Common Factors in Equity Option Returns*

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Abstract

We explore the factor structure in delta-hedged equity option returns. We find that both call and put options, including at-the-money and out-of-the-money, share the same factor structure. A sparse latent factor model generates a correlation of 0.96 between average and predicted option returns, with an average time-series R^2 of 0.89. A comparable performance is achieved with a characteristic-based model containing just three factors: an aggregate stock option market portfolio, a factor based on the difference between historical and implied volatilities, and a factor based on volatility of volatility. Stock return factors cannot explain these option factors.

JEL Classification: C14, G13, G17

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1 Introduction

The equity option market has experienced rapid growth in the past decade. Trading volume of equity options in the U.S. has increased from 3.7 billion contracts in 2012 to 9.6 billion contracts in 2022, according to the Options Clearing Corporation. The underlying stock shares of the traded equity options has reached a level of 3.8 billion per day, compared to 6.5 billion shares of stocks traded on exchanges.[1] Moreover, equity options play an increasingly important role in the portfolios of institutional investors as well as retail investors, evidenced by the recent surge of retail options trading activities.[2] Given the growing popularity of equity options among investors, a number of studies have explored the cross-sectional determinants and the predictability of equity option returns.[3] However, our understanding of the common factor structure driving the cross-section remains limited. How many common factors exist? Do the factors from call options differ from those of put options? Are common factors distinct across various moneyness levels? Are there factors in option returns that are not reflected in stock return factors? What is the economic interpretation of these factors? Additionally, what constitutes a good benchmark model for pricing the cross-section of equity option returns? Our paper is devoted to addressing these questions.

Previous studies have shown that implied volatility of equity options (Christoffersen, Fournier, and Jacobs, 2018) and idiosyncratic volatility of stock returns (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2016) display a strong factor structure. Our study focuses on delta-hedged equity option returns. These positions are not sensitive to changes in the underlying stock price but are primarily influenced by volatility movements. Therefore, delta-hedged equity returns, which reflect risk premium related to movements in volatility and higher-order moments, are also likely to obey a factor structure.

We study the factor structure in delta-hedged equity option returns using characteristic-sorted call and put option portfolios simultaneously. We consider 19 characteristics that have been shown to predict the cross-section of one-month at-the-money option returns. These

[1] Data source: Stock options trading volume data from options clearing corporation and stock trading volume from CBOE historical market volume data in 2022.

[2] See, for example, Bryzgalova, Pavlova, and Sikorskaya (Forthcoming)

[3] The firm-level and option-level predictors are summarized in Zhan, Han, Cao, and Tong (2022) and Bali, Beckmeyer, Moerke, and Weigert (Forthcoming)

characteristics are sourced from studies by Zhan, Han, Cao, and Tong (2022), Goyal and Saretto (2009), Cao and Han (2013), Vasquez (2017), Ruan (2020), Cao, Vasquez, Xiao, and Zhan (2023), and Vasquez and Xiao (Forthcoming). Our benchmark study involves 185 delta-hedged call option portfolios and 185 delta-hedged put option portfolios. These portfolios, sorted by 19 characteristics, cover the period from January 1996 to December 2021.

Using principal component analysis (PCA), we find that at most four factors, but possibly just three, suffice to fit the time-series and the cross-section of delta-hedged returns from both call and put options, including at-the-money (ATM) and out-of-the-money (OTM). Moreover, these factors are the same for call and put options, whether we test ATM or OTM positions. These common factors explain around 90% of the cross-sectional and time-series variation of the 370 characteristic-sorted portfolios.

We then seek the economic interpretation of the four PCA factor model, by determining the combination of candidate factors that best encapsulates its information. We consider 21 tradable factors from ATM option portfolio returns: 19 characteristic-based tradable factors constructed using long-short option strategies of the univariate sorted portfolios, the delta-hedged return of the S&P 500 index options, and the equal-weighted option portfolio (EWOP) of the 370 characteristic-based delta-hedged portfolios constructed with the 19 characteristics.

We generate all possible four-factor models from the 21 candidate factors derived from ATM call options, which amounts to 5,985 distinct models. We then evaluate these models using five performance metrics and select the top 2.5% performing models (150 models) for each metric. Our results highlight two critical factors for explaining the cross-section of delta-hedged equity option returns. The *log difference between historical realized volatility and implied volatility* (HV–IV) from Goyal and Saretto (2009) is crucial for maximizing the Sharpe ratio, enhancing the correlation between average and predicted returns, and minimizing the in-sample root mean squared pricing error. The *volatility of volatility* (VOV) from Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2023) is essential for capturing the tangency portfolio of the four PCA factors and minimizing the out-of-sample root mean squared pricing error. Additionally, the correlation between the first PCA and the equal-weighted option portfolio (EWOP) is 0.99. A model incorporating EWOP, VOV, and HV–IV performs on par with the benchmark four PCA factor model.

For robustness purposes, we test the performance of our model on four additional portfolio sets: 1) 364 OTM delta-hedged call and put portfolio returns constructed using the same 19 characteristics, 2) 2,978 ATM delta-hedged call and put portfolio returns formed on 149 characteristics distinct from the 19 characteristics used in the main analysis, 3) 149 long-short stock portfolio returns sorted by the 149 characteristics, and 4) 370 ATM delta-hedged call and put portfolio returns constructed with the original 19 characteristics, using different treatment of missing values in the dataset of the type described by Duarte, Jones, Mo, and Khorram (2023). The results demonstrate that both the latent factor model and the characteristic-based factor models yield a robust fit for all portfolios and databases, including extreme deciles. Two relevant observations follow these results.

First, we find that a characteristic-sparse factor model performs as well as a latent factor model in pricing delta-hedged equity option returns. This finding is in stark contrast with Kozak, Nagel, and Santosh (2020), who find that a characteristic-sparse factor model could not match the performance of a latent factor model based on a few principal components in the context of stock returns. This difference can be attributed to the fact that the factor structure in delta-hedged option returns is significantly stronger than that in stock returns. Our delta-hedged option return data show that a *four* PCA factor model yields a correlation between average and predicted returns of 0.96 and an average time-series R^2 of 0.89. In contrast, a *six* PCA factor model extracted from the dataset of 182 long-short stock returns, which we use in the Appendix, only produces a correlation between average and predicted returns of 0.30 and an average time-series R^2 of 0.54.

Second, our benchmark characteristic-based factor model is constructed using candidate factors from long-short *call* option portfolio returns. The correlation between call and put candidate factors based on the same characteristic is around 0.90 on average. In fact, using *put* factors slightly improves the performance of the characteristic-based model. Hence, all the results presented for the characteristic-based model can be considered a conservative estimate.

The Appendix offers supplementary results, which include a theoretical section that backs our empirical findings with a stylized model. In this model, delta-hedged option returns are exposed to volatility risk and volatility-of-volatility risk. We argue that volatility risk is potentially captured by HV–IV and that volatility-of-volatility risk is possibly captured by VOV. The Appendix also contains a comprehensive analysis of the factor structure in delta-hedged OTM option returns, as well as our study of the factor structure in delta-hedged equity option returns using the risk-premium PCA by Lettau and Pelger (2020a) and the instrumented PCA by Kelly, Pruitt, and Su (2019). In the Appendix we show that our option factors are not spanned by stock return factors. This result implies that our option factor model is suitable for delta-neutral option strategies that are exposed to vega and gamma, such as delta-neutral straddles or strangles. Other option trading strategies, such as bull spreads, spreads, or collars, that are also exposed to movements in the underlying security (non-zero delta), should concurrently employ our proposed option factor model and a factor model for pricing stock returns.

