to crash risk, it is not followed by long-term reversals, and survives the consideration of realistic levels of transaction costs. With this, our paper is the first to show that risk in the forward-looking and particularly informative options market is not only time-varying but also highly persistent over time and is well compensated by the corresponding option returns. Finally, we investigate possible explanations for the strategy's success. Our results are robust to alterations of the empirical setup.

**Keywords**: Option, Momentum, Factor Risk, Limits to Arbitrage.

**JEL classification**: G11, G12, G14, G40.

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†Finance Center, University of Münster. heiner.beckmeyer@wiwi.uni-muenster.de.
‡Olin Business School, Washington University in St. Louis. iliasfilippou@wustl.edu.
§Olin Business School, Washington University in St. Louis. zhou@wustl.edu.

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**Abstract**

In this paper, we propose a cross-sectional option momentum strategy that is based on the risk component of delta-hedged option returns. We find strong evidence of risk continuation in option returns. Specifically, options with a high risk component significantly outperform those with a low risk component. The risk-based option momentum strategy is highly profitable for different formation and holding periods, and it is more profitable than the recently discovered option momentum strategy of Heston et al. (2023). We show that risk-based option momentum is unrelated to their return-based option momentum and fully subsumes its performance. The strategy is not subject to crash risk, it is not followed by long-term reversals, and survives the consideration of realistic levels of transaction costs. With this, our paper is the first to show that risk in the forward-looking and particularly informative options market is not only time-varying but also highly persistent over time and is well compensated by the corresponding option returns. Finally, we investigate possible explanations for the strategy's success. Our results are robust to alterations of the empirical setup.

# 1. Introduction

Momentum is the most pervasive and widely examined asset pricing anomaly. It was first discovered by Jegadeesh and Titman (1993) (JT), and it is based on the notion that assets that performed well in the past will continue to outperform in the future. The strategy is highly profitable across asset classes (e.g., Asness, Moskowitz, and Pedersen, 2013) and offers returns that are hard to understand with standard models (see, e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; Li, 2018; Kelly, Moskowitz, and Pruitt, 2021). In a recent study, Heston et al. (2023) find that return momentum holds for options, too, and demonstrate that the return-based option momentum outperforms the stock momentum substantially.

In this paper, we propose a novel momentum strategy in the options market which is based on the persistent patterns of the risk component of option returns. In other words, we show that there is momentum in the component of option returns explained by common factors that is unrelated to conventional option momentum. Specifically, we estimate the latent factor model proposed by Kelly, Pruitt, and Su (2019). Then, we decompose option returns into two components, a *risk* component that is associated with the factors – the sum of the products of the estimated $\beta$s with the factors – and a *residual* component. We find that the risk component exhibits a strong momentum pattern which implies that options with a high risk-based return component in the previous month continue to have a high risk component in the subsequent period.

In comparison to the option momentum discovered by Heston et al. (2023), our momentum is risk-based. With a formation period of three months and a holding period of one month, our strategy offers an annualized Sharpe ratio of 5.19 when we ignore transaction costs, while the corresponding return-based option momentum strategy generates a Sharpe ratio of 3.34. We also find that our risk-based option momentum is profitable for longer horizons. For example, a risk-based option momentum strategy with formation and holding periods of 12 months generates a Sharpe ratio of 2.42, while the corresponding return-based option momentum strategy offers a Sharpe ratio of just 1.57. Overall, we find that the strategy is highly significant for formation periods from 1 to 120 months. Consistent with Heston et al. (2023), we do not find evidence of long-term reversals. Our results remain highly significant if we skip the most recent month in the estimation of the momentum signal as in Jegadeesh and Titman (1993).

Our paper is related to the work of Li, Yuan, and Zhou (2023), who show that an intraday risk-based momentum strategy is highly profitable in the stock market. In contrast, we focus on the options market and build a risk-based momentum strategy that is unrelated to the strategy in the equity market. To achieve this, we focus on monthly option returns that are delta-hedged daily so as to insulate our option returns from movements that are inherited from the underlying securities. In this way, we extract the risk component of option returns that is due to option-specific risks. It is worth noting that delta-hedged option returns exhibit better statistical properties, and they can be approximated by normal distributions compared to raw option returns (e.g., Zhan, Han, Cao, and Tong, 2022). In addition, they might contain more information regarding the mispricing of the option (Broadie, Chernov, and Johannes, 2009).

Our analysis is based on a large set of stock and option characteristics. We employ 73 option-level characteristics from Bali, Beckmeyer, Moerke, and Weigert (2023) and 153 stock-level characteristics from Jensen, Kelly, and Pedersen (2021). We standardize all characteristics cross-sectionally to lie between $-0.5$ and 0.5. To guard against overfitting on in-sample information, we focus on characteristics with statistically significant Sharpe ratios. Specifically, we form characteristic-managed portfolios each month that are sorted on a single characteristic. We find that 165 portfolios (out of 226) offer significant Sharpe ratios at the 5% significance level.

The risk adjustment of option returns is challenging due to the options' short maturities that do not allow for robust estimation of time-series betas. Furthermore, an option's moneyness fluctuates with changes in the underlying stock's price. Thus, options contracts do not have the same properties from month to month. To circumvent this issue, Büchner and Kelly (2022) apply *instrumental principal component analysis* (IPCA) of Kelly et al. (2019) for S&P 500 options, and Goyal and Saretto (2022) extend this analysis to individual equity options. The IPCA procedure includes information from both the option contract and the underlying security to instrument for the heterogeneity in options' sensitivity ($\beta$s) to latent risk factors. The extracted factors are strong predictors of the cross-section of option returns. Following Goyal and Saretto (2022), we focus on four latent factors to describe the systematic component of equity options. We show that the four factors can explain 17.8% of the variation in option returns and that additional factors only incrementally improve the model's fit. To control for potential forward-looking bias in our estimation, we also compute the factors out-of-sample using an expanding window.

From this IPCA model, we can estimate the risk and residual components of delta-hedged option returns. We build risk-based option momentum portfolios by sorting options into quintiles based on the previous months' risk momentum signal. We consider formation and holding periods that range from one to 120 months. We do not find evidence of short-term reversals, so we include the most recent month in the estimation of the signal. An option momentum strategy based on the residual from the IPCA model is not statistically significant. Our strategy survives the consideration of transaction costs, and we find that the net-of-fees performance is stronger for shorter maturities of approximately 20 days to expiration.

Our main analysis is based on equally-weighted portfolios. However, the illiquidity of the options that we consider might be a driver of the results if it is an important impediment to trading. To this end, we consider different weighting schemes. Specifically, we construct value-weighted and open-interest-weighted portfolios by considering the underlying stock's market capitalization and the options' dollar open interest, respectively. This way, we focus on more liquid options as well as options with highly liquid underlying stocks. We find that the risk-based option momentum strategy remains highly profitable and statistically significant for each weighting scheme. Interestingly, the return-based option momentum generates almost 50% lower returns in comparison to the risk-based option momentum strategy. We also show that our results are robust if we estimate the latent factors in an out-of-sample setting, which alleviates potential concerns regarding the role of forward-looking information in the estimation of $\beta$s.

We also examine the role of momentum crashes. Daniel and Moskowitz (2016) show that price momentum in the stock market tends to crash after economic recessions. We explore this possibility for risk-based option momentum and find that the strategy is not subject to momentum crashes. This is consistent with Heston et al. (2023), who find that the type of crash risk documented in Daniel and Moskowitz (2016) for stock momentum does not seem to appear in the return-based option momentum. Nevertheless, volatility might play an important role in our findings. For example, Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) show that the volatility exposure of a stock is a driver of stock momentum, and they propose a scaling in the momentum strategy that increases the investment in the strategy when volatility is low. Thus, we investigate if the performance of the option risk-based momentum strategy depends on different volatility regimes. We estimate the strategy's past volatility based on a six-month rolling window and consider subsamples for past volatilities that are above or below the full-sample median. In contrast to the volatility dependence that is documented for stock momentum, we find that the returns of the option risk-based momentum strategy are larger for high-volatility regimes. Moreover, the Sharpe ratio of the strategy is comparable across different volatility regimes, which seems to be the result of the strategy being compensation for risk.

We investigate possible explanations for the profitability of the risk-based option momentum strategy. Note that our risk-based option momentum strategy is inherently "born" with a risk-based explanation. In contrast, it took many years to develop both behavioral and rational explanations for the famous JT stock momentum (see, e.g., Chan, Jegadeesh, and Lakonishok, 1996; Barberis, Shleifer, and Vishny, 1998; Daniel et al., 1998; Hong and Stein, 1999). While the Heston et al. (2023) option momentum is similar to JT stock momentum in finding momentum by sorting on past asset returns, its economic drivers are largely unknown.

We first investigate whether option risk-based momentum and option momentum are related and whether the profitability of one strategy subsumes the performance of the other. We independently sort options into quintiles based on the signals of the two strategies. We consider a formation period of three months and a holding period of one month with no formation gap and find that option risk momentum fully subsumes the performance of option momentum. The risk-based option momentum strategy in contrast remains statistically and economically significant across different option momentum portfolios, generating returns that range from 13.7% to 22.0% per year. With this analysis, we demonstrate that risk-based option momentum dominates its return-based counterpart. We verify this result in predictive panel regressions of delta-hedged option returns on the lagged signal of the option risk-based momentum and option momentum as well as a number of option-level and stock-level characteristics. We find that the coefficient of the option risk-based momentum signal remains highly significant, while the coefficient of the return-based momentum signal is not statistically significant.

We also show that the profitability of the option risk-based momentum strategy is not driven by the ability of the IPCA model to describe option returns. Specifically, we extract the amount of return variation that the IPCA model can explain by regressing the return of each option on the four latent factors and documenting the resulting $R^2$. Then, we perform an independent double sort of delta-hedged option returns on the risk momentum signal and the estimated time-series $R^2$. We find that risk-based option momentum is significant regardless of the level of the $R^2$, and interestingly the strategy is more profitable for lower, albeit still positive, levels of $R^2$. The latter finding highlights the disconnect between the performance of the IPCA and the profitability of the strategy.

Another potential explanation of the performance of the option risk-based momentum is that investors do not manage to fully adjust their expectations regarding the future volatility of the underlying stock when investing in options. To investigate this channel, we compute the average implied volatility of each quintile of the strategy and evaluate the implied volatility spread, which is defined as the difference between the realized and implied volatility. We again find a negative and statistically significant pattern. Further analyses show that the performance of the strategy is partly driven by its ability to short options for which their implied volatilities are expected to exceed their underlying volatilities realized in the next month and invest in options for which the opposite is true. Furthermore, we show that sorting options based on the risk-based momentum signals produces a highly persistent spread between future realized and today's implied volatilities that lasts for more than 24 months into the future. Not only do investors fail to adequately forecast the underlying stock's volatility (Goyal and Saretto, 2009), their forecast errors show remarkable persistence, which we exploit with our risk-based option momentum strategy.

Our results are robust to a number of alterations of the empirical design. Specifically, our estimation of the IPCA model allows for time variation in the factor realizations and factor sensitivities (e.g., betas). We show that our results are robust when we do not allow for time variation in the betas or the factor realizations or when we fix both. We also find that our strategy offers high Sharpe ratios when we estimate the latent factors using only option or stock characteristics. Furthermore, the risk-based momentum strategy is economically and statistically significant for at-the-money and out-of-the-money options. Varying the number of latent factors does not change our results. A two-factor structure is sufficient for our risk-based option momentum to significantly outperform its return-based counterpart, additional factors further improve our strategy's performance.

The rest of the paper is organized as follows: Section 2 provides a literature review. Section 3 introduces the data and the methodology, Section 4 offers our main results, and Section 5 discusses different explanations of the strategy. Section 6 includes robustness checks, and Section 7 concludes.

## 2. Related Literature

Our paper contributes to two strands of the asset pricing literature. Firstly, we contribute to the equity options literature that attempts to uncover return predictability in the cross-section of individual option returns. Secondly, we contribute to the vast literature on the momentum strategy.

**Equity Options.** The Black-Scholes model implies that options are redundant assets. However, in markets with frictions, option prices are subject to different dimensions of risk apart from those implied by the underlying security (e.g., Garleanu, Pedersen, and Poteshman, 2008). Goyal and Saretto (2009) show that the implied volatility relative to the historical volatility is an important negative predictor of the cross-section of delta-hedged call option returns. Cao and Han (2013) find a negative relationship between delta-hedged equity option returns and the idiosyncratic volatility of the underlying stock. Zhan et al. (2022) examine the cross-sectional predictive ability of different stock characteristics for delta-hedged option returns and find strong evidence of predictability for a variety of predictors. Bali et al. (2023) employ nonlinear machine learning models and find strong evidence of out-of-sample predictability of delta-hedged option returns using a large number of option and stock characteristics.

**Stock and Option Momentum.** Daniel and Moskowitz (2016) provide an early survey of the literature. More recently, Kelly et al. (2021) focus on the return-based stock momentum and show that its payoff can be viewed as a compensation for time-varying covariance risk with factors based on the IPCA model of Kelly et al. (2019). The authors focus on the risk part of the strategy in the stock market by fixing the conditional factor realization at the mean. Specifically, the authors highlight that momentum could be characterized as a noisy estimate of a stock's conditional beta. In contrast, we are the first to discover the momentum pattern of risk in equity options. In addition, our setting allows for time variation in both factor realizations and factor betas. Heston et al. (2023) find strong evidence of momentum in the options market that is more pronounced than other asset classes. We show that option risk-based momentum is more profitable than option momentum and subsumes its profitability.

# 3. Data & Methodology

## 3.1. Data

**Returns.** We consider the universe of tradable options from OptionMetrics IvyDB between 1996 and 2021. It is well known that stocks' total returns (Jegadeesh and Titman, 1993) as well as their risk component exhibit momentum (Li et al., 2023). To assure that our results are not confounded by momentum in the underlying, we deviate from Heston et al. (2023) and delta-hedge our options positions every day. We follow the definition of Bali et al. (2023). Let the option contract's value be denoted by $O$, the value of the underlying stock as $S$, and the risk-free rate in month $t$ as $r_t^f$. The delta-hedged dollar gain over the period $(t, t+1)$ is then given by:

$$\Pi_{t+1} = O_{t+1} - O_t - \sum_{n=0}^{N-1} \Delta_{t_n} \left( S_{t_{n+1}} - S_{t_n} \right) - \sum_{n=0}^{N-1} \frac{r_{t_n}^f}{365} \left( O_{t_n} - \Delta_{t_n} S_{t_n} \right). \tag{1}$$

We scale the dollar gain by the initial value of the investment portfolio (Cao and Han, 2013):

$$r_{t+1} = \frac{\Pi_{t+1}}{|\Delta_t S_t - O_t|}. \tag{2}$$

**Filters.** We retain at-the-money option contracts for which the bid is positive, the offer exceeds the bid, the mid-price is at least \$0.125, the relative quoted spread is at most 50% of the mid, the implied volatility is available, and the open interest is positive.[1] Furthermore, option prices need to adhere to American option bounds. Finally, we require that the put (call) prices are monotonically increasing (decreasing) in the contract's strike price, iteratively retaining those contracts with the larger trading volume and a strike price closer to the current price of the underlying. We select the contracts that expire in roughly 50 days and retain the expiration date on which the majority of options expire. This is typically the third Friday of the month after the next. After applying the above filters, we choose the contract per underlying with the largest dollar open interest in $t$. To limit the influence of outliers and faulty records, delta-hedged option returns are winsorized at the 99% level.