This paper is related to the literature that explores the factor structure of options. Most of the research explores the factor structure of the S&P 500 index options returns: Jones (2006), Fournier, Jacobs, and Orłowski (Forthcoming), and Büchner and Kelly (2022). On the cross-section of options, Duan and Wei (2009) and Christoffersen, Fournier, and Jacobs (2018) study the factor structure of option prices, not option returns. We study the factor structure of the cross-section of at-the-money and out-of-the-money equity option returns. Importantly, we provide a factor model that future research can use as a benchmark to assess the risk-adjusted performance of option portfolio returns.

Another strand of literature focuses on option return predictability in the cross-section, not its factor structure, using machine learning, such as Brooks, Chance, and Shafaati (2018), Goyenko and Zhang (2022), and Bali, Beckmeyer, Moerke, and Weigert (Forthcoming). Different from these studies, our paper uses a latent approach to study the factor structure in the cross-section of equity option returns. Two concurrently developed and complementary papers approach this subject from different angles: Goyal and Saretto (2022) estimate a latent factor model and conclude that the options market is quite efficient, while Bali et al. (2023) propose a theoretically motivated factor model. Our paper, however, pursues a distinct objective. We aim to uncover the factor structure that drives the cross-section of call and put option returns simultaneously across moneyness levels, and propose a parsimonious model that captures it. To this end, we initially employ a latent approach to estimate the number of factors and the common factors in equity option returns. Then, we provide an economic interpretation of the estimated factor model by identifying which tradable factors best represent the latent ones.

The rest of the paper is organized as follows. Section 2 describes the data used for our empirical analysis and how the delta-hedged equity option portfolios are formed. In Section 3 we perform our main quantitative studies. We conclude in Section 4.

2 Data and Variables Description

2.1 Data and Sample Coverage

We obtain option data on individual stocks from the OptionMetrics Ivy DB database. Sample period is from January 1996 to December 2021. Implied volatility and Greeks are calculated by OptionMetrics using the binomial tree in Cox, Ross, and Rubinstein (1979). We obtain stock returns, prices and credit ratings from the Center for Research on Security Prices (CRSP); balance sheet data from Compustat and analyst coverage and forecast data from I/B/E/S.

We apply several filters to select the options in our sample. We only include common US stocks with CRSP share codes equal to 10 or 11. A firm is included only when an ATM call option and an ATM put option are both available and satisfy the following filters. First, we exclude options if the open interest is zero, the bid quote is zero, the bid quote is smaller than the ask quote, or the average of the bid and ask price is lower than 0.125 dollars. We apply this filter when opening and closing the position: at the end of the month and at the end of the following month. Second, to remove the effect of early exercise premium in American options, we discard options whose underlying stock pays a dividend during the remaining life of the option. Therefore, options in our sample are very close to European style options. Third, we exclude all options that violate no-arbitrage restrictions. Fourth, we only keep options with moneyness between 0.8 and 1.2. In the main analysis, we estimate the number of factors in delta-hedged option portfolios from both call and put options. At the end of each month and for each stock with options, we select a call option and a put option that are the closest to being at-the-money with the shortest maturity among those options with more than one month to maturity. We drop options whose maturity is different from most options. Our final sample contains 204,376 firm-month observations for calls and puts. Importantly, our main findings are robust to imputing theoretical prices to firms that, at the end of the holding period, either have an option bid quote of zero, lack both bid and ask option prices, or have a missing underlying stock price, as documented in Section 3.5.

2.2 Construction of the Delta-Hedged Option Returns

Since an option is a derivative written on a stock, raw option returns are highly sensitive to stock returns. Following the literature, we study the return of delta-hedged options, such that the portfolio return is not sensitive to the movement of the underlying stock price. Empirical studies find that the average return of the delta-hedged option portfolios is negative for both indexes and individual stocks (Bakshi and Kapadia, 2003; Cao and Han, 2013; Carr and Wu, 2009). Bakshi and Kapadia (2003) show that the sign and the magnitude of delta-hedged gains are related to the variance risk premium and the jump risk premium (To decompose delta-hedged returns into jump risk and variance risk assets see Chen et al. (2023)). The delta-hedged option position is constructed by holding a long position in a option, hedged by a short position of delta shares on the underlying stock. The definition of delta-hedged option gain follows Bakshi and Kapadia (2003) and is given by

$$\Pi_{t,t+\tau} = O_{t+\tau} - O_t - \int_t^{t+\tau} \Delta_u dS_u - \int_t^{t+\tau} r_u(O_u - \Delta_u S_u)du,$$

where O_t represents the price of an European option at time t, S_t represents the price of the stock at time t, $\Delta_t = \frac{\partial C_t}{\partial S_t}$ is the option delta at time t, and r_t is the annualized risk-free rate at time t. We consider a portfolio of an option that is hedged discretely N times over the period $[t, t+\tau]$, where the hedge is rebalanced at each date t_n, $n = 0, 1, ..., N-1$. Bakshi and Kapadia (2003) show in a simulation setting that the use of the Black-Scholes hedge ratio has a negligible bias on delta-hedged gains. The discrete delta-hedged option gain up to maturity $t+\tau$ is defined as

$$\Pi_{t,t+\tau} = O_{t+\tau} - O_t - \sum_{n=0}^{N-1} \Delta_{t_n}[S_{t_{n+1}} - S_{t_n}] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}(O_{t_n} - \Delta_{t_n} S_{t_n}), \tag{1}$$

where O_t is the price of the option, S_t is the price of the stock, Δ_{t_n} is the delta of the option at time t_n, r_{t_n} is the annualized risk free rate, and a_n is the number of calendar days between t_n and t_{n+1}. This definition is used to compute the delta-hedged gain for call and put options by using the corresponding price and delta. We start the position at the end of the month and close the position at the end of the following month. We work with monthly returns in the empirical analysis.

To make delta-hedged gains comparable across stocks and across call and put options, we use delta-hedged option returns defined as the delta-hedged option gain $\Pi_{t,t+\tau}$ scaled by the stock price S. Some studies scale the option gain by the initial investment of the delta-hedged portfolio, $|O - \Delta \times S|$, where O is the option price, and Δ is positive for calls and negative for puts. This leads to a situation where the scaled delta-hedged put returns are consistently lower than the scaled delta-hedged call returns. To ensure comparability of returns between calls and puts, we adopt the methodology proposed by Bakshi and Kapadia (2003) and used in Büchner and Kelly (2022), where the delta-hedged gain of both calls and puts is scaled by the stock price. This scaling approach is theoretically supported by Bakshi and Kapadia (2003) who demonstrate that the delta-hedged gains for calls and puts are directly proportional to both volatility and the underlying stock price.

2.3 Test Portfolios and Factor Candidates in the Equity Option Market

In the literature on the cross-section of stock returns, long-short portfolios are commonly used as stock return factors. These factors, such as the size factor, the value factor, or the momentum factor, are constructed with portfolios composed by stocks ranked by certain characteristic, such as market capitalization, book-to-market ratio, or lagged 12-month return. We follow the same procedure for the equity option market and consider the predictors of option returns documented in the literature. These predictors are then used to sort portfolios and construct the list of candidate factors. The characteristics that predict option returns are:

(1) Size: the natural logarithm of the market value of the firm's equity.

(2) Stock return idiosyncratic volatility (Ivol). Cao and Han (2013) find that delta-hedged equity option returns decrease monotonically with an increase in the idiosyncratic volatility of the underlying stock.

(3) The log difference between historical realized volatility and the Black-Scholes implied volatility for at-the-money options (HV–IV). Goyal and Saretto (2009) find that the higher the difference, the higher the future straddle return of the equity option.

(4) The slope of volatility term structure (IV_slope): the difference between long-term and short-term implied volatilities. Vasquez (2017) finds that straddle portfolios with high slopes of the volatility term structure outperform straddle portfolios with low slopes.