[1] We define "at-the-money" as contracts for which the standardized strike $\left|\frac{\log(K/S)}{iv \times \sqrt{\text{ttm}}}\right| \leq 1$, where $S$ is the underlying's price, $K$ the option's strike price. ttm its time-to-maturity and $iv$ its implied volatility.

**Risk Adjustment.** A risk adjustment for option returns is notoriously difficult. Their short maturity makes it impossible to estimate $\beta$s in standard time-series regressions (Fama and MacBeth, 1973). Furthermore, their moneyness changes whenever the underlying changes. We therefore do not have access to contracts with exactly the same properties from month to month. Büchner and Kelly (2022) address this issue and estimate *instrumental principal component analysis (IPCA)* for S&P 500 index options. Goyal and Saretto (2022) extend this approach to equity options. IPCA relates option $i$'s exposure to $K$ latent factors $F_{t+1}$ using observable characteristics of the option, $z_{i,t}$:

$$r_{i,t+1} = \beta_{i,t} F_{t+1} + \varepsilon_{i,t+1}, \qquad \beta_{i,t} = z_{i,t} \Gamma_\beta, \tag{3}$$

where $\Gamma_\beta$ is the factor loading matrix. By including information about the option contract (i.e., its implied volatility, moneyness, and maturity) and the underlying stock (i.e., the stock's market capitalization or book-to-market ratio) in the estimation of $\beta$s, IPCA circumvents the issues outlined above. Furthermore, the latent factor structure in $F_{t+1}$ is estimated to best explain the cross-section of option returns in each month $t+1$. The IPCA specification on Eq. (3) has the additional benefit that $\beta$s are time-varying and respond to changes in the characteristics profile of option $i$.

The system of first-order conditions is given by:

$$\begin{aligned} \widehat{F}_{t+1} &= \left(\widehat{\beta}_t' \widehat{\beta}_t\right)^{-1} \widehat{\beta}_t' R_{t+1}, \quad \forall t \\ vec(\widehat{\Gamma}_{\beta)} &= \left(\sum_{t=1}^{T-1} \mathcal{Z}_t' \mathcal{Z}_t \otimes \widehat{F}_{t+1} \widehat{F}_{t+1}'\right)^{-1} \left(\sum_{t=1}^{T-1} \left[\mathcal{Z}_t \otimes \widehat{F}_{t+1}'\right]' R_{t+1}\right), \end{aligned} \tag{4}$$

where $\beta_t$ and $R_{t+1}$ are the stacked beta and returns of size $N_{t+1}$. Latent factor realizations are obtained from month-by-month cross-sectional regressions of excess returns on $\beta$s (Fama and MacBeth, 1973). $\Gamma_\beta$ are the coefficients of regressing individual option returns on the latent factors $F_{t+1}$ interacted with stacked characteristics $\mathcal{Z}_t$. We follow Kelly et al. (2019) and estimate the system of first-order conditions with an alternating least squares approach.

Alongside the options' returns, IPCA requires observable characteristics in $\mathcal{Z}$ as input. We rely on a large set of 73 option-level characteristics taken from Bali et al. (2023) and 153 stock-level characteristics from Jensen et al. (2021). Following standard practice in the literature, we rank each characteristic cross-sectionally and standardize its values to lie between $-0.5$ and 0.5 for each month. Finally, we also add a constant characteristic. To guard against overfitting on in-sample information, we retain those characteristics that produce valuable investment advice between 1996 and 2021. In each month, we form characteristic-managed portfolios (CMPs), sorted on a single characteristic $z$:

$$x_{t+1}^{z} = \frac{\sum_{i=1}^{N_{t+1}} z_{i,t} \times r_{i,t+1}}{N_{t+1}}. \tag{5}$$

Out of these 226 CMPs (+ an equally-weighted portfolio using the constant characteristic), 165 generate a Sharpe ratio significant at the 5%-level. To assess a Sharpe ratio's statistical significance, we follow the test described in Lo (2002).[2] We show the resulting Sharpe ratios for each CMP alongside identifying information for the sorting characteristic in Appendix A. We identify pairs of characteristics pairs that are correlated by $|\rho| \geq 95\%$. From each identified pair, we retain that characteristic which is available for more asset$\times$month observations. In total, this drops 10 characteristics from our dataset and thus leaves us with 155 (including a constant) characteristics which we use to instrument variation in $\beta$s.

We follow Goyal and Saretto (2022) and use a $K = 4$ latent factor model to describe the systematic component of equity option returns. In our own testing, we find that a

[2]We are aware of the concerns raised by Mertens (2002) about the statistical test in Lo (2002) but follow the literature in applying it.

Table 1: $R^2$ of $K$-factor IPCA Models

The table shows the variation of option returns explained by $K$-factor IPCA models. The in-sample $R^2$ and out-of-sample $R^2_{OOS}$ in the second row, respectively. The out-of-sample estimation uses information until $t$ to estimate $\Gamma_{\beta,\boldsymbol{t}}$ of Eq. (3) are provided. We estimate $f_{\boldsymbol{t},t+1}$ using a cross-sectional regression with option returns in $t+1$. This regression relies on portfolio weights known in $t$ without using forward-looking information.

| $K \rightarrow$ | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| $R^2$ | 0.112 | 0.161 | 0.171 | 0.178 | 0.183 | 0.188 |
| $R^2_{OOS}$ | 0.111 | 0.149 | 0.158 | 0.164 | 0.167 | 0.171 |

four-factor model describes option returns well and drives out the explanatory power of characteristics $\mathcal{Z}$ not already captured by $\beta$s and factors. To illustrate this fact, Table 1 shows the fraction of variation explained by a $K$-factor IPCA model. We show the results for IPCA models fitted in-sample, i.e., with all available information. We also estimate IPCA out-of-sample. Specifically, using an expanding window, we first estimate IPCA with information until month $t$ to obtain $\Gamma_{\beta,\boldsymbol{t}}$. Next, we calculate the out-of-sample factor return $f_{t+1,\boldsymbol{t}}$ in a cross-sectional regression on option returns in $t+1$. This regression uses portfolio weights known in $t$, thereby assuring that no forward-looking information enters the out-of-sample estimation of IPCA.

The first row shows in-sample $R^2$s. A single-factor model already explains 11.1% of option return variation. Increasing the number of factors $K$ quickly increases the amount of variation explained. The $K = 4$-factor model proposed by Goyal and Saretto (2022) explains 17.8% of the variation in option returns. Increasing the number of factors further does little to improve this. The results are fairly robust out-of-sample, a circumstance that Kelly, Palhares, and Pruitt (2020) ascribe to the parsimonious structure of IPCA. Most of the heterogeneity in factor sensitivities arises from variation in *observable* option characteristics. This makes IPCA robust out-of-sample. Our preferred $K = 4$-factor model explains 16.4% of the variation in option returns out-of-sample.

**Risk Momentum.** With a description of an option's systematic component at hand, we can decompose its return into that the portion explained by common risk factor and the remaining idiosyncratic part:

$$r_{i,t+1} = \underbrace{\beta_{i,t} F_{t+1}}_{= \text{Risk}_{i,t+1}} + \underbrace{\varepsilon_{i,t+1}}_{= \text{Residual}_{i,t+1}} \tag{6}$$

From this decomposition, we construct the typical momentum signal following Jegadeesh and Titman (1993) and Heston et al. (2023) for a formation period of $f$ months. A formation gap of $g$ months may be used to exclude possible short-term reversal effects in option returns. We find little evidence of a short-term reversal in option returns, such that we set $g = 0$ in most of our analyses. Option $i$'s momentum signal is, therefore, the average return for the months between $t - f$ and $t - g$:

$$\mathit{MomSignal}_{i,t} = \frac{1}{f - g} \sum_{\tau=g}^{f} r_{i,t-\tau}. \tag{7}$$

Similarly, we construct the momentum signal from the risk component alone (Li et al., 2023):

$$\mathit{RiskMomSignal}_{i,t} = \frac{1}{f - g} \sum_{\tau=g}^{f} \text{Risk}_{i,t-\tau}. \tag{8}$$

Finally, we sort options into quintiles based on *MomSignal* or *RiskMomSignal* and follow each quintile's option return over a holding period of $h > 0$ months. We are interested in

$$\mathit{RiskMom}_{t+h} = \prod_{\tau=1}^{h} \left(1 + r_{t+\tau}^{Q5} - r_{t+\tau}^{Q1}\right) - 1. \tag{9}$$

which is the return on the high-minus-low spread portfolio between the highest and lowest *MomSignal*. The spread returns on the *RiskMomSignal* quintiles are computed similarly.

# 4. Risk Momentum in Option Returns

## 4.1. Risk Momentum Outperforms Return-based Momentum

We begin our analysis with a comparison between the return-based option momentum discovered by Heston et al. (2023) and our novelty brought on by separately considering trends in the risk component of option returns.

In Figure 1, we show annualized Sharpe ratios for the two strategies for a variety of different formation periods $f$ and holding periods $h$. For all combinations of $f$ and $h$ we find that *RiskMom* outperforms the return-based option momentum. For example, a $h = 1$ month investment based on risk-adjusted returns over the past $f = 3$ months generates an annualized Sharpe ratio of 5.19, which compares well to the 3.54 achieved with the return-based momentum. *RiskMom* is also valuable for longer-term investments. Holding the invested portfolio constant for $h = 12$ months achieves a Sharpe ratio of 2.25 with signals based on the risk-adjusted return over the past $f = 12$ months. Failing to adjust option returns for risk decreases the trend-following Sharpe ratio to 1.59.

Table 2 compares the performance of the two trend-following strategies in option returns in more detail. We also consider a momentum strategy based on the residual return component shown in Eq. (6). Next to the returns of the high-minus-low spread portfolio, we also show the results for the individual quintile portfolio sorted on either signal. Newey and West (1987) t-statistics with twelve lags are shown in brackets below the average annualized returns.

Panel A of Table 2 produces a number of interesting facts about the performance of *RiskMom*. First, the returns of the high-minus-low spread portfolio are highly significant for signal formation periods as short as $f = 1$ months up to $f = 120$ months. The resulting average return, however, is decreasing in the length of this formation window.

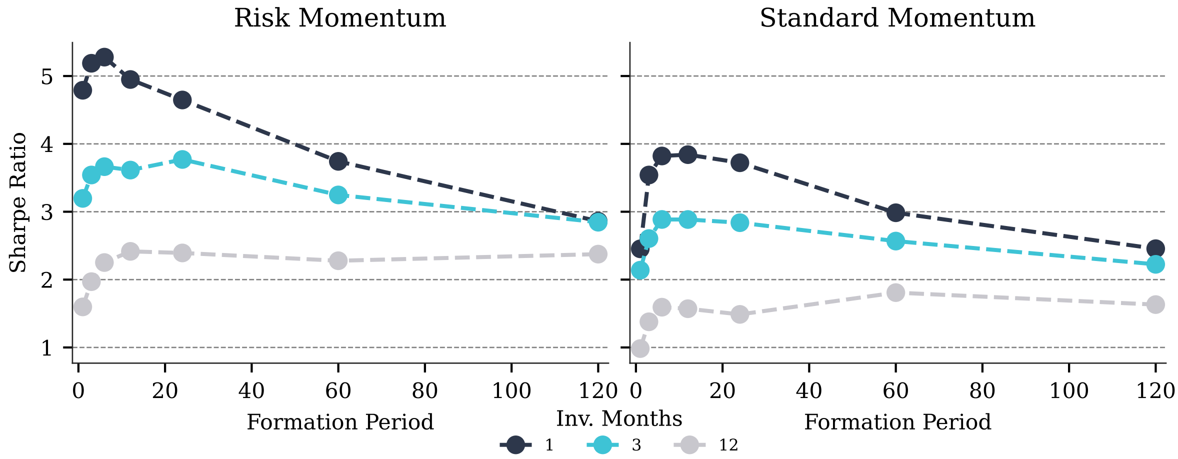


Fig. 1. Comparison of Risk-based and Return-based Option Momentum

The figure shows the annualized Sharpe ratios for risk-based and return-based option momentum. We consider three different investment periods, ranging from the next month, over the next quarter, to the next year. Furthermore, we consider a number of formation periods over which the trend-following signal is generated.

Second, between 60% and 80% of the strategy's returns are from its short leg. Risk-based trend-following is especially successful in identifying previous losing options that continue to perform poorly in the future. We investigate the role of persistence in forecast errors of future realized variance to explain this in Section 5.3. Third, returns are monotonically increasing across *RiskMom* quintiles for all formation periods considered.

This compares well to the sorts on the return-based momentum shown in Panel B: only for formation periods of $f = 24$ and $f = 60$ months are the quintile returns monotonically increasing. Overall we find that the profitability of return-based momentum is significantly smaller in magnitude. For example, for a formation period of $f = 3$ months, returns of *RiskMom* are more than twice as large as those of the return-based momentum. Panel C shows that residual momentum is unable to produce meaningful return spreads. In fact, we document an inverse U-shaped pattern across residual momentum quintiles. The returns of the first and last quintile tend to be smaller than the returns of the moderate quintile and of similar magnitude. This renders the high-minus-low returns insignificant.

The results shown here are equally-weighting options in each portfolio. In Section 4.3 we show that the results hold when weighting options by their dollar open interest or their underlying's market capitalization. We also highlight that *RiskMom* survives realistic levels of transaction costs. Furthermore, we show that sorting options into deciles as opposed to quintiles improves our results further. We decide to stick to quintile sorts for their greater diversification benefits and an easier presentation of the results.

## 4.2. Long-term Investments.

In the previous section we show that the risk component of option returns generates significantly larger momentum profits than a signal based on the overall option return does. In that analysis, we focus on returns over the next month. In Table 3 we investigate if *RiskMom* holds valuable investment advice for long-term investments. For this, we use the risk momentum signals generated in $t$ and hold the investment fixed for a total of $h$ investment months, wherein $h$ varies between one month and a total of 120 months. Returns are annualized to allow for easy comparison.

Panel A shows that *RiskMom* continues to work for longer investment periods. Consider an investor with a $h = 6$ months investment horizon. A risk-based momentum signal generated from the past three months of risk-adjusted option returns averages returns of 13.4% per year. For a two-year investment horizon, the same information generates returns of 6.3% per year. We find economically negligible risk-based momentum returns only for investment horizons that are longer than two years. In total, we document a remarkable stability of the profits generated by risk-adjusted trend-following in the options market.

Table 2 shows that a longer formation period decreases short-term returns. In con-

## Table 2: Investment Performance

The table shows average returns of quintiles based on risk-based, return-based, and residual option momentum for a variety of formation months. We also provide the results for the high-minus-low portfolio (HmL). The t-statistics are presented in parentheses, which use Newey and West (1987) standard errors with twelve lags.

| Formation | Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Months | 1 | 2 | 3 | 4 | 5 | HmL |
| | | | Panel A: Risk Momentum | | | |
| 1 | −0.156 | −0.033 | −0.005 | 0.014 | 0.043 | 0.199 |
| | (−8.12) | (−2.85) | (−0.50) | (1.17) | (3.04) | (10.56) |
| 3 | −0.151 | −0.032 | −0.005 | 0.015 | 0.044 | 0.196 |
| | (−8.32) | (−2.84) | (−0.43) | (1.33) | (2.92) | (11.19) |
| 6 | −0.149 | −0.031 | −0.003 | 0.016 | 0.044 | 0.193 |
| | (−8.64) | (−2.75) | (−0.26) | (1.37) | (2.89) | (11.79) |
| 12 | −0.136 | −0.027 | −0.002 | 0.014 | 0.040 | 0.175 |
| | (−8.96) | (−2.45) | (−0.20) | (1.23) | (2.63) | (11.42) |
| 24 | −0.118 | −0.021 | −0.000 | 0.014 | 0.033 | 0.151 |
| | (−8.98) | (−1.98) | (−0.02) | (1.11) | (2.33) | (12.06) |
| 60 | −0.090 | −0.015 | −0.003 | 0.004 | 0.018 | 0.108 |
| | (−7.47) | (−1.35) | (−0.27) | (0.32) | (1.35) | (10.27) |
| 120 | −0.069 | −0.018 | −0.008 | −0.007 | 0.003 | 0.072 |
| | (−5.57) | (−1.40) | (−0.64) | (−0.57) | (0.24) | (10.14) |
| | | | Panel B: Momentum | | | |
| 1 | −0.097 | −0.016 | −0.000 | 0.005 | −0.030 | 0.067 |
| | (−6.22) | (−1.42) | (−0.04) | (0.47) | (−2.16) | (6.72) |
| 3 | −0.100 | −0.018 | −0.001 | 0.004 | −0.013 | 0.087 |
| | (−6.25) | (−1.58) | (−0.10) | (0.36) | (−0.96) | (8.90) |
| 6 | −0.104 | −0.017 | −0.001 | 0.004 | −0.006 | 0.098 |
| | (−6.40) | (−1.59) | (−0.05) | (0.31) | (−0.43) | (9.37) |
| 12 | −0.103 | −0.015 | −0.001 | 0.006 | 0.003 | 0.107 |
| | (−7.23) | (−1.45) | (−0.09) | (0.51) | (0.24) | (9.66) |
| 24 | −0.090 | −0.011 | −0.002 | 0.004 | 0.007 | 0.097 |
| | (−7.39) | (−1.01) | (−0.22) | (0.35) | (0.49) | (9.67) |
| 60 | −0.076 | −0.014 | −0.003 | 0.001 | 0.005 | 0.081 |
| | (−6.63) | (−1.31) | (−0.26) | (0.12) | (0.34) | (8.59) |
| 120 | −0.063 | −0.014 | −0.010 | −0.006 | −0.007 | 0.057 |
| | (−5.27) | (−1.13) | (−0.82) | (−0.47) | (−0.45) | (8.55) |
| | | | Panel C: Residual Momentum | | | |
| 1 | −0.061 | −0.000 | −0.001 | −0.015 | −0.061 | −0.000 |
| | (−4.23) | (−0.04) | (−0.07) | (−1.28) | (−4.53) | (−0.07) |
| 3 | −0.057 | −0.008 | −0.003 | −0.012 | −0.048 | 0.009 |
| | (−3.95) | (−0.67) | (−0.30) | (−1.08) | (−3.53) | (1.93) |
| 6 | −0.056 | −0.005 | −0.004 | −0.016 | −0.043 | 0.013 |
| | (−4.01) | (−0.43) | (−0.37) | (−1.45) | (−3.21) | (2.36) |
| 12 | −0.049 | −0.007 | −0.004 | −0.015 | −0.035 | 0.014 |
| | (−3.76) | (−0.66) | (−0.38) | (−1.30) | (−2.68) | (2.60) |
| 24 | −0.038 | −0.005 | −0.006 | −0.012 | −0.033 | 0.005 |
| | (−3.26) | (−0.43) | (−0.53) | (−1.01) | (−2.53) | (1.18) |
| 60 | −0.031 | −0.009 | −0.010 | −0.012 | −0.025 | 0.006 |
| | (−2.71) | (−0.82) | (−0.87) | (−1.07) | (−1.85) | (1.53) |
| 120 | −0.032 | −0.012 | −0.013 | −0.015 | −0.027 | 0.004 |
| | (−2.63) | (−0.99) | (−1.11) | (−1.14) | (−2.02) | (0.80) |

Table 3: Different Investment Months and Formation Gaps

The table shows the average returns of the high-minus-low portfolios for risk-based option momentum for a variety of formation months, formation gap, and investment months combinations. The t-statistics are presented in parentheses, which use Newey and West (1987) standard errors with $\min(12, h)$ lags.

| Formation | Investment Months | | | | | | |
|---|---|---|---|---|---|---|---|
| Months | 1 | 3 | 6 | 12 | 24 | 60 | 120 |
| | | | Panel A: No Formation Gap | | | | |
| 1 | 0.199 | 0.158 | 0.123 | 0.085 | 0.052 | 0.021 | 0.010 |
| | (10.56) | (10.96) | (10.88) | (11.02) | (12.36) | (19.26) | (13.71) |
| 3 | 0.196 | 0.164 | 0.133 | 0.094 | 0.059 | 0.024 | 0.012 |
| | (11.19) | (11.08) | (11.43) | (12.53) | (13.96) | (19.91) | (16.50) |
| 6 | 0.193 | 0.165 | 0.134 | 0.098 | 0.063 | 0.026 | 0.013 |
| | (11.79) | (11.39) | (11.41) | (13.73) | (12.94) | (18.78) | (16.08) |
| 12 | 0.175 | 0.152 | 0.128 | 0.097 | 0.064 | 0.026 | 0.014 |
| | (11.42) | (11.44) | (12.02) | (13.99) | (10.81) | (15.71) | (16.92) |
| 24 | 0.151 | 0.132 | 0.112 | 0.086 | 0.058 | 0.024 | 0.013 |
| | (12.06) | (12.34) | (12.90) | (13.46) | (10.11) | (10.31) | (9.62) |
| 60 | 0.108 | 0.097 | 0.083 | 0.066 | 0.047 | 0.022 | 0.013 |
| | (10.27) | (11.57) | (12.49) | (13.25) | (11.02) | (7.84) | (6.46) |
| 120 | 0.072 | 0.065 | 0.057 | 0.046 | 0.036 | 0.019 | 0.011 |
| | (10.14) | (12.42) | (13.28) | (15.25) | (15.42) | (8.61) | (7.76) |
| | | | Panel B: Formation Gap of 1 Month | | | | |
| 3 | 0.168 | 0.141 | 0.115 | 0.084 | 0.053 | 0.021 | 0.011 |
| | (11.02) | (11.21) | (10.95) | (12.80) | (17.58) | (16.05) | (14.80) |
| 6 | 0.171 | 0.150 | 0.123 | 0.091 | 0.058 | 0.024 | 0.013 |
| | (12.24) | (11.74) | (11.75) | (14.79) | (17.27) | (15.00) | (15.24) |
| 12 | 0.162 | 0.141 | 0.120 | 0.092 | 0.061 | 0.025 | 0.013 |
| | (11.52) | (11.63) | (12.23) | (14.46) | (13.06) | (12.90) | (15.31) |
| 24 | 0.142 | 0.125 | 0.107 | 0.082 | 0.056 | 0.024 | 0.013 |
| | (12.12) | (12.71) | (13.31) | (13.87) | (12.07) | (12.13) | (12.46) |
| 60 | 0.101 | 0.091 | 0.079 | 0.063 | 0.045 | 0.022 | 0.013 |
| | (10.26) | (11.89) | (13.17) | (13.40) | (12.68) | (12.61) | (10.51) |
| 120 | 0.070 | 0.062 | 0.055 | 0.046 | 0.036 | 0.019 | 0.011 |
| | (9.96) | (11.91) | (13.06) | (15.69) | (16.91) | (13.51) | (12.24) |

trast, we show that it is advisable to generate risk-based momentum signals from longer formation periods in Table 3. For example, for an investment period of $h = 12$ months, basing the generation of the momentum signal on the past three to 24 months generates larger returns of $8.6\% - 9.8\%$ compared to 8.5% for a one-month formation period.

In Panel B of Table 3, we replicate the previous analysis with a formation gap of $g = 1$ month. Jegadeesh and Titman (1993) propose this step in their original paper on stock momentum to separate the momentum signal from short-term reversals prevalent in stock returns. We find little evidence of short-term reversals in option returns. In fact, the returns *with* a formation gap in Panel B of Table 3 tend to be slightly lower than those obtained *without* a formation gap in Panel A. This effect is slowly washed out as we a) increase the formation period $f$, or b) the holding period $h$.

## 4.3. Liquidity and Transaction Costs

**Impact of Liquidity.** The previous results are based on equally weighting the returns of the options contracts in each quintile portfolio. Differences in the overall liquidity of each option, however, may inhibit an investor's ability to implement the strategy with equal weights. We, therefore, consider two alternative weighting schemes which take the liquidity of the option *and* the underlying stock into account.

First, we weight options by their underlying's market capitalization in month $t$. The results are found in Table B2. Our main results hold up well: *RiskMom* with a formation period of $f = 3$ months generates 7.8% over the next month, compared to the return-based option momentum's 3.5%. Most of this performance is again driven by the short leg. The remaining patterns are very similar to the baseline results provided in Table 2.

Second, we weight options by their dollar open interest to directly incorporate a notion of option liquidity. The results in Table B3 show a remarkable success of *RiskMom*. For a formation period of $f = 1$ month, the strategy averages returns of 11.8% per month (highly significant), compared to just 2.2% (insignificant if measured at the 1%-level). Increasing the formation period to $f = 3$ months leaves *RiskMom*'s returns unchanged but leads to better *Mom* profits. Still, its returns are more than 50% lower than those of *RiskMom*.

**Transaction Costs.** While transaction costs in the options market are high (Ofek, Richardson, and Whitelaw, 2004), Muravyev and Pearson (2020) show that effective costs are much lower than what option quotes imply. They show that different trader groups can benefit from substantially lower costs. For example, their "Algo" traders pay roughly 20% of the quoted spread and the effective average spread paid in the options market amounts to about three quarters of what is quoted. We incorporate these considerations when investigating the impact of transaction costs on the profitability of *RiskMom*. While trading the option is likely to represent the majority of costs faced by an investor following the strategy, she will also have to rebalance her delta-hedge using the underlying on a daily basis. We therefore include not only expected costs of trading the option but also the implied fees of hedging with the underlying.

Finally, it is natural to assume that the investor strategically avoids options for which the expected return fails to exceed her transaction cost expectations. One way she can achieve this is by focusing on options for which the expected return signal is more "extreme", i.e., options which are expected to generate larger returns. We follow Heston et al. (2023) and consider high-minus-low return spreads of decile portfolios sorted on *RiskMomSignal*. At the same time, she may incorporate expected transaction costs. For this, we first follow Heston et al. (2023) once more and consider only options with a quoted ask-to-bid spread below 10% of the mid-quote. Second, we directly incorporate a forecast for the transaction costs our investor is expecting to face. Let $q_{i,t}$ denote the fees for contract $i$ that the investor expects to have to pay. Then the investor's after-cost return expectation of option $i$ is given by:

$$\begin{aligned} \mathbb{E}_t^{\text{net}}[r_{i,t}] &= \textit{RiskMomSignal}_{i,t} - q_{i,t}, \quad \text{if } \textit{RiskMomSignal}_{i,t} > 0, \\ \mathbb{E}_t^{\text{net}}[r_{i,t}] &= \textit{RiskMomSignal}_{i,t} + q_{i,t}, \quad \text{if } \textit{RiskMomSignal}_{i,t} < 0. \end{aligned} \tag{10}$$

If $\mathbb{E}_t^{\text{net}}[r_{i,t}]$ fails to be positive for previous buys ($\textit{RiskMomSignal} > 0$), our investor discards the option. The opposite applies to previous sells. We use the option's current

Table 4: The Impact of Transaction Costs

The table shows after-cost average returns for risk-based option momentum (*RiskMom*). We account for both the costs of trading the options contract, as well as the daily delta-hedge with the underlying. We assume that the investor has to pay a fraction of the quoted spreads from the option and the underlying and that she incorporates the current quoted spread in her decision to buy and sell options. The details of this adjustment are provided in Section 4.3. Panel A considers options with roughly 50 days to expiration as in our main analyses. Panel B considers options that mature within the next month. Trading these options has the benefit that the investor does not have to close the options position, which would incur the large option transaction costs once more. We consider a simple decile-sorted strategy (Deciles), a strategy that employs the cost-mitigation approach detailed in Section 4.3 (+ CM), and a strategy that additionally value-weights options by their dollar open interest (+ VW). The t-statistics are shown in parentheses and obtained with Newey and West (1987) standard errors with twelve lags.

| | % Quoted Option Spread + Costs of Hedging with Underlying | | | | | |
|---|---|---|---|---|---|---|
| | 0% | 15% | 25% | 50% | 75% | 100% |
| | Panel A: Roughly 50 Days to Expiration | | | | | |
| Deciles | 0.279 | 0.123 | 0.019 | −0.240 | −0.498 | −0.755 |
| | (12.77) | (7.52) | (1.27) | (−11.71) | (−15.21) | (−16.20) |
| Deciles + CM | 0.163 | 0.093 | 0.066 | −0.002 | −0.069 | −0.137 |
| | (8.54) | (5.92) | (4.65) | (−0.19) | (−6.60) | (−11.07) |
| Deciles + CM + VW | 0.156 | 0.092 | 0.072 | 0.022 | −0.027 | −0.077 |
| | (7.69) | (5.43) | (4.40) | (1.38) | (−1.60) | (−3.97) |
| | Panel B: Roughly 20 Days to Expiration | | | | | |
| Deciles | 0.346 | 0.281 | 0.238 | 0.129 | 0.021 | −0.088 |
| | (8.19) | (7.49) | (6.85) | (4.41) | (0.75) | (−2.99) |
| Deciles + CM | 0.280 | 0.264 | 0.249 | 0.211 | 0.173 | 0.135 |
| | (5.84) | (4.60) | (4.43) | (3.96) | (3.40) | (2.76) |
| Deciles + CM + VW | 0.339 | 0.319 | 0.306 | 0.275 | 0.244 | 0.212 |
| | (4.23) | (3.41) | (3.32) | (3.07) | (2.80) | (2.50) |

quoted bid-ask spread as a simple measure of expected transaction costs.[3] Finally, she may consider the overall liquidity of each contract and weight her portfolio by the contracts' dollar open interest. Table B3 shows that *RiskMom* continues to work well for value-weighted portfolios.

Table 4 reports the results. We vary the effective spreads paid between FRAC = 15% and FRAC = 100% of the quoted spreads of the option and the underlying. As we employ various cost-mitigation techniques to mimic the strategic behavior of option investors

[3]We express the quoted bid-ask spread relative to the investment value of the hedged option portfolio, $|\Delta_t S_t - O_t|$.

following our strategy, which changes the considered sample, we also reproduce the results in the absence of trading fees. We consider a simple decile-sorted strategy (Deciles), a strategy following the cost-mitigation approach detailed above (Deciles + CM), as well as a strategy that additionally value-weights option contracts by their dollar open interest (Deciles + CM + VW).

In Panel A, we follow our main analyses and consider options that mature in roughly 50 days on the third Friday of the month after the next. For a simple decile-sorted strategy, we find that profits turn insignificant for FRAC=25%. For larger spreads, the strategy's returns turn significantly negative. Employing the cost-mitigation approach detailed above helps: returns remain highly significant for FRAC=25% but turn insignificant or negative for larger cost levels. The same applies to the value-weighted portfolio with cost mitigation.