(5) Book-to-market ratio (BM): the ratio of book equity to market equity.

(6) Credit rating (Credit): Credit ratings are provided by Standard & Poor's and are mapped to 22 numerical values, where 1 corresponds to the highest rating (AAA) and 22 corresponds to the lowest rating (D). Vasquez and Xiao (Forthcoming) find that credit rating is a strong predictor of future option returns. Options with lower credit rating have more negative delta-hedged returns in the future.

(7) Volatility of volatility (VOV): Standard deviation of implied volatility change in the past month. Ruan (2020) and Cao et al. (2023) find that volatility of volatility is negatively related to future equity option returns.

(8) Stock illiquidity measure (Illiquidity): the average of the daily ratio of the absolute stock return to dollar volume over the previous month, proposed in Amihud (2002).

(9) Stock return reversal (Reversal): lagged one-month return.

(10) Stock return momentum (Mom): the cumulative return on the stock over the 11 months ending at the beginning of the previous month.

(11) Cash flow variance (VarCF): variance of the monthly ratio of cash flow to market value of equity over the last 60 months. Cash flow is net income plus depreciation and amortization scaled by market value of equity.

(12) Cash-to-assets ratio (Cash): the value of corporate cash holdings over the value of the firm's total assets.

(13) Analyst earnings forecast dispersion (Disp): standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast.

(14) One-year new issues (ShareIss1Y): the change in shares outstanding in the past one year.

(15) Five-year new issues (ShareIss5Y): the change in number of shares outstanding in the past five years.

(16) Profit margin (PM): earnings before interest and tax scaled by revenues.

(17) Stock price (Close): The log of stock price at the end of last month.

(18) Profitability (Profit): earnings divided by book equity in which earnings are defined as income before extraordinary items.

(19) Total external financing (Xfin): net share issuance plus net debt issuance minus cash dividends, scaled by total assets.

Characteristics (1), and (9) to (19) have been shown to have predictability for cross section of option returns in Zhan et al. (2022). At the end of each month, we sort all stock options into 10 portfolios based on the 19 characteristics described above.[4] We start the position at the end of the month, hedge its delta exposure on a daily basis, and close it at the end of following month. Their corresponding delta-hedged option returns are calculated according to Section 2.2. We consider 370 option portfolios, 185 ATM delta-hedged call and 185 ATM delta-hedged put option portfolios sorted by 19 different characteristics, as test assets such that they have enough heterogeneity and the underlying risk premium associated factors can be identified. The 19 candidate factors for either calls or puts are the long-short return spreads, 10-1 (5-1 for credit rating), based on the 19 characteristics. We also consider two additional candidate factors related to common volatility risk:

(20) Delta-hedged S&P 500 call option return (SPX_DH_call): a proxy for the market volatility risk in Coval and Shumway (2001) and Carr and Wu (2009). It is constructed in a similar manner than the delta-hedged return for individual stocks.

(21) Equal-weighted option portfolio return (EWOP): equal-weighted option portfolio return of all 370 characteristic-sorted delta-hedged call and put option portfolios, used as a

[4]For credit rating we sort into 5 quintiles because there are less than 10 different ratings in some months, which leads to missing data in portfolio returns.

measure to capture the aggregate stock option market risk.

[Table 1 around here]

Table 1 presents summary statistics of the returns of the 21 candidate factors for call options (Panel A) and put options (Panel B). We report the mean, standard deviation, skewness, kurtosis, 10th, 25th, 50th, 75th, and 90th percentiles. The 21 candidate factors include the 19 long-short portfolios of the option returns predictors, the delta-hedged call returns of the S&P 500 index options, and the EWOP.

The table shows that the average return spreads range from -1.22% to 1.24% with standard deviations ranging from 0.16 to 1.00. The highest mean option returns in absolute value are observed for HV–IV, IV_slope, and VOV. In the Appendix, we report the decile returns, long-short returns, along with t-statistics in Table A1 for calls and Table A2 for puts. We are able to replicate most of the results from the original papers. The tables show that the long-short returns constructed by buying the top decile and selling the bottom decile are significantly different from zero for all predictors. The delta-hedged equity option returns increase for nine characteristics (Size, HV–IV, IV_slope, BM, Reversal, ShareIss5y, PM, Profit, and stock Price), while they decrease for nine characteristics (Ivol, Credit, VOV, Illiquidity, VarCF, Cash, Disp, ShareIss1y, and Xfin). We observe that the delta-hedged return of the S&P 500 index options is on average negative, which represents the negative price of variance risk documented in previous papers. The return of the EWOP is also negative on average.

3 Empirical Procedure and Results

Our empirical study aims to thoroughly investigate if a factor model can explain the time-series and cross-section of delta-hedged equity option returns.

We begin by addressing several key questions: Does the cross-section of delta-hedged equity option returns display a factor structure? If this is the case, how many common factors drive these returns? Further, do the factors associated with call options differ from those associated with put options? We use latent factor estimation methods to provide answers to these questions in Section 3.1.

Statistical factors derived from latent methods can be difficult to interpret. Therefore, after addressing the above questions, we explore in Section 3.2 whether a set of existing, tradable candidate factors known for predicting option returns can capture the information contained in the statistical factors. This approach enables us to construct a parsimonious, interpretable factor model for pricing the cross-section of at-the-money (ATM) delta-hedged equity option returns.

In Sections 3.3, 3.4, and 3.5 we test the robustness of our results. Sections 3.3 uses out-of-the-money (OTM) call and put options portfolios. Section 3.4 uses a set of 2,978 equity option return portfolios constructed using an alternative set of 149 firm characteristics, respectively. Section 3.5 uses an augmented dataset with imputed missing values. In Appendix A.4, we assess whether the factors that drive the cross-section of delta-hedged equity option returns are independent from those associated with the cross-section of stock returns. Appendices A.2, A.3, and A.5 contain further robustness checks.

3.1 The Factor Structure in Delta-Hedged Equity Option Returns

In this section, we use the machinery developed for estimating factor models to study if the cross-section of delta-hedged option portfolio returns displays a factor structure. We first estimate the number of factors and the common factors from a set of ATM delta-hedged equity option returns modeling an approximate linear factor structure as defined in Chamberlain and Rothschild (1983).[5] More precisely, let r_{it} be the response variable for the ith cross-section unit at time t ($i = 1, 2, ..., N$, and $t = 1, 2, ..., T$). Explicitly, r_{it} is the return on a delta-hedged option portfolio i at time t. The response variables r_{it} depend on K empirical factors $f_t = (f_{1t}, ..., f_{Kt})'$. That is,

$$r_t = \alpha + Bf_t + \epsilon_t,$$

[5]The advantage of working with approximate factor models as opposed to the classic exact factor models (e.g., Ross (1976)) is that the former allows for a certain degree of correlation across idiosyncratic terms while the latter imposes an orthogonality condition on the covariance matrix of the idiosyncratic component.

where $r_t = (r_{1t}, ..., r_{Nt})'$ is the N-vector of response variables at time t, $\alpha = (\alpha_1, ..., \alpha_N)$ is the N-vector of individual intercepts, B is the $N \times K$ matrix of factor loadings, and $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})'$ is the N-vector of idiosyncratic components at time t. The idiosyncratic components ϵ_{it} can be weakly cross-sectionally and time-series correlated.