Of course, if the costs of trading in the options market represent the majority of total costs faced by our investor, she potentially benefits from trading shorter-term options. Options that mature within the investment period alleviate the need to close the option position at the end of month $t + 1$ through a second transaction in the options market. The potential drawback of this strategy is that she could be left with a large stock position, depending on the settlement price of the underlying relative to the option's strike. To understand if the benefits or drawbacks predominate, we consider a strategy on options that expire in roughly 20 days in Panel B of Table 4. The simple decile strategy generates significant returns for up to FRAC=50%. Returns are indistinguishable from zero for FRAC=75% and turn negative if the investor had to pay the full quoted spread on each contract. Employing our simple cost-mitigation approach works well. Returns remain significant for all levels of transaction costs. Even if the investor had to pay the full quoted spread of the option and for the daily delta-hedge, *RiskMom* would average 13.5% per year, with a t-statistic of 2.76. Employing the cost-mitigation approach on value-

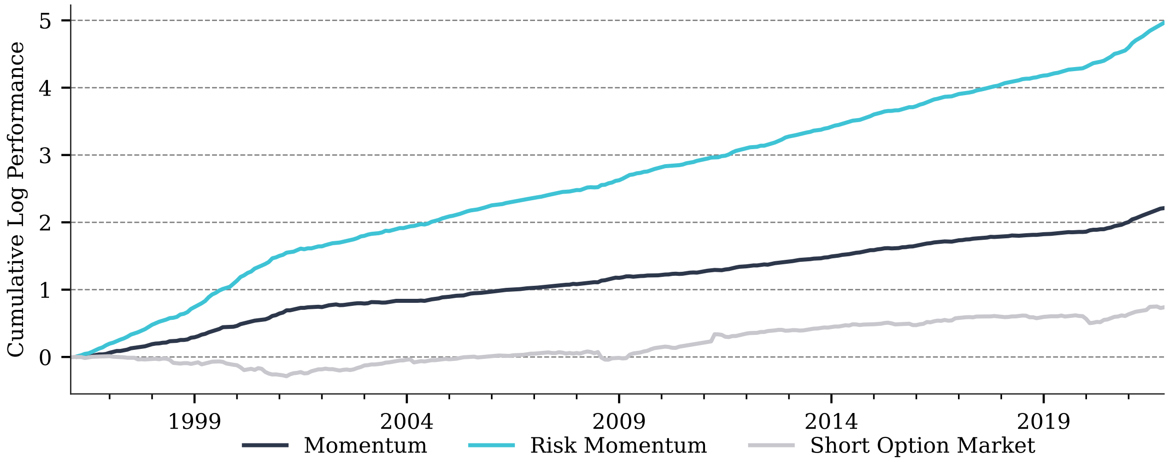


Fig. 2. Cumulative Performance

The figure shows the cumulative log return of investing $1 in the return-based option momentum, risk-based option momentum, or a short investment in the overall options market.

weighted portfolios also generates significant returns for all levels of transaction costs. These results show that *RiskMom* is a viable strategy on its own even after fees. Of course, in reality investors will likely want to a employ a number of different strategies, which in conjunction may lead to even more profitable investments compared to the single-strategy performance we are showing here.

## 4.4. Past Volatility and Option Risk Momentum

Daniel and Moskowitz (2016) show that stock momentum is prone to crashes in the aftermath of economic recessions. Previous losers rapidly gain in value, outperforming previous winners. The returns of the resulting high-minus-low momentum strategy are negative and can wipe out much of the gains made in previous years. Daniel and Moskowitz (2016) argue that this behavior resembles that of a short option: in most years, the seller receives a fee, but occasionally the strategy blows up.

We show the cumulative log performance of *RiskMom*, *Mom* as well as a short investment in the dollar open interest-weighted option market. For the trend-following strategy, we focus on a formation period of $f = 3$ months and no formation gap. We find no evidence of momentum crashes for *RiskMom* or *Mom*. In fact, the return paths are remarkably smooth, with few overall drawdowns. The figure also illustrates the continued outperformance of *RiskMom* over *Mom*. The cumulative log performance gap between the two strategies increases throughout our sample. Both strategies outperform a simple short investment in the options market. Furthermore, their performance does not degrade over time. This is impressive in light of Green, Hand, and Zhang (2017)'s result that momentum, along with many other characteristic-based strategies, fail to deliver significant returns in the stock market post-2003. For the stock market, Beckmeyer and Wiedemann (2023) that show investors may use a simple machine learning strategy to resurrect momentum's profits. For the options market, we document persistently good performance of our risk-based momentum strategy.

Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) show that stock momentum is significantly more robust when investors manage its volatility exposure. In times of high volatility, the authors propose to scale back the investment in the momentum strategy and increase the investment whenever momentum volatility is low. Following this evidence, Barroso and Wang (2021) investigate which explanation for momentum put forth in the literature best explains its return patterns and its positive payoff. We follow that paper and investigate if *RiskMom*'s returns depend on the current volatility regime. For this, we estimate the strategy's past volatility on a six-month rolling basis and record the average returns over the next month. We do so separately for the subsamples for which the past volatility is above or below its full-sample median.

In Table 5, we show that the returns of *RiskMom* are *larger* when past volatility was high. This is in contrast to Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015), who show that stock momentum profits are larger after periods of low volatility. The Sharpe ratio of *RiskMom*, however, is comparable across both regimes,

Table 5: Performance by Past Volatility

The table shows average returns, t-statistics based on Newey and West (1987) standard errors with twelve lags, and Sharpe ratios conditional on the past volatility regime. We compute the rolling volatility for risk-based, return-based, and residual option momentum over the past twelve months and split the sample by whether this past volatility is above or below the unconditional median.

| | Momentum | Risk Momentum | Residual Momentum |
|---|---|---|---|
| | Panel A: Past Volatility Above Median | | |
| Mean | 0.110 | 0.234 | 0.001 |
| t-stat | 6.505 | 7.788 | 0.177 |
| SR | 3.794 | 5.229 | 0.072 |
| | Panel B: Past Volatility Below Median | | |
| Mean | 0.063 | 0.154 | 0.018 |
| t-stat | 13.937 | 12.115 | 5.786 |
| SR | 3.763 | 6.033 | 1.067 |

and the returns are highly significant throughout our sample. Results for return-based option momentum are comparable but of significantly smaller magnitude both in returns and Sharpe ratios for both regimes. The returns of residual momentum are insignificant in periods of high volatility and significant but economically small at 1.7% per year in periods of low volatility.

## 5. What Explains *RiskMom*?

In this section we discuss possible explanations for the remarkable returns of our *RiskMom* option strategy. For this, we first examine in Section 5.1 in how far risk-based momentum differs from standard option momentum, and show that the former subsumes the latter. In Section 5.2 we show that *RiskMom* works well for all options and not just those that the IPCA model describes best, which counters the idea that the risk-adjustment is merely a way to drive out noise from the return process. Finally, in Section 5.3 we relate *RiskMom*'s success to persistence in the forecast errors made by option investors about the future volatility of the underlying. Of course, our risk-based option momentum strategy is inherently "born" with a risk-based explanation: it is based on the trend in the risk-based option return component after all. Furthermore, the long-term investment results in Table 3 rule out an overreaction story. Returns are persistently positive even for holding periods up to $h = 120$ months.

## 5.1. Is Risk-Based Momentum Different?

As a first step, we perform an independent double sort on *RiskMomSignal* defined in Eq. (8) and *MomSignal* defined in Eq. (7). This exercise allows us to understand if one of the two strategies subsumes the performance of the other by breaking up the correlation between them. We independently sort options into quintile portfolios for both signals and record the average return of each of the 25 ($5 \times 5$) portfolios. In parentheses, we also provide the resulting t-statistics using Newey and West (1987) standard errors with twelve lags. For both strategies, we use a formation period of $f = 3$ months, no formation gap $g$, and an investment horizon of $h = 1$ month.

We find a number of striking results: first and most importantly, *RiskMom* fully subsumes the performance of *Mom*. In fact, the returns of *Mom* are statistically insignificant for each *RiskMomSignal* quintile and also lack economic significance with annualized returns betwen $-1.3\%$ and $2.0\%$. *RiskMom* instead produces statistically and economically significant returns within each *MomSignal* quintile. We record a U-shaped pattern for the *RiskMom* high-minus-low portfolio. Its returns are highest within the extreme *MomSignal* quintiles, at 21.8% for quintile 1, 22.0% for quintile 5, and lowest for quintile 3 at 13.7%. Furthermore, returns are monotonically increasing for all *RiskMom* quintiles. For standard momentum, we only find this for the highest *RiskMom* quintile. Overall, this exercise shows that *RiskMom* explains and dominates the returns of standard option

Table 6: Double Sort on Risk-based and Standard Option Momentum

The table shows the average annualized returns of 25 ($5 \times 5$) portfolios, independently sorted on *RiskMomSignal* and *MomSignal* as defined in Eq. (8) and Eq. (7). For both strategies, we use a formation period of $f = 3$ months, no formation gap $g$, and an investment horizon of $h = 1$ month. We also provide the results for the high-minus-low risk momentum portfolio (HmL). T-statistics are presented in parentheses, which use Newey and West (1987) standard errors with twelve lags.

| Mom | Risk Momentum Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Portf. | 1 | 2 | 3 | 4 | 5 | HmL |
| 0 | −0.185 | −0.046 | −0.014 | 0.023 | 0.033 | 0.218 |
| | (−9.84) | (−3.97) | (−1.12) | (1.75) | (1.83) | (12.13) |
| 1 | −0.103 | −0.026 | −0.003 | 0.014 | 0.036 | 0.139 |
| | (−5.72) | (−2.18) | (−0.24) | (1.11) | (2.57) | (8.13) |
| 2 | −0.096 | −0.021 | 0.000 | 0.018 | 0.041 | 0.137 |
| | (−6.31) | (−1.90) | (0.00) | (1.56) | (2.81) | (7.96) |
| 3 | −0.115 | −0.021 | −0.000 | 0.017 | 0.045 | 0.161 |
| | (−6.43) | (−1.72) | (−0.02) | (1.40) | (2.87) | (8.16) |
| 4 | −0.168 | −0.045 | −0.011 | 0.009 | 0.052 | 0.220 |
| | (−8.91) | (−3.44) | (−0.84) | (0.79) | (3.13) | (11.37) |
| HmL | 0.017 | 0.002 | 0.003 | −0.013 | 0.020 | 0.002 |
| | (1.52) | (0.24) | (0.60) | (−1.84) | (1.46) | (0.12) |

momentum, warranting a deeper discussion as to why *RiskMom* works so well.

## 5.2. Explanatory Power and Risk Momentum

A possible explanation for *RiskMom*'s success is that the risk adjustment via IPCA drives out noise from the option returns. The systematic component is less plagued by measurement errors and recording issues. As a consequence, *RiskMomSignal* is a better description of past returns. If this were the case, we should expect to find a positive relationship between *RiskMom*'s profits and how well IPCA describes an option's returns.

To investigate this, we first extract the amount of return variation that our IPCA model can explain. For each option, we perform a simple time-series regression of its returns on the $K = 4$ latent IPCA factors and record the resulting $R^2$s. We do so for all options that enter our sample for at least 24 months. Then, we perform an independent double sort on *RiskMomSignal* and the $R^2$s mentioned before. We record the resulting

Table 7: Risk-based Option Momentum and IPCA's $R^2$

The table shows the results of an independent double sort into quintiles on risk-based option momentum and the firm's unconditional $R^2$ from the $K = 4$ factor IPCA model for option returns. For *RiskMom*, we use a formation period of $f = 3$ months, no formation gap $g$, and an investment horizon of $h = 1$ month. We also provide the results for the high-minus-low risk momentum portfolio (HmL). T-statistics are presented in parentheses, which use Newey and West (1987) standard errors with twelve lags.

| $R^2$ | Risk Momentum Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Portf. | 1 | 2 | 3 | 4 | 5 | HmL |
| 1 | −0.204 | −0.033 | −0.002 | 0.015 | 0.047 | 0.251 |
| | (−13.96) | (−4.10) | (−0.26) | (1.51) | (3.48) | (17.90) |
| 2 | −0.136 | −0.030 | −0.007 | 0.017 | 0.038 | 0.174 |
| | (−9.28) | (−2.78) | (−0.72) | (1.57) | (2.96) | (13.62) |
| 3 | −0.121 | −0.027 | −0.008 | 0.012 | 0.039 | 0.160 |
| | (−6.96) | (−2.39) | (−0.74) | (0.91) | (2.68) | (8.81) |
| 4 | −0.107 | −0.022 | −0.003 | 0.014 | 0.046 | 0.153 |
| | (−6.29) | (−1.78) | (−0.23) | (0.95) | (2.51) | (8.32) |
| 5 | −0.109 | −0.015 | 0.001 | 0.014 | 0.038 | 0.146 |
| | (−5.51) | (−1.03) | (0.08) | (1.00) | (1.67) | (5.50) |

average returns of each of the 25 ($5 \times 5$) portfolios alongside their t-statistic in Table 7.

*RiskMom*, in fact, works best for those options with the lowest $R^2$. Among options with the lowest $R^2$, the average *RiskMom* return amounts to a highly significant 25.1% per year. The strategy's returns decline monotonically for higher $R^2$ portfolios but remain large and importantly highly significant at 14.6% for options that IPCA explains best. We again find a monotonic return pattern across *RiskMomSignal* quintiles within each $R^2$ bucket. All in all, *RiskMom* is not explained by how well IPCA itself describes an option's returns.

## 5.3. Sticky Expectations

A reasonable explanation for *RiskMom*'s performance is a failure of investors to adjust their expectations of future stock volatility when investing in options. They do account for risk in some way or another, for example, by employing a similar factor model as we do. But the implied volatilities of options stay detached from future realized volatilities

Table 8: *RiskMom* is a Sort on the Spread Between Realized and Implied Volatility

The table shows average implied ($iv$) and realized volatilities ($rv$) for quintile portfolios sorted on *RiskMomSignal* of Eq. (8). We compare today's $iv_t$ of the included options with the underlying's $rv$ today $t$ and in the next month $(t+1)$ over which we measure *RiskMom*'s returns. We also provide the results for the high-minus-low *RiskMom* portfolio.

| | Risk Momentum Portfolio | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | HmL |
| $iv_t$ | 0.643 | 0.477 | 0.422 | 0.399 | 0.400 | −0.243 |
| $rv_t$ | 0.545 | 0.443 | 0.407 | 0.394 | 0.410 | −0.135 |
| $rv_{t+1}$ | 0.546 | 0.444 | 0.407 | 0.392 | 0.410 | −0.137 |
| $rv_t - iv_t$ | −0.095 | −0.033 | −0.015 | −0.005 | 0.011 | 0.106 |
| $rv_{t+1} - iv_t$ | −0.097 | −0.033 | −0.015 | −0.007 | 0.009 | 0.106 |
| $\mathcal{P}(rv_{t+1} > iv_t)$ | 0.262 | 0.301 | 0.317 | 0.327 | 0.351 | 0.090 |

even after this risk adjustment. In line with this, Lochstoer and Muir (2022) document that agents have slow-moving beliefs about stock volatility from survey data. They initially underreact to volatility shocks and overreact with a delay. In Table 8, we show that sorting in *RiskMomSignal* produces portfolios that have monotonically decreasing implied volatilities. Options in the lowest quintile portfolio show an average $iv_t$ of 0.64 compared to just 0.40 for options in the highest quintile. The spread for the resulting *RiskMom* strategy amounts to −0.243 for the average month. We see a similar but far less pronounced spread in *realized* volatilities of the underlying: quintile 1 averages an $rv_t$ of just 0.545 compared to 0.41 for quintile 5. Similar numbers emerge in the next month, i.e., for $rv_{t+1}$ with a high-minus-low spread of −0.137. Investors expectations of future volatility tend to be too large for options in the lowest *RiskMom* quintile and roughly correct for the highest *RiskMom* quintile.