To estimate the number of factors K in delta-hedged option returns, we use as response variables the ATM delta-hedged put and call portfolios defined in Section 2.3 ($N = 370$ portfolios) during the entire sample period from January 1996 to December 2021 ($T = 312$ months). As a preliminary step, we plot in Figure 1 Panel A the largest fifteen eigenvalues from the sample second-moment matrix of the "doubly demeaned" delta-hedged portfolio returns.[6] The figure, known as a "Scree plot", suggests the presence of about four common factors where one of them has much stronger explanatory power than the other three factors. The Eigenvalue Ratio (ER) and Growth Ratio (GR) estimators from Ahn and Horenstein (2013) shown in Panel B paint a similar picture. They identify a single dominant factor with a secondary peak at the fourth ratio, suggesting the presence of up to three additional weaker factors.

[Figure 1 around here]

We now turn our focus to a detailed examination of the factor structure in delta-hedged equity option returns. We use latent estimation techniques to consistently estimate the factors and factor loadings directly from the data. Our primary tool for this process is Principal Component Analysis (PCA), used to extract the latent factors. If the data follows an approximate factor model containing K factors, as the dimension of the panel (N, T) increases, the K eigenvectors of the second moment matrix corresponding to the largest K eigenvalues are consistent estimators of the factors (Bai and Ng, 2002; Connor and Korajczyk, 1986)).[7] In recent years, PCA has gained significant popularity in asset pricing, leading to the

[6]Let x_{it} be the observed value of response variable i. Then, the "doubly demeaned" data is $x_{it} - \bar{x}_i - \bar{x}_t + \bar{x}$, where $\bar{x}_i = \sum_{t=1}^{T} x_{it}/T$, $\bar{x}_t = \sum_{i=1}^{N} x_{it}/N$, and $\bar{x} = \sum_{i=1}^{N} \bar{x}_i/N$. Ahn and Horenstein (2013) recommend using doubly demeaned data when estimating the number of factors with eigenvalue-based methods to reduce the one-factor bias problem arising in finite samples when the response variables have means different than zero.

[7]We apply PCA to the second-moment matrix of delta-hedged option returns without subtracting the mean from the data, as suggested by Bai and Ng (2002). Lettau and Pelger (2020a) show that the PCA estimator is more efficient when estimated from this matrix rather than from the covariance matrix (the second-moment

development of numerous variations of the technique, for instance, see Kozak et al. (2018), Kelly et al. (2019), Lettau and Pelger (2020b), Giglio et al. (2021), Giglio and Xiu (2021), and Huang et al. (2022). However, we choose to utilize traditional PCA, as our findings remain qualitatively similar across different estimation methodologies. For additional comparison, Appendix A.3 contains results using the risk-premium PCA by Lettau and Pelger (2020a) and the instrumented PCA by Kelly et al. (2019).

It is crucial to note that these factors are estimated simultaneously from both ATM call options and ATM put options. We now test whether there are any factors specific to each dataset. This allows us to check whether calls and puts share the same factor structure or whether there are contract-specific factors. To do so, we apply the Gagliardini, Ossola, and Scaillet (GOS) estimator in Gagliardini, Ossola, and Scaillet (2019). The GOS estimator scrutinizes the error terms generated by a factor model and tests whether these errors are weakly cross-sectionally correlated or share at least one common factor. By assessing if the common factors estimated from the combined dataset capture all common factors in the individual datasets, we can determine if there are factors in call options or put options that are not shared across contracts. Table 2 shows the number of factors found in the residuals of the call and put databases as we sequentially add one of the common factors estimated from the two datasets together.

[Table 2 around here]

As we incrementally add a common estimated factor to each database, the number of factors identified in the residuals progressively decreases. After the addition of four (or more) factors, we find no additional factors in the residuals. We conclude that ATM delta-hedged call and put options share the same four factors.

So far we have shown that the factor structure in ATM delta-hedged returns from both call and put options can be summarized by four common factors, estimated using PCA. Moreover, these factors are the same for both types of option contracts. Next, we determine how relevant these factors are in explaining the cross-section of delta-hedged equity option

matrix from demeaned data).

returns. For this purpose, we evaluate their performance in-sample and out-of-sample. We use a 120-month window for out-of-sample testing to estimate factor scores and loadings for a given period (t). These estimates are then used to construct the factors and estimate the pricing error for the subsequent period ($t+1$).

We consider several measures to evaluate the pricing performance of the PCA factor models: Sharpe ratio of tangency portfolios ($\mathrm{SR_{DH}}$), correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$ where t_α is the t-statistics to test the null hypothesis of $\alpha = 0$,[8] out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of the distribution-free mean-variance efficiency test statistics F_{max} by Gungor and Luger (2016).

$\mathrm{SR_{DH}}$ is calculated for the mean-variance tangency portfolio constructed from the factors, which combines the factors to achieve the highest possible ratio. Note that the Sharpe ratio of the delta-hedged option portfolio, $\mathrm{SR_{DH}}$, is not comparable to the Sharpe ratio in other asset classes, such as stocks and bonds. Different from holding a stock or bond, rebalancing the option portfolio to be delta neutral requires additional investment to purchase or sell the underlying stock during the holding period. We denote the Sharpe ratio in our context as $\mathrm{SR_{DH}}$ to differentiate from the conventional Sharpe ratio. The Sharpe ratios in this paper are reported at monthly frequency.

We calculate average return and predicted return $\hat{B}\hat{f}_t$ for the 370 portfolios, where $\hat{B}$ and $\hat{f}_t$ are estimated using the full sample. Adjusted R^2s are obtained by running time-series regressions of portfolio returns on the factor model. RMSPE is root mean square pricing error, calculated as $\sqrt{\sum_1^N \hat{\alpha}^2/N}$, where N is the number of test assets. t_α is the t-statistics of the estimated intercept $\hat{\alpha}$ in the time-series regressions of portfolio returns on the factor model. We then calculate the percentage of times that $|t_\alpha| > 3$.

To test the mean-variance efficiency hypotheses, we consider the distribution-free method proposed by Gungor and Luger (2016), which allows for unknown forms of nonnormalities as well as time-varying conditional variances and covariances among the model residuals. This nonparametric bounds test is implemented with Monte Carlo (MC) resampling techniques. While the usual GRS-type tests are not computable when the number of test assets is too

[8] We follow Harvey, Liu, and Zhu (2016) by imposing the hurdle of $|t_\alpha| > 3$.

large, the power of this test potentially increases along both the time and cross-section dimensions. We report the p-value of the mean-variance efficiency test statistics F_{max} using 500 random samples.[9] Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq 5\%$ and report the liberal MC p-value when the liberal MC p-value $\geq 5\%$. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values.

[Figure 2 around here]

Figure 2 presents the in-sample and out-of-sample $\mathrm{SR}_{\mathrm{DH}}$ and RMSPE for six models. These models sequentially incorporate the first PCA factor to the sixth PCA factor. Two important patterns emerge from this figure. First, the second PCA factor proves to be vital for the performance of the models. Second, the out-of-sample performance of the models closely mirrors their in-sample performance.

[Table 3 around here]

Table 3 provides a complete report of the performance metrics for the six PCA models. The results show a remarkable performance from the first and second factors. With just these two factors, the cross-sectional metric corr Avg(r) and Pred(r) stands at 94%, while the time-series average adjusted R^2 is 0.87. On the other hand, these two factors alone still yield an F_{max} that does not reject the null hypothesis of all pricing errors being zero. Importantly, the correlation between the average return and the predicted return for the second PCA factor alone is 0.93, subsuming almost all the cross-sectional explanatory power in these two factors. The first PCA factor alone absorbs most of the time-series explanatory power among these two factors.

There is a minor yet non-negligible increase in performance when the fourth factor is added to the model. Interestingly, the inclusion of the third factor appears irrelevant, as it does not enhance any of the performance metrics we analyze. The percentage of portfolios

[9] All results related to F_{max} stay robust using 1,000 random samples.

with $|t_\alpha| > 3$ drops from 14% in the two-factor model to 9% in the four-factor model. At the same time, the p-values of the F_{max} statistics become indeterminate with the addition of the fourth factor. Hence, we further support our initial results that four factors suffice to span the space in which delta-hedged equity option returns comove.