Taken together, this results in a spread between $rv$s and $iv$s that a) is large at 0.106 for the HmL portfolio and b) highly persistent over time, with near equal numbers in $t$ and $t+1$. The spread between $rv$ and $iv$ is an important determinant of (expected) option returns. For example, in the standard Heston (1993) model, expected delta-hedged option returns are a function of this differential (Cremers, Halling, and Weinbaum, 2015).

*RiskMom* is able to short options with implied volatilities that are expected to exceed the realized volatility of their underlying stock in the next month. In fact, for only 26.2% of options in portfolio 1, we find that $rv_{t+1} > iv_t$. This number increases monotonically up to portfolio 5 (35.1%).

We next investigate the persistence of the spread between future realized volatility $rv_{t+1}$ and today's implied volatility $iv_t$ for the high-minus-low *RiskMom* portfolio. Specifically, we sort options into quintiles based on *RiskMomSignal* in month $t = 0$ and investigate the average spread between $rv_{t+1}$ and $iv_t$ in months $t - 12$ to $t + 24$. The results are shown in Figure 3. We find a number of interesting results on the persistence of volatility spreads that *RiskMom* is able to capture. First, the average $rv_{t+1} - iv_t$ spread is always positive, suggesting that *RiskMom* is able to effectively differentiate over- from under-priced options. Second, the realized future volatility spread is high for up to 24 months into the future, and slowly approach +4% in month $t + 20$. Furthermore, it is also high in the 12 months before $t$, averaging above +6%. Third, the volatility spread is largest at around the end of the formation period. In this setting we have once more opted for a *RiskMom* strategy with a formation period of $f = 3$ months. In the first month after the formation period, the spread between $rv_{t+1} - iv_t$ amounts to 0.106 on average. Three months later it is still large and above 0.08 Overall, these results suggest that *RiskMom* is able to capitalize on the persistence of volatility forecast errors made by investors in the options market.

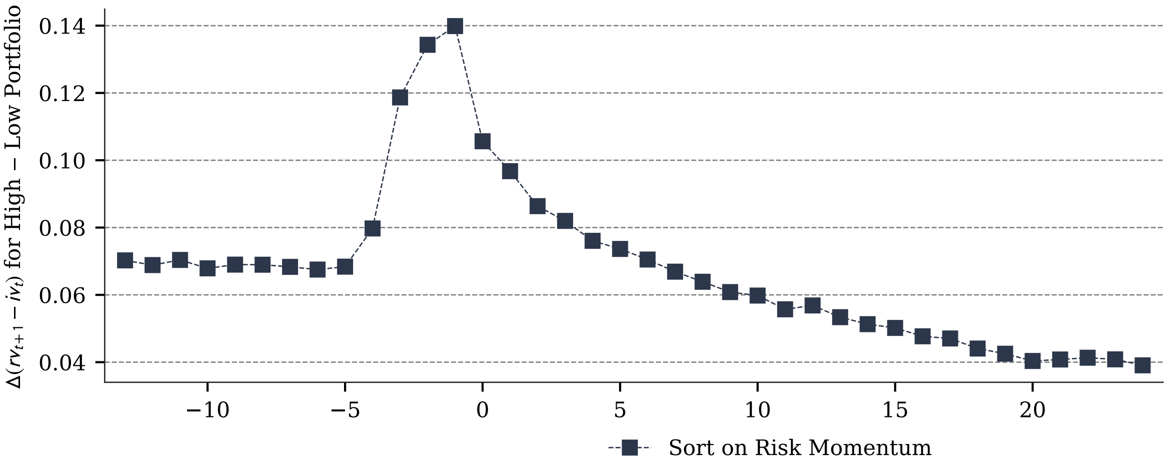


Fig. 3. Persistence in $rv_{t+1} - iv_t$ for *RiskMom*

The figure shows the resulting spread between time $t$'s implied volatility ($iv_t$) and the realized volatility of the underlying over the next month ($rv_{t+1}$) of options sorted by *RiskMomSignal* in month $t = 0$. We show the results for the high-minus-low *RiskMom* portfolio. Note that $t = 0$ marks the first investment month, as we are comparing time $t$'s immplied volatility with realized volatility in $t + 1$.

# 6. Robustness

**Variation in Risk vs. Variation in Sensitivity To Risk.** Our previous results use a sophisticated method to adjust option returns for risk. In the IPCA model shown in Eq. (3), both factor realizations and factor sensitivities ($\beta$s) are allowed to vary over time. The former is estimated through period-by-period cross-sectional regressions. The latter vary over time with observable characteristics of the option. We now assess the relative importance of time variation in either of these parts.

In Panel A of Table 9 we fix option $\beta$s by running a time-series regression for each option's returns on the $K = 4$ factors from the IPCA model. The resulting $\beta$ is thus constant per option. To perform these regressions, we require that each option is available in our sample for at least 24 months. This approach uses as much data as the factor momentum methodology of Ehsani and Linnainmaa (2022), but is distinct from it and comes with a few additional benefits. Factor momentum requires the selection of a suitable set of factors, which not only inform us about the risk-return trade-off in the

Table 9: Variation in Risk vs. Variation in Sensitivity To Risk

The table shows average returns, t-statistics based on Newey and West (1987) standard errors with twelve lags, and Sharpe ratios for different ways of adjusting for risk. Specifically, instead of allowing both factors and $\beta$s to vary over time as in our baseline specification for IPCA, we fix $\beta$s in Panel A, which we obtain by regressing each option's returns on the $K = 4$ factors. In Panel B, we instead fix the factor realizations at their full-sample mean. Panel C fixes both factor realizations at their mean and $\beta$s at their unconditional values.

| | Momentum | Risk Momentum | Residual Momentum |
|---|---|---|---|
| | | Panel A: Fixed Betas, $\beta_i \times F_{t+1}$ | |
| Mean | 0.080 | 0.217 | −0.023 |
| t-stat | 9.432 | 11.345 | −3.386 |
| SR | 3.215 | 4.350 | −0.907 |
| | | Panel B: Fixed Factors, $\beta_{i,t} \times \bar{F}$ | |
| Mean | 0.084 | 0.169 | 0.032 |
| t-stat | 8.996 | 10.451 | 3.971 |
| SR | 3.335 | 3.959 | 1.208 |
| | | Panel C: Fixed Both, $\beta_i \times \bar{F}$ | |
| Mean | 0.084 | 0.075 | 0.033 |
| t-stat | 8.996 | 3.935 | 4.669 |
| SR | 3.335 | 1.378 | 1.032 |

options market but also display return continuation. Adding useless factors or factors that are highly correlated will greatly impact factor momentum returns. At the same time, sorting by many factors essentially nets out much of the benefits of individual factors and makes it difficult to understand the portfolio's aggregate risk exposure.

Our IPCA formulation alleviates both issues, as it is designed to find a parsimonious and low-dimensional factor structure that best fits the cross-section of option returns using characteristic-instrumented $\beta$s. The performance of *RiskMom* is affected by fixing $\beta$s. While average returns remain high at 21.7% for a strategy with a formation period of $f = 3$ months, Sharpe ratios decrease substantially to 4.35 compared to almost 5.19 achieved when also allowing for time-variation in $\beta$s. Interestingly, we find some evidence of a residual reversal in this specification. The residual portion averages modest returns of $-2.3\%$ per year at a Sharpe ratio of $-0.91$.

Instead of fixing $\beta$s, we fix factor realizations at their mean in Panel B of Table 9. This approach is similar to Kelly et al. (2021), who seek an explanation for stock momentum in an IPCA setting. *RiskMom*'s profits remain highly significant at an average return of 16.9% per year and a Sharpe ratio of 3.96. In this setup, the residual *momentum* works reasonably well at a Sharpe ratio above 1.21 and average returns of 3.2% per year.

Finally, we fix both $\beta$s using the time-series regression approach detailed above as well as factor realizations at their mean. The results are shown in Panel C of Table 9. *RiskMom*'s returns remain highly significant at 7.5% per year but the Sharpe ratio drops noticeably to 1.38. Importantly, however, the residual component did not make up for this return drop, and its performance is comparable to the specification in Panel B. We require temporal variation both in risk sensitivities and risk prices in order to adequately capture the trend inherent in the risk component of option returns.

**Option vs. Stock Characteristics.** We next assess the relative importance of including stock- vs. option-level information when adjusting option returns for risk. The IPCA specification in Eq. (3) uses characteristics of an option to instrument for heterogeneity in the sensitivities to the latent risk factors. We now restrict the information set fed into IPCA to either option- *or* stock-level characteristics and refit IPCA with either information set. Bali et al. (2023) show that option-level characteristics are most informative about predicting future option returns but also that their interplay with information about the underlying generates the most profitable investment advice. A breakdown of which category each characteristic falls into is provided in Appendix A.

In Panel A of Table 10, we restrict the information set to option-level characteristics only. Average returns drop to 16.3% but remain highly significant with a t-value above 9. The Sharpe ratio decreases from 5.19 to 4.13 but continues to outperform that of

Table 10: Stock- vs. Option-Level Information

The table shows average returns, t-statistics based on Newey and West (1987) standard errors with twelve lags, and Sharpe ratios for IPCA models with only stock-level or option-level information to instrument variation in $\beta$s. In Panel A, we include only option-level characteristics. In Panel B, only stock-level characteristics are included. A breakdown of which category each characteristic falls into is provided in Appendix A.

| | Momentum | Risk Momentum | Residual Momentum |
|---|---|---|---|
| | Panel A: Option-Level Characteristics Only | | |
| Mean | 0.084 | 0.163 | 0.031 |
| t-stat | 8.996 | 9.587 | 6.567 |
| SR | 3.335 | 4.134 | 1.382 |
| | Panel B: Stock-Level Characteristics Only | | |
| Mean | 0.084 | 0.148 | 0.044 |
| t-stat | 8.996 | 10.225 | 7.668 |
| SR | 3.335 | 3.812 | 2.250 |

the return-based option momentum. We obtain the results in Panel B using only *stock*-level characteristics. Average returns are lower at 14.8% but also highly significant. The Sharpe ratio amounts to 3.81. Residual momentum is profitable for both specifications, suggesting that the risk adjustment achieved is insufficient to capture all trend-following components in option returns. For our baseline strategy, which uses all information, residual momentum generates economically insignificant returns of just 1% per year. Overall, adjusting option returns with either option- or stock-level characteristics produces a more profitable trend-following strategy. All the same, a risk adjustment with both information sources is beneficial with significantly larger (risk-adjusted) returns.

**Controlling for Option and Stock Characteristics.** Our previous analysis examines the relationship between $RiskMomSignal$ and future delta-hedged option returns in a non-parametric way. In this section, we run a predictive panel regression with time and firm fixed effects of future delta-hedged option returns on the signal of option risk-based momentum as well as the signal of option momentum and a number of controls. Specif-

Table 11: Controlling for Option and Stock Characteristics

The table shows the results of regressing individual delta-hedged option returns $r_{i,t+1}$ on the lagged *RiskMomSignal* and *MomSignal* (both are normalized using their full sample mean and standard deviation), as well as a number of option- and stock-specific characteristics, and fixed effects. As controls, we include the option's dollar open interest (DOI), its volatility spread $iv - rv$ and the implied volatility slope (Vasquez, 2017), its bid-ask spread (BAS), as well as the underlying's book-to-market ratio (B/M), idiosyncratic volatility with respect to the Fama and French (1993) 3-factor model (IVOL), its market equity (Size) and Jegadeesh and Titman (1993) stock momentum (StockMom). All controls are cross-sectionally rank-standardized between −0.5 and 0.5. The table reports the coefficients from a panel regression. T-statistics are shown in parentheses and obtained with standard errors that are clustered by option and month.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *RiskMomSignal* | 0.106 | 0.099 | 0.052 | 0.043 |
| | (10.52) | (9.96) | (5.53) | (4.64) |
| *MomSignal* | | 0.016 | 0.032 | 0.009 |
| | | (1.61) | (3.50) | (0.92) |
| DOI | | | 0.000 | −0.000 |
| | | | (0.69) | (−0.67) |
| $iv - rv$ | | | −0.082 | −0.086 |
| | | | (−4.74) | (−4.50) |
| $iv$ Slope | | | −0.077 | −0.011 |
| | | | (−1.01) | (−0.12) |
| BAS | | | 0.017 | 0.077 |
| | | | (0.45) | (1.46) |
| B/M | | | 0.023 | 0.033 |
| | | | (2.80) | (2.87) |
| IVOL | | | −3.182 | −3.833 |
| | | | (−7.02) | (−7.36) |
| Size | | | −0.000 | −0.000 |
| | | | (−3.18) | (−0.45) |
| StockMom | | | −0.004 | −0.005 |
| | | | (−0.94) | (−0.93) |
| Month-FE | Yes | Yes | Yes | Yes |
| Option-FE | No | No | No | Yes |

ically, we account for stock and option characteristics. We include the option's dollar open interest (DOI), its volatility spread $iv - rv$, the slope of its implied volatility curve ($iv$ Slope, Vasquez, 2017), its bid-ask spread (BAS), as well as the underlying's book-to-market ratio (B/M), idiosyncratic volatility with respect to the Fama and French (1993) 3-factor model (IVOL), its market equity (Size) and Jegadeesh and Titman (1993) stock momentum (StockMom). All controls are cross-sectionally rank-standardized between −0.5 and 0.5, and *RiskMomSignal* and *MomSignal* are normalized for easier comparison.

Table 11 shows the results of the predictive panel regression of delta-hedged option returns on lagged $RiskMomSignal$ and control variables. We cluster the standard errors by option and month. In line with our previous findings, we show that $RiskMomSignal$ is a strong positive predictor of delta-hedged option returns. In the second column, we include the signal of the option momentum strategy, and we find that $RiskMomSignal$ remains positive and statistically significant. Instead, the coefficient of the option momentum strategy is not statistically significant. This aligns with our previous findings, which demonstrate that option risk momentum subsumes option momentum. We also show that our results remain significant after including option-level and stock-level control variables, as well as option fixed effects in the regression.

**Varying $K$.** The number of latent factors $K$ determines how well our IPCA model can describe option returns. Our main specifications use $K = 4$ factors, following the evidence in Goyal and Saretto (2022) and our own testing. In Table 12 we vary the number of latent factors $K$ between 1 and 6, and record *RiskMom*'s mean returns, its statistical significance, and Sharpe ratio. $K = 2$ factors are enough for *RiskMom* to outperform the return-based option momentum with an annualized mean return of 18.5% and a Sharpe ratio of 4.88. In comparison, the return-based momentum achieves an average return of 8.4% and a Sharpe ratio of 3.36. A single factor is insufficient to uncover the great profitability of risk-based option momentum. Increasing the number of latent factors improves average realized returns up to $K = 4$ factors. The Sharpe ratios instead continue to increase as $K$ increases. Our choice of $K = 4$ latent factors is therefore sensible as it a) adequately explains average option returns (Goyal and Saretto, 2022), and b) is sufficiently expressive to uncover *RiskMom*'s potential. Importantly, the strategy's returns are highly significant for all numbers of factors $K$.