Up until now, we have shown that a four PCA factor model is sufficient to capture the comovement in ATM delta-hedged equity call and put option returns. This model fits the data well both in-sample and out-of-sample. In the next section, we explore the economic interpretation of the four PCA factor model by studying which of the 21 candidate factors discussed in Section 2.3 explains the information contained in this model the best. Given that we find four common factors (potentially only three relevant for pricing), many of the 21 candidate factors proposed as predictors may contain redundant information. Therefore, it is crucial to identify the candidate factors that best capture the relevant information in the latent factors.

3.2 Selecting the Candidate Factors

In this section, our objective is to derive an economic interpretation for the four-factor PCA model identified in Section 3.1 and to establish a benchmark factor model for pricing the cross-section of equity option returns. We explore various candidate factors to determine the ones that best capture the information represented by the PCA model. These candidate factors include the long-short return spreads on 19 characteristics, in addition to the returns from the equal-weighted option portfolio (EWOP) and the delta-hedged S&P index option factor. Definitions for these candidate factors can be found in Section 2.3.

[Figure 3 around here]

We begin by analyzing the correlation matrix between candidate factors in call options and put options. The diagonal of the correlation heatmap in Figure 3 reveals that call and put option candidate factors of the same characteristic are highly correlated, with the correlation coefficient hovering around 0.9. The high correlation suggests that either call or put option returns could be used as factor candidates, as they essentially contain very similar information.

We now proceed to select the model with candidate factors that most effectively mirrors the four PCA factor model. As predicted by the results in Ahn and Horenstein (2022), the equal-weighted option portfolio returns (EWOP) is the first PCA factor. The correlation coefficient between these two factors is 0.999. Given that the first PCA is fundamental for capturing the time-series variation in delta-hedged option returns, a model with candidate factors must include EWOP, which serves as a proxy for the aggregate stock option market.[10]

In our quest for a parsimonious model that fits the cross-section of delta-hedged equity option returns, we generate all possible four-factor models from the 21 factor candidates. These are derived from call options and include the 19 candidate factors, EWOP, and the delta-hedged S&P index option factor.[11] This results in a total of 5,985 distinct models.

To pinpoint a model with candidate factors that mirror the cross-sectional fit of the four PCA factor model, we compute five performance metrics for each of the 5,985 models. These metrics are: a) SR_{DH} of the candidate factor model's tangency portfolio; b) the R^2 of regressing the tangency portfolio of the four PCA factor model on the candidate factor model;[12] c) the correlation between average returns and the predicted returns of the candidate model; d) RMSPE; and e) OOS RMSPE using a 120-month window. For each of the five metrics, we select the top 2.5% performing models (150 models) and record the frequency of each candidate factor's appearance in the top-performing models. The results are displayed in Figure 4.

[Figure 4 around here]

The figure shows that HV–IV is the crucial factor for maximizing SR_{DH}, appearing in all models within the top 2.5% of top-performing models for this metric. This factor also stands out as the most important in enhancing the correlation between average returns and the

[10] EWOP can be defined as the average of the 185 call or 185 put portfolio returns or as the average of the 370 portfolio returns. Alternatively, EWOP can also be defined as the average of individual call returns, individual put returns, or individual call and put returns. The correlation among different definitions of EWOP is above 0.97.

[11] The results remain qualitatively the same if we use put options as candidate factors, which aligns with the high correlation between call and put factor candidates shown in the diagonal of Figure 3.

[12] To calculate this metric we first construct the tangency portfolio of the PCA factors. We then compute the R^2 generated by regressing the candidate factor model on this portfolio.

model's predicted returns, as well as in minimizing the in-sample RMSPE. Concurrently, the key factor for capturing the tangency portfolio of the four PCA factors is VOV. This factor is also the most relevant for minimizing OOS RMSPE. In conclusion, VOV and HV–IV emerge as the most prominent candidate factors for explaining the cross-section of delta-hedged equity option returns among our set of 21 candidate factors. The results are consistent with our theoretical model in Appendix A.1 where stock volatility has a factor structure and volatility factors are driven by a stochastic volatility model. In this model, delta-hedged option gains are driven by risk premia related to volatility and volatility-of-volatility factors. The long-short delta-hedged option returns ranked by HV-IV and by the volatility of implied volatility are potential proxies for volatility risk and volatility-of-volatility risk.

Note that the S&P 500 delta-hedged call index (SPX_DH_call) scarcely appears in the top-performing models across any of the performance metrics. The delta-hedged S&P 500 option return does not serve as a clean measure of market aggregator for equity option returns because correlation risk premium is embedded in delta-hedged S&P 500 returns (See Driessen, Maenhout, and Vilkov (2009)). This finding highlights the need for using EWOP in a factor model for equity option returns.

From the analysis of Figure 4, other factors such as Cash, Illiquidity, VarCF, and Close also appear relevant. Our theoretical results in Appendix A.1, combined with the empirical strength of the HV - IV and VOV factors, motivate us to examine factor models that include the EWOP, HV - IV, and VOV factors. We use the same performance metrics as in Table 3 to evaluate models that include only these factors, as well as models that augment these factors with other factors that appear empirically important but for which the theoretical motivation is not apparent, including Cash, Illiquidity, VarCF, and Close factors. The results are reported in Table 4. For comparison, we also present the performance of the four PCA factor model and a model employing all 19 candidate factors plus EWOP (totaling 20 factors). For completeness, we present results using candidate factors from delta-hedged *call* portfolio returns (Panel A), as well as those from delta-hedged *put* portfolio returns (Panel B).

[Table 4 around here]

Overall, a model incorporating EWOP, VOV, and HV–IV mirrors the performance of the benchmark four PCA factor model. Including Cash as a factor seems to provide additional information, thereby marginally enhancing the model's goodness-of-fit, both in-sample and out-of-sample. However, the other candidate factors used to augment the model with the three principal ones appear redundant. Interestingly, models employing candidate factors from put options seem to outperform those from call options in terms of RMSPE, percentage of $|t_\alpha| > 3$, and OOS RMSPE. The three candidate factors from put options performs on par with models featuring four candidate factors from call options. For the remainder of the paper, we focus on results with candidate factors derived from call options, as these provide a conservative estimate of the model's performance.

[Figure 5 around here]

Figure 5 illustrates the relationship between average return and predicted return for four models: (a) the four PCA factor model, (b) a model incorporating all 19 factor candidates plus EWOP (20 factors), (c) a model including EWOP, VOV, and HV–IV, and (d) a model with EWOP, VOV, HV–IV, and Cash. This figure highlights how each model fits extreme decile portfolios. From a visual standpoint, a model with only EWOP, VOV, and HV–IV achieves a similar level of fit than any of the other models. Importantly, all four models - and particularly our three-candidate-factor model (Figure 5 Panel C) - provide a good fit of extreme decile portfolios.

[Table 5 around here]

Table 5 reports the means, the alphas, and the corresponding t-statistics of the 17 (16) long-short strategies not included in the three (four) candidate-factor model using call and put option factors. The three-candidate-factor model includes EWOP, VOV, and HV–IV, and the four-candidate-factor model adds Cash to the three-candidate-factor model. Results show that only 5 (8) out of 17 long-short returns have a t-statistics surpassing the hurdle of 3 after regressing call (put) strategies on the three-candidate-factor model. Then, only 2

(5) out of 16 long-short returns have a t-statistic greater than 3 after regressing call (put) strategies on the four-candidate-factor model. Importantly, in most cases, the factor model dramatically reduces the size of the candidate factors' risk-premium. The magnitude of alphas from the factor models for the call (put) candidate factors are on average 1/7 (1/3) of the mean return of the long-short factors.[13]

In summary, a parsimonious model consisting of three candidate factors captures the pricing information from the four PCA model.[14] Among the candidate factors, the equal-weighted option portfolio (EWOP) captures commonalities in the time-series dimension. The cross-section dimension is effectively explained by long-short strategies based on the volatility of volatility (VOV) and the difference between historical and implied volatilities (HV–IV). The inclusion of Cash as a factor marginally enhances the model's performance. Although the performance of the candidate factors is derived from a model constructed with call option portfolios for pricing both call and put options, we find a mild improvement when put portfolios are used to build the pricing model. Importantly, long-short strategies constructed based on the same characteristic exhibit a high correlation between calls and puts (approximately 0.90). This observation strengthens the findings in Section 3.1, which affirm a shared factor structure between the two contracts.

3.3 Pricing Out-of-the-money Delta-hedged Option Returns

In this section, we examine the performance of both the four PCA factor model and the candidate factor models, constructed from at-the-money (ATM) call options, in explaining out-of-the-money (OTM) delta-hedged option portfolios.

For OTM calls (puts), we choose the option with moneyness closest but greater (lower) than 1.1 (0.9). A firm is included only when four options are simultaneously available: an ATM call, an ATM put, an OTM call, and an OTM put. Additionally, the moneyness of the OTM call (put) must be strictly higher (lower) than that of the ATM call (put). The robustness sample contains 53,729 firm-month observations with four options for each firm.

[13] These results further improve when we utilize factor models with candidate factors from put option portfolio returns to control for common risks. As stated earlier, employing call candidate factors to construct the models provides a conservative estimate of their performance.

[14] As we noted when analyzing Table 3, one of the PCA factors (PCA3) does not seem to contain relevant pricing information.

Table 6 reports the same performance metrics for testing OTM option portfolios as in Table 4. The test assets are 364 OTM call and put option portfolios sorted by 19 characteristics. We exclude portfolios with missing return data. The factor models are: a model with four PCA factors, a model with EWOP, VOV and HV–IV, and a model with EWOP, VOV, HV–IV, and Cash.

[Table 6 around here]

The table shows that all models display comparable performance. The correlation between average return and predicted return hovers around 0.85, while the average adjusted R^2 stands at 0.60. Between 4% and 9% of $|t_\alpha|$ values are larger than 3. The RMSPE and OOS RMSPE are marginally higher than those for ATM options, as shown in Table 4. The F_{max} statistics is inconclusive for all factor models. SR_{DH} is the same as in Table 4 because the factor models are the same. Overall, our findings indicate that the four PCA factor model and the two candidate factor models proficiently explain the returns of OTM option portfolios.

An in-depth analysis of the factor structure of OTM delta-hedged returns is available in Appendix A.2. This reveals that both OTM call and OTM put options are driven by the same latent factors. These factors can also be encapsulated by the same long-short characteristic-sorted portfolios as ATM options (EWOP, VOV, and HV-IV). Further, it shows that candidate factors constructed with OTM delta-hedged options correlate at approximately 0.90 with their ATM counterparts, as depicted in Figure A5. Collectively, the results from this section and the aforementioned Appendix indicate that ATM and OTM delta-hedged call and put option returns share the common factors

3.4 Pricing a Different Set of Portfolios

In this section, we analyze the performance of the four PCA factor model and the candidate factor models using a different set of test assets. We construct portfolios of call and put options based on 149 characteristics that are different from the original 19 characteristics used to derive the candidate factor models in Section 3.2. The definition and reference of the characteristics are listed in Table A3 in the Appendix. The 149 characteristics are obtained from Chen and Zimmermann (2022) after filtering out characteristics that generate more than 10% of missing values. Note that while the predictability of these characteristics has been studied in the stock market, it has not been studied in the cross-section of option returns. Figure A1 reports the correlation heatmap in absolute value of the long-short ATM call option portfolio returns. The figure illustrates that, in general, long-short strategies on the 149 characteristics are not too highly correlated.

[Table 7 around here]

Table 7 reports summary statistics of the long-short ATM delta-hedged option returns of calls and puts sorted on these 149 variables. Overall, the 149 variables have substantial predictive power. The mean long-short portfolio returns (in absolute value) for calls and puts is 0.270% with an average t-statistic of 6.4. Out of the 298 long-short call and put portfolios, 59% have a risk premium with $|t_\alpha| > 3$. Details of the portfolio sorts by these characteristics are provided in Table A4.

[Table 8 around here]

Table 8 presents the performance of three factor models - the four PCA factor model, the candidate factor model with EWOP, VOV, and HV–IV, and a third model that adds Cash to the previous model - on these alternative test assets. We report the results for both the 298 long-short portfolios and the 2,978 delta-hedged call and put option portfolios sorted on these 149 characteristics (we exclude two portfolios with missing data). Panel A shows the performance metrics for the three models using the 2,978 characteristic-sorted portfolios as test assets, while Panel B provides results using the 298 long-short portfolio returns as test assets. The proposed models effectively account for the cross-sectional variation of these alternative test assets, explaining a large portion of their risk premiums. The correlation between the average return and the returns predicted by the model is consistently around 0.90. The F_{max} test results are inconclusive for all models when using 2,978 portfolios as test assets. When we use the 298 long-short strategies as test assets, only the candidate factor model augmented with Cash generates an inconclusive F_{max} test.

[Figure 6 around here]

Finally, Figure 6 illustrates the relationship between the average return of the alternative test assets and the predicted return for these assets, as implied by four factor models: (a) the four PCA factor model, (b) a model incorporating all 19 factor candidates plus EWOP (20 candidate factor model), (c) a model including EWOP, VOV, and HV–IV, and (d) a model with EWOP, VOV, HV–IV, and Cash. The figure depicts the pricing performance of the models for the extreme decile portfolios separately. It shows that both the PCA and the various candidate factor models exhibit a proficient fit for all portfolios, including the extreme decile ones.

3.5 Treatment of Missing Data

In our main analysis, we exclude observations from our sample if, at the end of the holding period, the bid for either the call or the put equals zero, or if either the option price (bid and ask) or the underlying stock price is missing. This standard cleaning procedure has the advantage of obviating the need to assign theoretical prices to assets in the absence of market prices. However, very low or very high option prices result in high delta-hedged returns. The filter therefore creates a downward bias in delta-hedged returns. As reported in Duarte et al. (2023), such bias in option-related literature is widespread and, under specific conditions, leads to false discoveries of anomalies in the option market. The results in this section show that our main findings are robust after accounting for this bias. We use several imputation methods to fill in the missing values and use the new dataset to evaluate the impact on factor selection and performance of factor models.

To impute a missing option price, we employ seven distinct methodologies. The first five methodologies compute a theoretical option price, the sixth methodology sets the price equal to the intrinsic price, and the seventh methodology takes the average of the five theoretical option prices ("Average all"). These methodologies are briefly outlined below and discussed in greater detail in Appendix A.5. An imputed theoretical price is considered valid only if it falls below the ask price and above the bid price (which may be zero). We follow these steps to impute an option price: First, we set the price to one of the five theoretical option prices or to the "Average all" price. Second, in cases where a theoretical price cannot be determined, we set the option price equal to the intrinsic value of the option. Third, when the stock price is unavailable at the end of the holding period due to the delisting or acquisition of the firm, we calculate the option price and delta-hedged option return up to the date of delisting or acquisition. Firms are excluded if the delisting or acquisition date coincides with the trading date. Our imputations methods are:

(1) Mid option price (Mid). Since bid price is equal to zero, the option price is equal to mid price = ask price/2.