Table 12: Varying the Number of Latent IPCA Option Factors

The table shows average returns, t-statistics based on Newey and West (1987) standard errors with twelve lags, and Sharpe ratios of our *RiskMom* strategy using IPCA models with with a varying number of latent factors $K$ to adjust for risk.

| $K \rightarrow$ | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Mean | 0.082 | 0.185 | 0.192 | 0.196 | 0.194 | 0.194 |
| t-stat | 4.709 | 9.961 | 10.654 | 11.187 | 11.398 | 11.491 |
| SR | 1.854 | 4.881 | 5.066 | 5.188 | 5.210 | 5.235 |

**Out-of-the-money Options.** Most studies that identify sources of option return variation focus on short-term at-the-money contracts (Cao and Han, 2013; Goyal and Saretto, 2022). We follow their lead throughout our analyses. In this subsection, we instead seek to understand if *out-of-the-money* puts and calls also display (risk-based) momentum. This essentially serves as an out-of-sample test by using a completely different sample than before. We consider out-of-the-money puts, with a standardized strike between $-10$ and $-1$, as well as out-of-the-money calls, for which the standardized strike lies between 1 and 10. We fit a separate IPCA model with $K = 4$ latent factors to this out-of-the-money options sample and report the results in Table 13.

Panel A replicates our results using at-the-money contracts: *RiskMom* outperforms return-based option momentum with an impressive Sharpe ratio of 5.2 and average returns just shy of 20% per year. The resulting residual momentum is economically and statistically insignificant. Panel B shows the results for out-of-the-money options. First note that the overall profitability is subdued: the return-based option momentum generates returns of just 4.4% and a Sharpe ratio of 0.51, comparable to an investment in the stock market. *RiskMom* continues to perform significantly better than the return-based option momentum. Average returns using out-of-the-money options amount to 12.7% with a Sharpe ratio of 1.19. We again find that momentum based on the residual is insignificant, both economically and statistically.

Table 13: *RiskMom* Based On At-the-money vs. Out-of-the-money Options

The table shows average returns, t-statistics based on Newey and West (1987) standard errors with twelve lags, and Sharpe ratios for *RiskMom* using at-the-money options in Panel A and out-of-the-money options in Panel B. We adjust for risk by fitting an IPCA model with $K = 4$ latent factors to each set of options.

| | Momentum | Risk Momentum | Residual Momentum |
|---|---|---|---|
| | | Panel A: At-the-money Options | |
| Mean | 0.087 | 0.196 | 0.009 |
| t-stat | 8.902 | 11.187 | 1.927 |
| SR | 3.541 | 5.188 | 0.489 |
| | | Panel B: Out-of-the-money Options | |
| Mean | 0.044 | 0.127 | 0.017 |
| t-stat | 2.366 | 6.605 | 1.069 |
| SR | 0.505 | 1.187 | 0.216 |

**Out-of-Sample Risk Adjustment.** To adjust option returns for risk, we rely on the IPCA specification in Eq. (3). To estimate the model's $\Gamma_\beta$ matrix, which maps observable option characteristics to variation in $\beta$s, we rely on information from the full sample available to us. Note that this only applies to the $\Gamma_\beta$ matrix and not the factors. The factors are the result of cross-sectional regressions on realized option returns in $t+1$, with portfolio weights that are already known in month $t$ from $\Gamma_\beta$ and characteristics $\mathcal{Z}_t$. To assure that our results also hold up if we perform the risk adjustment on a rolling basis, we use the out-of-sample IPCA estimates detailed in Section 3. The resulting profits of *RiskMom* are shown in Table C4. We again use the familiar strategy with a $f = 3$ months formation period as an example. It averages highly significant returns of 15.6% per year and continues to work for all formation periods $f$ considered. While there is a slight drag on *RiskMom*'s performance when we avoid forward-looking information, the strategy continues to perform well, and it continues to significantly outperform a simple option-based momentum strategy.

# 7. Conclusion

In this paper, we propose a novel cross-sectional risk-based option momentum strategy. Specifically, we find that the risk component of option returns demonstrates a strong momentum pattern which implies that there is risk continuation in equity options. We focus on delta-hedged option returns to guard against movements of option prices that are due to the underlying stocks.

Using 73 option-level and 153 stock-level characteristics, we apply IPCA to extract four latent factors that capture a large fraction of the variation of option returns. We build risk-based option momentum portfolios by allocating delta-hedged option returns into quintiles based on the past performance of their risk component. We consider formation and holding periods that range from one to 120 months. We find that a risk-based momentum strategy with a formation period of three months and a holding period of one month offers an annualized Sharpe ratio as high as 5.19. The strategy is highly profitable for various formation and holding periods, remains highly profitable when accounting for the liquidity of the options contracts, and survives realistic levels of transaction costs. The strategy is profitable for both at-the-money and out-of-the-money options.

We also compare the performance of the option risk-based momentum strategy with the option momentum of Heston et al. (2023). We find that our option-based risk momentum is more profitable. Using double-sorts, we show that option risk-based momentum remains highly significant for different levels of the option momentum signal. On the other hand, option momentum is fully subsumed by risk momentum. Consistent with Heston et al. (2023), we find no evidence of short-term or long-term reversals. The strategy is significant even for longer formation periods that range from 12 to 120 months, and, importantly, it does not exhibit momentum crashes.

Our results are robust to a number of alterations to the empirical setup. We show that the profitability of the strategy is unrelated to the ability of the IPCA model to describe option returns. We find that the number of latent factors that we use in our analysis does not drive our results. We also show that the performance of the strategy is partly driven by its ability to short options for which the implied volatility is expected to exceed the underlying realized volatility in the next period. Our results are robust to time-invariant factor realizations and factor betas of the IPCA model.

Overall, our results suggest that, although options are highly risky assets, the momentum based on their risk component appears the greatest among all asset classes tested so far. High risk is indeed compensated by high returns, after all.

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# Internet Appendix for
# "A New Option Momentum: Compensation for Risk"

by Heiner Beckmeyer, Ilias Filippou, & Guofu Zhou

*Not for Publication*

# Appendix A. Characteristic-Managed Portfolios

The following table shows the whole set of 224 characteristics used in the estimation of IPCA (Eq. (3)) and the subsequent sorts into *RiskMom* (Eq. (6)). Alongside the feature's name, we provide a short description, its original source in the literature and whether it was extracted solely from information of the underlying or if option-based information entered. We also show the full-sample Sharpe ratios of characteristic-managed portfolio for each characteristic (Eq. (5)) using the option sample detailed in Section 3. Finally, we provide the statistical significance of this Sharpe ratio using the statistical test of Lo (2002).

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| age | Firm age | Underlying | Jiang Lee and Zhang (2005) | 1.39 | ** |
| ailliq | Absolute illiquidity | Options | Cao and Wei (2010) | −1.96 | *** |
| aliq_at | Liquidity of book assets | Underlying | Ortiz-Molina and Phillips (2014) | −0.70 | |
| aliq_mat | Liquidity of market assets | Underlying | Ortiz-Molina and Phillips (2014) | 0.20 | |
| ami_126d | Amihud Measure | Underlying | Amihud (2002) | −2.55 | *** |
| amihud | Amihud illiquidity per bucket | Options | Amihud (2002) | 1.63 | *** |
| at_be | Book leverage | Underlying | Fama and French (1992) | 0.88 | * |
| at_gr1 | Asset Growth | Underlying | Cooper Gulen and Schill (2008) | 0.73 | *** |
| at_me | Assets-to-market | Underlying | Fama and French (1992) | 0.66 | |
| at_turnover | Capital turnover | Underlying | Haugen and Baker (1996) | 2.67 | *** |
| atm_civpiv | At-the-money put vs. call implied volatility | Options | | −1.53 | *** |
| atm_dcivpiv | Change in atm put vs. call implied volatility | Options | An Ang Bali and Cakici (2014) | −2.15 | *** |
| atm_iv | At-the-money implied volatility (maturity-specific) | Options | | −3.18 | *** |
| be_gr1a | Change in common equity | Underlying | Richardson et al. (2005) | 0.54 | * |
| be_me | Book-to-market equity | Underlying | Rosenberg Reid and Lanstein (1985) | 0.16 | |
| beta_60m | Market Beta | Underlying | Fama and MacBeth (1973) | −1.02 | ** |
| beta_dimson_21d | Dimson beta | Underlying | Dimson (1979) | 0.36 | |
| betabab_1260d | Frazzini-Pedersen market beta | Underlying | Frazzini and Pedersen (2014) | −0.34 | |
| betadown_252d | Downside beta | Underlying | Ang Chen and Xing (2006) | −0.43 | |
| bev_mev | Book-to-market enterprise value | Underlying | Penman Richardson and Tuna (2007) | 0.24 | |
| bidaskhl_21d | The high-low bid-ask spread | Underlying | Corwin and Schultz (2012) | −2.03 | *** |
| bucket_dvol | Option bucket dollar volume | Options | | −0.50 | |
| bucket_vol | Option bucket volume | Options | | −1.41 | *** |
| bucket_vol_share | Relative option bucket volume | Options | | −1.17 | *** |
| capex_abn | Abnormal corporate investment | Underlying | Titman Wei and Xie (2004) | 1.59 | *** |
| capx_gr1 | CAPEX growth (1 year) | Underlying | Xie (2001) | 0.65 | ** |
| capx_gr2 | CAPEX growth (2 years) | Underlying | Anderson and Garcia-Feijoo (2006) | 0.76 | ** |
| capx_gr3 | CAPEX growth (3 years) | Underlying | Anderson and Garcia-Feijoo (2006) | 0.83 | *** |
| cash_at | Cash-to-assets | Underlying | Palazzo (2012) | −1.94 | *** |
| chcsho_12m | Net stock issues | Underlying | Pontiff and Woodgate (2008) | −1.67 | *** |
| civpiv | Near-the-money put vs. call implied volatility | Options | Bali and Hovakimian (2009) | −0.94 | ** |
| coa_gr1a | Change in current operating assets | Underlying | Richardson et al. (2005) | 1.46 | *** |
| col_gr1a | Change in current operating liabilities | Underlying | Richardson et al. (2005) | 0.94 | *** |
| cop_at | Cash-based operating profits-to-book assets | Underlying | | 1.87 | *** |
| cop_atl1 | Cash-based operating profits-to-lagged book assets | Underlying | Ball et al. (2016) | 2.11 | *** |
| corr_1260d | Market correlation | Underlying | Assness, Frazzini, Gormsen, Pedersen (2020) | 2.98 | *** |
| coskew_21d | Coskewness | Underlying | Harvey and Siddique (2000) | 0.59 | ** |
| cowc_gr1a | Change in current operating working capital | Underlying | Richardson et al. (2005) | 0.83 | ** |
| dbnetis_at | Net debt issuance | Underlying | Bradshaw Richardson and Sloan (2006) | −0.31 | |
| dciv | Change in atm call implied volatility | Options | An Ang Bali and Cakici (2014) | −1.97 | *** |
| debt_gr3 | Growth in book debt (3 years) | Underlying | Lyandres Sun and Zhang (2008) | 0.66 | * |
| debt_me | Debt-to-market | Underlying | Bhandari (1988) | 0.80 | |
| delta | Delta | Options | Buchner and Kelly (2020) | 1.26 | *** |

Continued on Next Page

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| demand_pressure | Option Demand Pressure | Options | | −2.77 | *** |
| dgp_dsale | Change gross margin minus change sales | Underlying | Abarbanell and Bushee (1998) | 0.29 | |
| div12m_me | Dividend yield | Underlying | Litzenberger and Ramaswamy (1979) | 1.35 | *** |
| doi | Dollar open interest | Options | | −0.66 | * |
| dolvol_126d | Dollar trading volume | Underlying | Brennan Chordia and Subrahmanyam (1998) | 2.47 | *** |
| dolvol_var_126d | Coefficient of variation for dollar trading volume | Underlying | Chordia Subrahmanyam and Anshuman (2001) | −3.40 | *** |
| dpiv | Change in atm put implied volatility | Options | An Ang Bali and Cakici (2014) | −0.91 | *** |
| dsale_dinv | Change sales minus change Inventory | Underlying | Abarbanell and Bushee (1998) | −0.41 | |
| dsale_drec | Change sales minus change receivables | Underlying | Abarbanell and Bushee (1998) | −1.01 | *** |
| dsale_dsga | Change sales minus change SG&A | Underlying | Abarbanell and Bushee (1998) | 0.61 | * |
| dso | Stock vs. option volume in USD | Options | Roll Schwartz and Subrahmanyam (2010) | 3.54 | *** |
| dvol | Dollar trading volume | Options | Cao and Wei (2010) | 0.68 | * |
| earnings_variability | Earnings variability | Underlying | Francis et al. (2004) | −2.44 | *** |
| ebit_bev | Return on net operating assets | Underlying | Soliman (2008) | 2.37 | *** |
| ebit_sale | Profit margin | Underlying | Soliman (2008) | 2.63 | *** |
| ebitda_mev | Ebitda-to-market enterprise value | Underlying | Loughran and Wellman (2011) | 1.72 | *** |
| embedlev | Embedded Leverage | Options | Karakaya (2014) | 4.04 | *** |
| emp_gr1 | Hiring rate | Underlying | Belo Lin and Bazdresch (2014) | 0.21 | |
| eq_dur | Equity duration | Underlying | Dechow Sloan and Soliman (2004) | −1.14 | ** |
| eqnetis_at | Net equity issuance | Underlying | Bradshaw Richardson and Sloan (2006) | −1.82 | *** |
| eqnpo_12m | Equity net payout | Underlying | Daniel and Titman (2006) | 1.90 | *** |
| eqnpo_me | Net payout yield | Underlying | Boudoukh et al. (2007) | 2.24 | *** |
| eqpo_me | Payout yield | Underlying | Boudoukh et al. (2007) | 1.82 | *** |
| f_score | Pitroski F-score | Underlying | Piotroski (2000) | 1.29 | *** |
| fcf_me | Free cash flow-to-price | Underlying | Lakonishok Shleifer and Vishny (1994) | 2.40 | *** |
| fnl_gr1a | Change in financial liabilities | Underlying | Richardson et al. (2005) | 1.02 | *** |
| fric | Contribution of market frictions to expected returns | Options | Hiraki and Skiadopoulos (2020) | −1.05 | *** |
| gamma | Gamma | Options | Buchner and Kelly (2020) | 3.61 | *** |
| gammaps | Pastor and Stambaugh liquidity measure | Options | Pastor and Stambaugh (2003) | 0.41 | |
| gp_at | Gross profits-to-assets | Underlying | Novy-Marx (2013) | 2.32 | *** |
| gp_atl1 | Gross profits-to-lagged assets | Underlying | | 2.41 | *** |
| hkurt | Historic kurtosis | Options | | −2.10 | *** |
| hskew | Historic skewness | Options | | −0.60 | ** |
| hvol | Historic Volatility | Options | | 1.58 | *** |
| illiq | Illiquidity | Options | Bao Pan and Wang (2011) | 0.09 | |
| intrinsic_value | Intrinsic value-to-market | Underlying | Frankel and Lee (1998) | 1.38 | *** |
| inv_gr1 | Inventory growth | Underlying | Belo and Lin (2011) | 0.70 | *** |
| inv_gr1a | Inventory change | Underlying | Thomas and Zhang (2002) | 1.56 | *** |
| iskew_capm_21d | Idiosyncratic skewness from the CAPM | Underlying | | −0.82 | ** |
| iskew_ff3_21d | Idiosyncratic skewness from the Fama-French 3-factor model | Underlying | Bali Engle and Murray (2016) | −0.66 | ** |
| iskew_hxz4_21d | Idiosyncratic skewness from the q-factor model | Underlying | | −0.63 | * |
| iv | Implied volatility | Options | Buchner and Kelly (2020) | −3.55 | *** |
| iv_rank | Implied volatility rank vs. last year | Options | | −2.09 | ** |

Continued on Next Page

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| ivarud30 | Option implied variance asymmetry | Options | Huang and Li (2019) | 3.03 | *** |
| ivd | Implied volatility duration | Options | Schlag Thimme and Weber (2020) | 4.16 | *** |
| ivol_capm_21d | Idiosyncratic volatility from the CAPM (21 days) | Underlying | | −2.25 | *** |
| ivol_capm_252d | Idiosyncratic volatility from the CAPM (252 days) | Underlying | Ali Hwang and Trombley (2003) | −2.17 | *** |
| ivol_ff3_21d | Idiosyncratic volatility from the Fama-French 3-factor model | Underlying | Ang et al. (2006) | −2.36 | *** |
| ivol_hxz4_21d | Idiosyncratic volatility from the q-factor model | Underlying | | −2.41 | *** |
| ivrv | Implied volatility minus realized volatility | Options | Bali and Hovakimian (2009) | −3.77 | *** |
| ivrv_ratio | Implied volatility minus realized volatility ratio | Options | | −3.01 | *** |
| ivslope | Implied volatility slope | Options | Vasquez (2017) | −0.35 | |
| ivvol | Volatility of atm volatility | Options | Baltussen van Bekkum and van der Grient (2018) | −1.65 | *** |
| kz_index | Kaplan-Zingales index | Underlying | Lamont Polk and Saa-Requejo (2001) | −0.11 | |
| lnoa_gr1a | Change in long-term net operating assets | Underlying | Fairfield Whisenant and Yohn (2003) | 1.79 | *** |
| lti_gr1a | Change in long-term investments | Underlying | Richardson et al. (2005) | 0.79 | ** |
| m_degree | Standardized strike | Options | | −1.26 | *** |
| market_equity | Market Equity | Underlying | Banz (1981) | 2.56 | *** |
| mid | Option mid price | Options | | 1.19 | *** |
| mispricing_mgmt | Mispricing factor: Management | Underlying | Stambaugh and Yuan (2016) | −0.12 | |
| mispricing_perf | Mispricing factor: Performance | Underlying | Stambaugh and Yuan (2016) | 2.87 | *** |
| modos | Modified stock vs. option volume | Options | Johnson and So (2012) | 2.03 | *** |
| ncoa_gr1a | Change in noncurrent operating assets | Underlying | Richardson et al. (2005) | 1.88 | *** |
| ncol_gr1a | Change in noncurrent operating liabilities | Underlying | Richardson et al. (2005) | 1.29 | *** |
| netdebt_me | Net debt-to-price | Underlying | Penman Richardson and Tuna (2007) | 1.36 | *** |
| netis_at | Net total issuance | Underlying | Bradshaw Richardson and Sloan (2006) | −1.69 | *** |
| nfna_gr1a | Change in net financial assets | Underlying | Richardson et al. (2005) | −0.53 | * |
| ni_ar1 | Earnings persistence | Underlying | Francis et al. (2004) | 0.87 | *** |
| ni_be | Return on equity | Underlying | Haugen and Baker (1996) | 2.51 | *** |
| ni_inc8q | Number of consecutive quarters with earnings increases | Underlying | Barth Elliott and Finn (1999) | 1.26 | *** |
| ni_ivol | Earnings volatility | Underlying | Francis et al. (2004) | −2.98 | *** |
| ni_me | Earnings-to-price | Underlying | Basu (1983) | 2.01 | *** |
| niq_at | Quarterly return on assets | Underlying | Balakrishnan Bartov and Faurel (2010) | 2.92 | *** |
| niq_at_chg1 | Change in quarterly return on assets | Underlying | | 0.17 | |
| niq_be | Quarterly return on equity | Underlying | Hou Xue and Zhang (2015) | 2.69 | *** |
| niq_be_chg1 | Change in quarterly return on equity | Underlying | | 0.52 | |
| niq_su | Standardized earnings surprise | Underlying | Foster Olsen and Shevlin (1984) | 0.58 | |
| nncoa_gr1a | Change in net noncurrent operating assets | Underlying | Richardson et al. (2005) | 1.72 | *** |
| noa_at | Net operating assets | Underlying | Hirshleifer et al. (2004) | 2.78 | *** |
| noa_gr1a | Change in net operating assets | Underlying | Hirshleifer et al. (2004) | 1.59 | *** |
| nopt | Number of options trading | Options | | 1.71 | *** |
| o_score | Ohlson O-score | Underlying | Dichev (1998) | −3.26 | *** |
| oaccruals_at | Operating accruals | Underlying | Sloan (1996) | 1.63 | *** |
| oaccruals_ni | Percent operating accruals | Underlying | Hafzalla Lundholm and Van Winkle (2011) | −1.61 | *** |
| ocf_at | Operating cash flow to assets | Underlying | Bouchard, Krüger, Landier and Thesmar (2019) | 2.69 | *** |
| ocf_at_chg1 | Change in operating cash flow to assets | Underlying | Bouchard, Krüger, Landier and Thesmar (2019) | −0.06 | |

Continued on Next Page

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| ocf_me | Operating cash flow-to-market | Underlying | Desai Rajgopal and Venkatachalam (2004) | 1.88 | *** |
| ocfq_saleq_std | Cash flow volatility | Underlying | Huang (2009) | −3.13 | *** |
| ocgo | Disposition Effect | Options | Bergsma Fodor and Tedford (2020) | 1.63 | *** |
| oi | Open interest | Options | | −1.88 | *** |
| oistock | Open interest vs. stock volume | Options | | −1.17 | *** |
| op_at | Operating profits-to-book assets | Underlying | | 2.43 | *** |
| op_atl1 | Operating profits-to-lagged book assets | Underlying | Ball et al. (2016) | 2.61 | *** |
| ope_be | Operating profits-to-book equity | Underlying | Fama and French (2015) | 2.53 | *** |
| ope_bel1 | Operating profits-to-lagged book equity | Underlying | | 3.11 | *** |
| opex_at | Operating leverage | Underlying | Novy-Marx (2011) | −0.03 | |
| optspread | Option bid-ask spread | Options | | −1.05 | *** |
| pba | Proportional bid-ask spread | Options | Cao and Wei (2010) | 0.65 | * |
| pcpv | Put-call parity deviations | Options | Ofek Richardson and Whitelaw (2004) | 1.10 | *** |
| pcratio | Put-call ratio | Options | Blau Nguyen and Whitby (2014) | 1.65 | *** |
| pfht | Modified illiquidity measure based on zero returns | Options | Fong Holden and Trzcinka (2017) | 0.46 | |
| pi_nix | Taxable income-to-book income | Underlying | Lev and Nissim (2004) | 0.61 | * |
| pifht | An extended FHT measured based on zero returns | Options | | 0.49 | |
| pilliq | Percentage illiquidity | Options | Cao and Wei (2010) | 1.02 | *** |
| piroll | Extended Roll's measure | Options | Goyenko Holden and Trzcinka (2009) | 0.72 | ** |
| ppeinv_gr1a | Change PPE and Inventory | Underlying | Lyandres Sun and Zhang (2008) | 1.66 | *** |
| prc | Price per share | Underlying | Miller and Scholes (1982) | 3.09 | *** |
| prc_highprc_252d | Current price to high price over last year | Underlying | George and Hwang (2004) | 1.95 | *** |
| pzeros | Illiquidity measure based on zero returns | Options | Lesmond 1999 | 0.46 | |
| qmj | Quality minus Junk: Composite | Underlying | Assness, Frazzini and Pedersen (2018) | 2.36 | *** |
| qmj_growth | Quality minus Junk: Growth | Underlying | Assness, Frazzini and Pedersen (2018) | 0.31 | |
| qmj_prof | Quality minus Junk: Profitability | Underlying | Assness, Frazzini and Pedersen (2018) | 2.67 | *** |
| qmj_safety | Quality minus Junk: Safety | Underlying | Assness, Frazzini and Pedersen (2018) | 2.53 | *** |
| rd5_at | R&D capital-to-book assets | Underlying | Li (2011) | −2.84 | *** |
| rd_me | R&D-to-market | Underlying | Chan Lakonishok and Sougiannis (2001) | −2.98 | *** |
| rd_sale | R&D-to-sales | Underlying | Chan Lakonishok and Sougiannis (2001) | −2.18 | *** |
| resff3_12_1 | Residual momentum t-12 to t-1 | Underlying | Blitz Huij and Martens (2011) | 0.36 | |
| resff3_6_1 | Residual momentum t-6 to t-1 | Underlying | Blitz Huij and Martens (2011) | 0.25 | |
| ret_12_1 | Price momentum t-12 to t-1 | Underlying | Fama and French (1996) | 0.88 | ** |
| ret_12_7 | Price momentum t-12 to t-7 | Underlying | Novy-Marx (2012) | 0.92 | *** |
| ret_1_0 | Short-term reversal | Underlying | Jegadeesh (1990) | 0.39 | |
| ret_3_1 | Price momentum t-3 to t-1 | Underlying | Jegedeesh and Titman (1993) | 0.36 | |
| ret_60_12 | Long-term reversal | Underlying | De Bondt and Thaler (1985) | 2.25 | *** |
| ret_6_1 | Price momentum t-6 to t-1 | Underlying | Jegadeesh and Titman (1993) | 0.63 | |
| ret_9_1 | Price momentum t-9 to t-1 | Underlying | Jegedeesh and Titman (1993) | 0.75 | * |
| rmax1_21d | Maximum daily return | Underlying | Bali Cakici and Whitelaw (2011) | −1.86 | *** |
| rmax5_21d | Highest 5 days of return | Underlying | Bali, Brown, Murray and Tang (2017) | −1.65 | *** |
| rmax5_rvol_21d | Highest 5 days of return scaled by volatility | Underlying | Assness, Frazzini, Gormsen, Pedersen (2020) | 0.74 | ** |
| rnk182 | 182-day risk-neutral kurtosis | Options | | 2.81 | *** |

Continued on Next Page

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| rnk273 | 273-day risk-neutral kurtosis | Options | | 2.77 | *** |
| rnk30 | 30-day risk-neutral kurtosis | Options | | 3.81 | *** |
| rnk365 | 365-day risk-neutral kurtosis | Options | | 2.61 | *** |
| rnk91 | 91-day risk-neutral kurtosis | Options | | 3.21 | *** |
| rns182 | 182-day risk-neutral skewness | Options | Borochin Chang and Wu (2020) | 0.53 | |
| rns273 | 273-day risk-neutral skewness | Options | Borochin Chang and Wu (2020) | −0.82 | ** |
| rns30 | 30-day risk-neutral skewness | Options | Borochin Chang and Wu (2020) | 2.76 | *** |
| rns365 | 365-day risk-neutral skewness | Options | Borochin Chang and Wu (2020) | −1.52 | *** |
| rns91 | 91-day risk-neutral skewness | Options | Borochin Chang and Wu (2020) | 2.30 | *** |
| roll | Roll's measure of illiquidity | Options | Roll (1984) | 0.67 | * |
| rskew_21d | Total skewness | Underlying | Bali Engle and Murray (2016) | −0.70 | ** |
| rvol_21d | Return volatility | Underlying | Ang et al. (2006) | −1.87 | *** |
| sale_bev | Assets turnover | Underlying | Soliman (2008) | 1.20 | *** |
| sale_emp_gr1 | Labor force efficiency | Underlying | Abarbanell and Bushee (1998) | 0.11 | |
| sale_gr1 | Sales Growth (1 year) | Underlying | Lakonishok Shleifer and Vishny (1994) | 0.64 | ** |
| sale_gr3 | Sales Growth (3 years) | Underlying | Lakonishok Shleifer and Vishny (1994) | 0.55 | |
| sale_me | Sales-to-market | Underlying | Barbee Mukherji and Raines (1996) | 1.30 | ** |
| saleq_gr1 | Sales growth (1 quarter) | Underlying | | 0.64 | ** |
| saleq_su | Standardized Revenue surprise | Underlying | Jegadeesh and Livnat (2006) | 0.59 | |
| seas_11_15an | Years 11-15 lagged returns, annual | Underlying | Heston and Sadka (2008) | −0.06 | |
| seas_11_15na | Years 11-15 lagged returns, nonannual | Underlying | Heston and Sadka (2008) | −0.46 | |
| seas_16_20an | Years 16-20 lagged returns, annual | Underlying | Heston and Sadka (2008) | −0.16 | |
| seas_16_20na | Years 16-20 lagged returns, nonannual | Underlying | Heston and Sadka (2008) | −0.17 | |
| seas_1_1an | Year 1-lagged return, annual | Underlying | Heston and Sadka (2008) | 0.62 | ** |
| seas_1_1na | Year 1-lagged return, nonannual | Underlying | Heston and Sadka (2008) | 0.16 | |
| seas_2_5an | Years 2-5 lagged returns, annual | Underlying | Heston and Sadka (2008) | 0.89 | *** |
| seas_2_5na | Years 2-5 lagged returns, nonannual | Underlying | Heston and Sadka (2008) | 0.03 | |
| seas_6_10an | Years 6-10 lagged returns, annual | Underlying | Heston and Sadka (2008) | 0.42 | |
| seas_6_10na | Years 6-10 lagged returns, nonannual | Underlying | Heston and Sadka (2008) | 0.06 | |
| shrtfee | Implied shorting fees | Options | Muravyev and Pearson (2020) | 1.44 | *** |
| skewiv | IV skew | Options | Xing Zhang and Zhao (2010) | 0.04 | |
| so | Stock vs. option volume | Options | Roll Schwartz and Subrahmanyam (2010) | 2.50 | *** |
| stdamihud | Standard deviation of Amihud's illiquidity measure | Options | | 1.46 | *** |
| sti_gr1a | Change in short-term investments | Underlying | Richardson et al. (2005) | 0.60 | * |
| taccruals_at | Total accruals | Underlying | Richardson et al. (2005) | 0.91 | *** |
| taccruals_ni | Percent total accruals | Underlying | Hafzalla Lundholm and Van Winkle (2011) | −1.75 | *** |
| tangibility | Asset tangibility | Underlying | Hahn and Lee (2009) | −1.98 | *** |
| tax_gr1a | Tax expense surprise | Underlying | Thomas and Zhang (2011) | 0.95 | *** |
| theta | Theta | Options | Buchner and Kelly (2020) | 3.29 | *** |
| tlm30 | Tail loss measure | Options | Vilkov and Xiao (2012) | −0.17 | |
| toi | Total option open interest | Options | | 0.34 | |
| turnover | Option turnover | Options | | −1.40 | *** |
| turnover_126d | Share turnover | Underlying | Datar Naik and Radcliffe (1998) | −1.20 | *** |

Continued on Next Page

| Feature | Description | Information Source | Source | SR | sig |
|---|---|---|---|---|---|
| turnover_var_126d | Coefficient of variation for share turnover | Underlying | Chordia Subrahmanyam and Anshuman (2001) | −3.68 | *** |
| vega | Vega | Options | Buchner and Kelly (2020) | −1.79 | *** |
| vol | Trading volume in options | Options | | 0.04 | |
| volga | Volga | Options | Buchner and Kelly (2020) | −2.48 | *** |
| vs_change | Change in weighted put-call spread | Options | Cremers and Weinbaum (2010) | −1.77 | *** |
| vs_level | Weighted put-call spread | Options | Cremers and Weinbaum (2010) | −0.97 | ** |
| z_score | Altman Z-score | Underlying | Dichev (1998) | 1.20 | *** |
| zero_trades_126d | Number of zero trades with turnover as tiebreaker (6 months) | Underlying | Liu (2006) | 1.17 | *** |
| zero_trades_21d | Number of zero trades with turnover as tiebreaker (1 month) | Underlying | Liu (2006) | 1.49 | *** |
| zero_trades_252d | Number of zero trades with turnover as tiebreaker (12 months) | Underlying | Liu (2006) | 1.19 | ** |

Done.