(2) Black-Scholes-Merton model (BSM). We use the implied volatility surface (IVS) for calls (puts) from Optionmetrics to find the interpolated implied volatility of the call (put) with the corresponding strike price and time-to-maturity. With the interpolated implied volatility, we price the option using the BSM model.

(3) BSM model with put-call parity (BSM PC-parity): To price a call (put) option, we find the corresponding put (call) option at the end of the holding period with same underlying, strike price and time-to-maturity with a valid mid price (bid>0, ask>0 and ask>bid) and implied volatility. To account for the put-call spread, we compute the implied put-call spread surface as the difference of the call IVS minus the put IVS to find the interpolated put-call spread. We add the put (call) implied volatility of the valid put (call) option to the interpolated put-call spread to obtain the new implied volatility for the call (put). With this new implied volatility, we price the call (put) option using the BSM model.

(4) Prior five days' availability. We look for valid option prices (bid>0, ask>0 and ask>bid) in the previous five trading days before the end of the holding period. We select the price from the option with the closest date to the end of the holding period and perform a delta-gamma-vega-theta adjustment to get the theoretical price.

(5) After five days' availability. This methodology is equivalent to the "Prior five days availability" methodology but we use the next five days after the end of the holding period.

(6) Intrinsic option price. We use this imputation method when no theoretical price from

methods 1 to 5 is available. Equity options are American. Intrinsic price is the option value that results from exercising the option and it excludes the time value or extrinsic price.

(7) Average all. This method imputes the option price as the average of all the theoretically imputed prices from methods 1 to 5, when available.

Using the imputed data, the dataset expands from 204,376 to 264,864 firm-month observations with an ATM call and an ATM put options. Table A9 in Appendix A.5 reports the number of option prices imputed for each methodology. Most of the theoretical prices can be imputed using the "Mid" and the "BSM" methods. All prices can be imputed with the intrinsic option price when other imputation methods are unavailable. For an initial analysis of this augmented dataset, we examine the degree of common information shared among the candidate factors derived from the various imputation methods.

[Table 9 around here]

Table 9 reports the correlations between call option factors across the 19 long-short strategies (plus EWOP) generated by the "Average All" imputation method and other imputation methods including the benchmark dataset used in the main analyses of the paper.[15] The correlations between "Average All" and other imputation methods range from 0.97 to 1.00. The last column presents factor correlations between "Average All" and the benchmark dataset. While correlations between factors estimated from the treated and benchmark datasets decrease, they remain consistently high. Specifically, the correlations for the most relevant factors from the analysis in Section 3.2, EWOP, VOV, and HV-IV, are 0.99, 0.90, and 0.86, respectively. The high correlations observed across factors derived from different imputation methods suggests that these methods span the same space. Therefore, we use the "Average All" imputation method for subsequent comparison with our benchmark factor model. We refer to this dataset as the missing-value-treated or treated dataset.

In Appendix A.5, we estimate the number of factors present in the treated dataset. Our findings indicate that, at most four PCA factors, and potentially as few as three, are necessary to capture the common factor structure in delta-hedged equity option returns. This outcome

[15] Results using put option factors are almost identical.

is consistent with the results discussed in Section 3.1, based on the benchmark dataset.

Next, we select the candidate factor model that most effectively mirrors the four-factor PCA model estimated from the missing-value-treated dataset. We use 21 candidate factors: long-short factors for delta-hedged equity call options based on the 19 characteristics and EWOP from the treated dataset and the SPX_DH_CALL factor. As in Section 3.2, our selection is based on candidate factors derived from delta-hedged equity call options but using the missing-value-treated dataset.[16] We evaluate the performance of factor models using five metrics. For each metric, we select the top 2.5% of performing models from all possible 5,985 four-factor models, amounting to 150 models. We then record the frequency of each candidate factor's appearance in these top-performing models.

[Figure 7 around here]

Figure 7 reports the results for the five performance metrics. For SR_{DH}, HV-IV and Cash are the main factors for maximizing it, featuring in all models within the top 2.5% of highest-performing models for this metric. These factors also stand out as the most significant in enhancing the correlation between average returns and the model's predicted returns. Additionally, VOV emerges as the key factor in capturing the tangency portfolio of the four PCA factors, followed closely by HV-IV. For minimizing the RMSPE, HV-IV and EWOP prove to be the most crucial, whereas VOV, Cash, and EWOP are the most relevant for minimizing OOS RMSPE. In summary, EWOP, VOV, HV–IV, and Cash are identified as the most prominent candidate factors in explaining the cross-section of delta-hedged equity option returns in the treated dataset. This result closely mirrors our findings from the benchmark dataset, with Cash now appearing marginally more important than before.

We now proceed to test the performance of two three-factor models comprising EWOP, VOV, and HV-IV, as well as two four-factor models augmented with Cash. Panels A and B of Table 10 display results of factors constructed from the benchmark and the treated datasets. We test these models on 370 call and put delta-hedged portfolio returns sorted by

[16] Factors constructed from call options and put options also exhibit a high correlation in the dataset treated for missing values. The heatmap showing the correlation among these factors is in Appendix A.5.

19 characteristics from the treated dataset. For comparison, the first line presents metrics for the four-factor PCA model estimated from the treated dataset.[17]

[Table 10 around here]

Two principal results emerge from this table. First, a three-factor model performs comparably to a four-factor model, particularly in metrics crucial for explaining the cross-section. Second, benchmark and treated factors exhibit nearly equivalent effectiveness in explaining the treated portfolios. Additionally, the Sharpe ratios for the benchmark factors are higher, as anticipated, due to their larger mean values. This aspect will be further discussed in the next paragraph. Finally, the p-value of the F_{max} statistic is indeterminate for the three- and four-factor models using factors from the benchmark dataset. In contrast, for factors from the treated dataset, it is indeterminate only in the four-factor case.

[Table 11 around here]

The last objective of this section is to risk-adjust the 17 (16) long-short strategies computed with the treated dataset using the three- (four-) factor models.[18] Factor models are extracted from delta-hedged call options from the benchmark and treated dataset. Results are reported in Table 11. First, we compare the mean value of raw long-short returns of the 17 strategies from the benchmark (Table 5) and the treated (Table 11) datasets. The long-short average returns and their t-statistics are smaller in magnitude in the treated dataset. Three long-short strategies—momentum, reversal, and Shareiss5—for delta-hedged call options and two strategies for delta-hedged put options—momentum and reversal—report t-statistics (in absolute value) smaller than 3. These findings align with those in Duarte et al. (2023) that find that some previous findings are not robust when imputing missing values. As for the long-short mean returns for VOV, HV-IV, and Cash from the treated dataset (see Tables A10

[17]EWOP is always estimated from the response variables to be tested. In this case, EWOP comes from the missing-value-treated database.

[18]Figure A10 in Appendix A.5 illustrates the pricing power of the three- and four-factor benchmark models on portfolios in the extreme deciles of the treated dataset.

for calls and A11 for puts), they are of smaller magnitude than the ones in the benchmark dataset but remain highly significant with t-statistics (in absolute value) above 10.

Importantly, factor models from the benchmark dataset perform similarly to those from the treated dataset at explaining long-short call and put returns from the treated dataset. The benchmark three-factor model produces only one (two) alpha(s) with $|t| > 3$ in delta-hedged call (put) options while the treated three-factor model yields three (seven) such alphas. When augmenting the three-factor model with the Cash factor, it produces only two (zero) alpha(s) with $|t| > 3$ for calls (puts) for the benchmark model and zero (one) such alphas for the treated model. Overall, our results indicate that, after accounting for the missing values, our benchmark three-factor and four-factor models effectively price the cross-section of delta-hedged equity option returns in the treated dataset.