# Appendix B. Value-weighted Performance

In the specification in the main text, we focus on option-based momentum strategies that equally-weight the contracts in each quintile portfolio. In life trading, the investor is going to incorporate the liquidity of the contracts into his investment decision. We therefore replicate our main results of Table 2 using two weighting schemes. First, we weight each contract by the market capitalization of the underlying in Table B2. Second, we weight each contract by its own dollar open interest in Table B3.

Table B2: Investment Performance – Market Capitalization Weights

| Formation | Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Months | 1 | 2 | 3 | 4 | 5 | HmL |
| | Panel A: Risk Momentum | | | | | |
| 1 | −0.071 | −0.022 | −0.016 | −0.007 | 0.005 | 0.076 |
| | (−3.58) | (−1.87) | (−1.39) | (−0.66) | (0.45) | (6.28) |
| 3 | −0.074 | −0.021 | −0.017 | −0.006 | 0.004 | 0.078 |
| | (−4.40) | (−1.58) | (−1.58) | (−0.55) | (0.33) | (8.58) |
| 6 | −0.070 | −0.019 | −0.014 | −0.007 | 0.005 | 0.075 |
| | (−4.10) | (−1.60) | (−1.32) | (−0.63) | (0.41) | (8.16) |
| 12 | −0.064 | −0.021 | −0.011 | −0.006 | 0.004 | 0.067 |
| | (−4.04) | (−1.78) | (−0.96) | (−0.54) | (0.30) | (8.26) |
| 24 | −0.059 | −0.020 | −0.012 | −0.000 | 0.004 | 0.063 |
| | (−4.48) | (−1.56) | (−1.05) | (−0.04) | (0.34) | (9.67) |
| 60 | −0.053 | −0.011 | −0.009 | −0.003 | −0.000 | 0.053 |
| | (−4.03) | (−0.93) | (−0.74) | (−0.27) | (−0.01) | (10.50) |
| 120 | −0.041 | −0.012 | −0.006 | 0.004 | −0.000 | 0.041 |
| | (−2.69) | (−0.91) | (−0.41) | (0.32) | (−0.04) | (7.03) |
| | Panel B: Momentum | | | | | |
| 1 | −0.041 | −0.013 | −0.007 | −0.004 | −0.024 | 0.016 |
| | (−3.00) | (−1.17) | (−0.75) | (−0.36) | (−1.96) | (2.66) |
| 3 | −0.048 | −0.016 | −0.006 | −0.010 | −0.014 | 0.035 |
| | (−3.47) | (−1.50) | (−0.53) | (−0.99) | (−0.93) | (3.97) |
| 6 | −0.046 | −0.019 | −0.006 | −0.008 | −0.008 | 0.038 |
| | (−3.24) | (−1.93) | (−0.52) | (−0.84) | (−0.53) | (3.80) |
| 12 | −0.052 | −0.016 | −0.006 | −0.005 | −0.002 | 0.049 |
| | (−4.09) | (−1.68) | (−0.56) | (−0.45) | (−0.16) | (5.57) |
| 24 | −0.040 | −0.009 | −0.009 | −0.003 | 0.002 | 0.042 |
| | (−3.06) | (−0.88) | (−0.87) | (−0.26) | (0.15) | (4.81) |
| 60 | −0.035 | −0.009 | −0.006 | −0.002 | 0.003 | 0.038 |
| | (−2.91) | (−0.80) | (−0.57) | (−0.20) | (0.21) | (5.17) |
| 120 | −0.030 | −0.006 | −0.000 | −0.003 | 0.009 | 0.039 |
| | (−2.01) | (−0.48) | (−0.02) | (−0.25) | (0.53) | (3.43) |
| | Panel C: Residual Momentum | | | | | |
| 1 | −0.020 | −0.006 | −0.007 | −0.011 | −0.033 | −0.013 |
| | (−1.78) | (−0.53) | (−0.75) | (−0.97) | (−2.55) | (−2.15) |
| 3 | −0.016 | −0.010 | −0.011 | −0.010 | −0.027 | −0.011 |
| | (−1.53) | (−0.86) | (−1.13) | (−0.85) | (−1.97) | (−1.65) |
| 6 | −0.018 | −0.009 | −0.011 | −0.012 | −0.018 | −0.001 |
| | (−1.56) | (−0.92) | (−1.02) | (−1.12) | (−1.15) | (−0.09) |
| 12 | −0.016 | −0.012 | −0.007 | −0.011 | −0.012 | 0.004 |
| | (−1.47) | (−1.20) | (−0.71) | (−0.97) | (−0.81) | (0.43) |
| 24 | −0.009 | −0.008 | −0.007 | −0.011 | −0.013 | −0.003 |
| | (−0.76) | (−0.78) | (−0.67) | (−0.91) | (−0.82) | (−0.40) |
| 60 | −0.012 | −0.006 | −0.005 | −0.008 | −0.014 | −0.001 |
| | (−1.07) | (−0.53) | (−0.43) | (−0.59) | (−0.97) | (−0.17) |
| 120 | −0.008 | 0.001 | −0.005 | −0.000 | −0.010 | −0.002 |
| | (−0.67) | (0.07) | (−0.39) | (−0.02) | (−0.59) | (−0.21) |

## Table B3: Investment Performance – Dollar Open Interest Weights

| Formation | Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Months | 1 | 2 | 3 | 4 | 5 | HmL |
| | **Panel A: Risk Momentum** | | | | | |
| 1 | −0.131 | −0.042 | −0.034 | −0.019 | −0.013 | 0.118 |
| | (−7.30) | (−3.88) | (−2.87) | (−1.95) | (−1.23) | (8.77) |
| 3 | −0.131 | −0.046 | −0.028 | −0.022 | −0.009 | 0.122 |
| | (−7.82) | (−3.68) | (−2.62) | (−1.65) | (−0.76) | (8.85) |
| 6 | −0.134 | −0.037 | −0.025 | −0.023 | −0.008 | 0.126 |
| | (−8.12) | (−3.20) | (−2.47) | (−1.88) | (−0.71) | (10.17) |
| 12 | −0.122 | −0.038 | −0.025 | −0.013 | −0.012 | 0.110 |
| | (−8.38) | (−3.02) | (−2.28) | (−1.30) | (−0.97) | (9.89) |
| 24 | −0.115 | −0.036 | −0.021 | −0.011 | −0.011 | 0.105 |
| | (−8.04) | (−3.16) | (−1.85) | (−0.95) | (−0.86) | (9.98) |
| 60 | −0.089 | −0.036 | −0.016 | −0.016 | −0.014 | 0.074 |
| | (−6.47) | (−3.45) | (−1.38) | (−1.30) | (−1.28) | (7.26) |
| 120 | −0.078 | −0.033 | −0.021 | 0.002 | −0.014 | 0.064 |
| | (−5.52) | (−2.50) | (−1.71) | (0.16) | (−1.08) | (6.36) |
| | **Panel B: Momentum** | | | | | |
| 1 | −0.092 | −0.036 | −0.026 | −0.022 | −0.070 | 0.022 |
| | (−6.70) | (−3.15) | (−2.55) | (−1.87) | (−6.31) | (2.30) |
| 3 | −0.119 | −0.039 | −0.021 | −0.026 | −0.059 | 0.059 |
| | (−9.19) | (−3.40) | (−2.07) | (−2.37) | (−4.18) | (4.60) |
| 6 | −0.115 | −0.043 | −0.021 | −0.029 | −0.055 | 0.060 |
| | (−7.65) | (−3.76) | (−2.23) | (−2.61) | (−3.52) | (3.87) |
| 12 | −0.108 | −0.040 | −0.021 | −0.025 | −0.045 | 0.063 |
| | (−7.31) | (−4.20) | (−2.19) | (−2.47) | (−2.97) | (4.62) |
| 24 | −0.102 | −0.029 | −0.023 | −0.022 | −0.040 | 0.062 |
| | (−9.11) | (−2.90) | (−2.35) | (−1.87) | (−2.59) | (4.27) |
| 60 | −0.079 | −0.027 | −0.020 | −0.017 | −0.028 | 0.051 |
| | (−6.21) | (−2.53) | (−1.84) | (−1.54) | (−1.80) | (4.27) |
| 120 | −0.064 | −0.025 | −0.015 | −0.017 | −0.017 | 0.047 |
| | (−4.84) | (−1.88) | (−1.23) | (−1.50) | (−0.94) | (3.20) |
| | **Panel C: Residual Momentum** | | | | | |
| 1 | −0.070 | −0.026 | −0.021 | −0.029 | −0.090 | −0.020 |
| | (−5.72) | (−2.54) | (−2.29) | (−2.27) | (−6.52) | (−1.69) |
| 3 | −0.085 | −0.029 | −0.032 | −0.030 | −0.077 | 0.008 |
| | (−7.76) | (−2.74) | (−3.19) | (−2.50) | (−5.49) | (0.68) |
| 6 | −0.073 | −0.032 | −0.036 | −0.035 | −0.065 | 0.007 |
| | (−6.38) | (−2.90) | (−3.13) | (−3.34) | (−4.56) | (0.56) |
| 12 | −0.068 | −0.029 | −0.022 | −0.034 | −0.071 | −0.002 |
| | (−6.28) | (−2.89) | (−2.09) | (−3.62) | (−4.39) | (−0.16) |
| 24 | −0.056 | −0.028 | −0.024 | −0.029 | −0.069 | −0.012 |
| | (−6.55) | (−2.76) | (−2.33) | (−2.69) | (−3.94) | (−0.88) |
| 60 | −0.043 | −0.020 | −0.026 | −0.027 | −0.054 | −0.011 |
| | (−4.12) | (−1.96) | (−2.44) | (−2.02) | (−3.48) | (−1.04) |
| 120 | −0.035 | −0.013 | −0.020 | −0.034 | −0.042 | −0.006 |
| | (−3.75) | (−1.13) | (−1.45) | (−2.18) | (−2.70) | (−0.69) |

# Appendix C. Performance with Out-of-Sample Risk Adjustment

In Table C4, we replicate our main results of Table 2 using an out-of-sample risk adjustment through IPCA (Eq. (3)). IPCA is estimated without forward-looking information. Specifically, using an expanding window, we first estimate IPCA with information until month $t$ to obtain $\Gamma_{\beta,\boldsymbol{t}}$. Next, we calculate the out-of-sample factor return $f_{\boldsymbol{t},t+1}$ in a cross-sectional regression on option returns in $t+1$. This regression uses portfolio weights known in $t$, thereby assuring that no forward-looking information enters the out-of-sample estimation of IPCA.

Table C4: Investment Performance – Out-of-Sample Risk Adjustment

| Formation | Portfolio | | | | | |
|---|---|---|---|---|---|---|
| Months | 1 | 2 | 3 | 4 | 5 | HmL |
| | | | Panel A: Risk Momentum | | | |
| 1 | −0.142 | −0.031 | −0.012 | −0.002 | 0.018 | 0.160 |
| | (−6.26) | (−2.30) | (−0.96) | (−0.21) | (1.45) | (9.81) |
| 3 | −0.142 | −0.032 | −0.009 | 0.001 | 0.014 | 0.156 |
| | (−6.52) | (−2.26) | (−0.77) | (0.11) | (1.12) | (10.39) |
| 6 | −0.139 | −0.024 | −0.010 | 0.002 | 0.017 | 0.156 |
| | (−6.70) | (−1.79) | (−0.86) | (0.14) | (1.33) | (11.30) |
| 12 | −0.125 | −0.024 | −0.006 | 0.001 | 0.015 | 0.139 |
| | (−6.80) | (−1.74) | (−0.46) | (0.06) | (1.14) | (11.49) |
| 24 | −0.110 | −0.020 | −0.005 | 0.005 | 0.014 | 0.125 |
| | (−7.07) | (−1.51) | (−0.35) | (0.40) | (1.07) | (14.09) |
| 60 | −0.090 | −0.015 | −0.002 | 0.004 | 0.010 | 0.100 |
| | (−6.10) | (−1.09) | (−0.14) | (0.33) | (0.75) | (11.88) |
| 120 | −0.064 | −0.004 | −0.002 | 0.008 | 0.011 | 0.074 |
| | (−3.81) | (−0.26) | (−0.13) | (0.51) | (0.73) | (8.19) |
| | | | Panel B: Momentum | | | |
| 1 | −0.098 | −0.017 | −0.007 | −0.006 | −0.043 | 0.055 |
| | (−5.27) | (−1.30) | (−0.54) | (−0.48) | (−2.90) | (6.24) |
| 3 | −0.101 | −0.021 | −0.010 | −0.007 | −0.027 | 0.074 |
| | (−5.33) | (−1.61) | (−0.84) | (−0.54) | (−1.89) | (7.92) |
| 6 | −0.104 | −0.019 | −0.007 | −0.008 | −0.017 | 0.086 |
| | (−5.42) | (−1.54) | (−0.60) | (−0.66) | (−1.20) | (7.89) |
| 12 | −0.101 | −0.017 | −0.008 | −0.003 | −0.010 | 0.091 |
| | (−6.04) | (−1.34) | (−0.63) | (−0.25) | (−0.71) | (9.45) |
| 24 | −0.087 | −0.010 | −0.008 | −0.003 | −0.008 | 0.079 |
| | (−6.16) | (−0.79) | (−0.64) | (−0.25) | (−0.54) | (10.68) |
| 60 | −0.077 | −0.011 | −0.004 | 0.000 | −0.001 | 0.076 |
| | (−5.60) | (−0.90) | (−0.29) | (0.02) | (−0.06) | (11.56) |
| 120 | −0.056 | −0.005 | −0.001 | 0.003 | 0.008 | 0.063 |
| | (−3.84) | (−0.33) | (−0.07) | (0.18) | (0.43) | (8.62) |
| | | | Panel C: Residual Momentum | | | |
| 1 | −0.074 | −0.009 | −0.007 | −0.018 | −0.063 | 0.011 |
| | (−4.51) | (−0.66) | (−0.58) | (−1.33) | (−4.08) | (2.40) |
| 3 | −0.070 | −0.017 | −0.014 | −0.017 | −0.049 | 0.021 |
| | (−4.27) | (−1.35) | (−1.13) | (−1.30) | (−3.10) | (4.55) |
| 6 | −0.069 | −0.013 | −0.011 | −0.020 | −0.040 | 0.028 |
| | (−4.40) | (−1.10) | (−0.94) | (−1.64) | (−2.57) | (5.88) |
| 12 | −0.061 | −0.014 | −0.012 | −0.017 | −0.035 | 0.027 |
| | (−4.39) | (−1.17) | (−0.94) | (−1.24) | (−2.30) | (5.75) |
| 24 | −0.046 | −0.010 | −0.010 | −0.014 | −0.036 | 0.010 |
| | (−3.59) | (−0.81) | (−0.82) | (−1.06) | (−2.36) | (1.62) |
| 60 | −0.036 | −0.011 | −0.010 | −0.013 | −0.024 | 0.012 |
| | (−2.80) | (−0.85) | (−0.77) | (−0.90) | (−1.54) | (2.65) |
| 120 | −0.025 | 0.000 | −0.006 | −0.006 | −0.015 | 0.011 |
| | (−1.86) | (0.03) | (−0.39) | (−0.37) | (−0.85) | (1.63) |