4 Conclusion

Despite the extensive and ever-growing literature on common factors in stock returns, developed to understand the drivers of the equity risk premium, our understanding of the factor structure in the higher-order moment risk premia embedded in the cross-section of option returns is still limited. In this paper, we explore the common factors driving the comovement of delta-hedged equity option returns and propose an empirical factor model. This model can serve as a benchmark in future research for analyzing the cross-section of these option portfolio returns.

Using 19 firm characteristics, we construct 370 delta-hedged characteristic-sorted portfolios for both call and put options. Our findings indicate that a maximum of four PCA factors is necessary to explain their time series and cross-sectional behavior, and these factors are the same for both call and put option returns.

To identify the candidate factors that best capture the statistical model's pricing information, we generate the 5,985 possible four-factor models from the 21 factor candidates and analyze the top 2.5% performing models. The 21 factor candidates include the 19 long-short strategies of the characteristic-sorted option portfolios, the delta-hedged return of the S&P 500 index, and the equal-weighted return of the 370 call and put option portfolio (EWOP).

We find that three candidate factors are sufficient to capture most of the relevant information in the latent factors, thereby explaining the time-series and cross-section of delta-hedged equity option returns. These three factors are EWOP, the long-short option portfolio based on the volatility of implied volatility (VOV), and the long-short option portfolio based on the difference between historical and implied volatilities (HV-IV). The latter two factors explain the cross-section dimension, while EWOP fits the time-series. Adding a fourth factor, the value of corporate cash holdings over the total value of the firm's assets (Cash), offers a marginal improvement to the model's fit. Other factors, however, appear redundant.

The explanatory power of our proposed factor model extends to out-of-the-money option portfolios, to 2,978 delta-hedged call and put equity option portfolio returns, which are based on 149 different characteristics, and to an expanded database with treated missing values. Finally, our option factors have almost no relation to stock returns factors. Therefore, higher-order moment risk premia is driven by different factors than the equity risk premium in the stock market.

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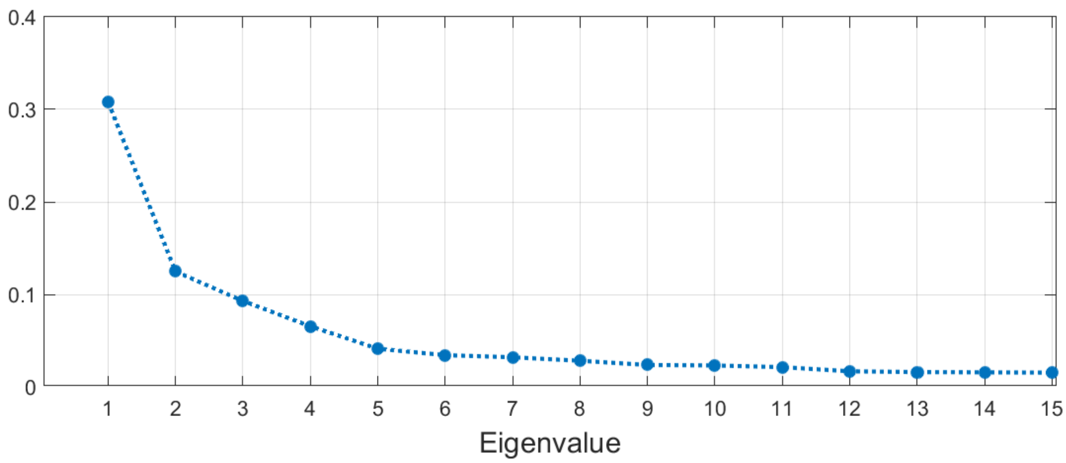
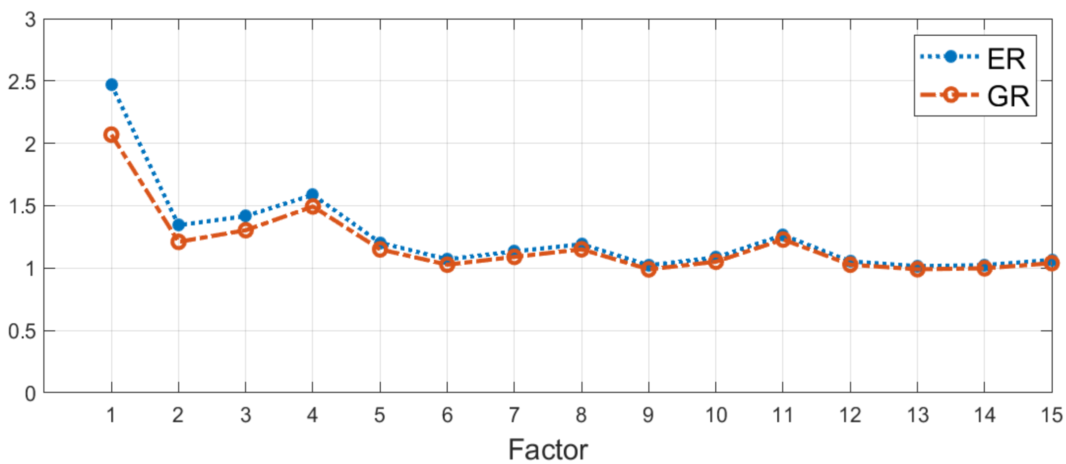
Figure 1: Scree Test for At-the-money Call and Put Option Returns

(a) The Scree Plot

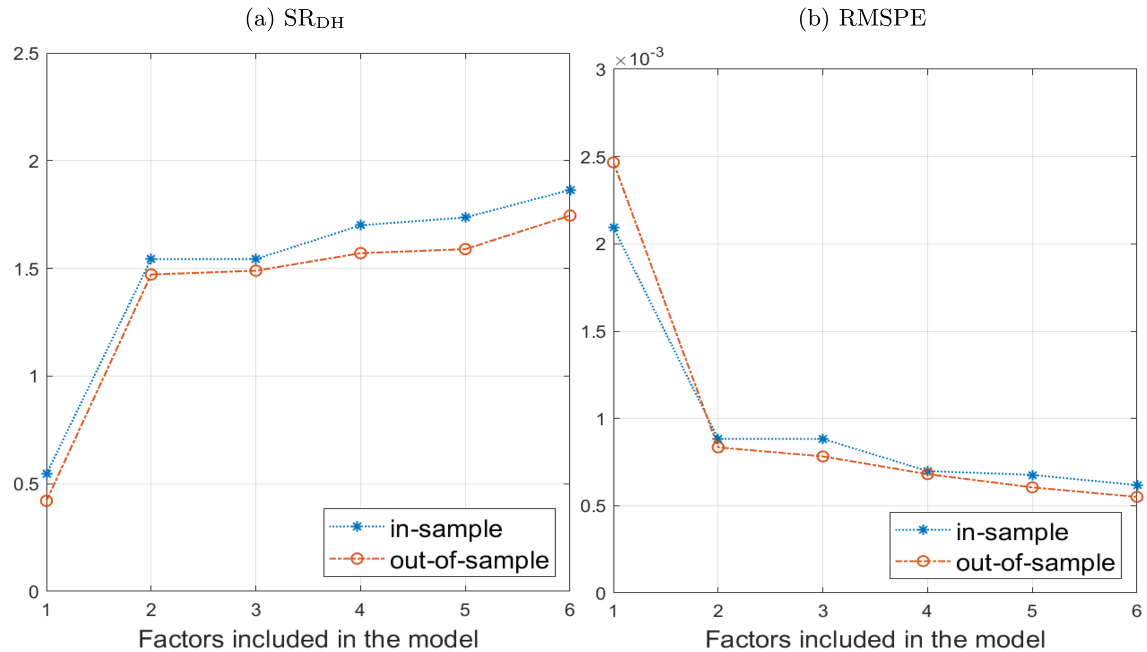


(b) GR and ER Values



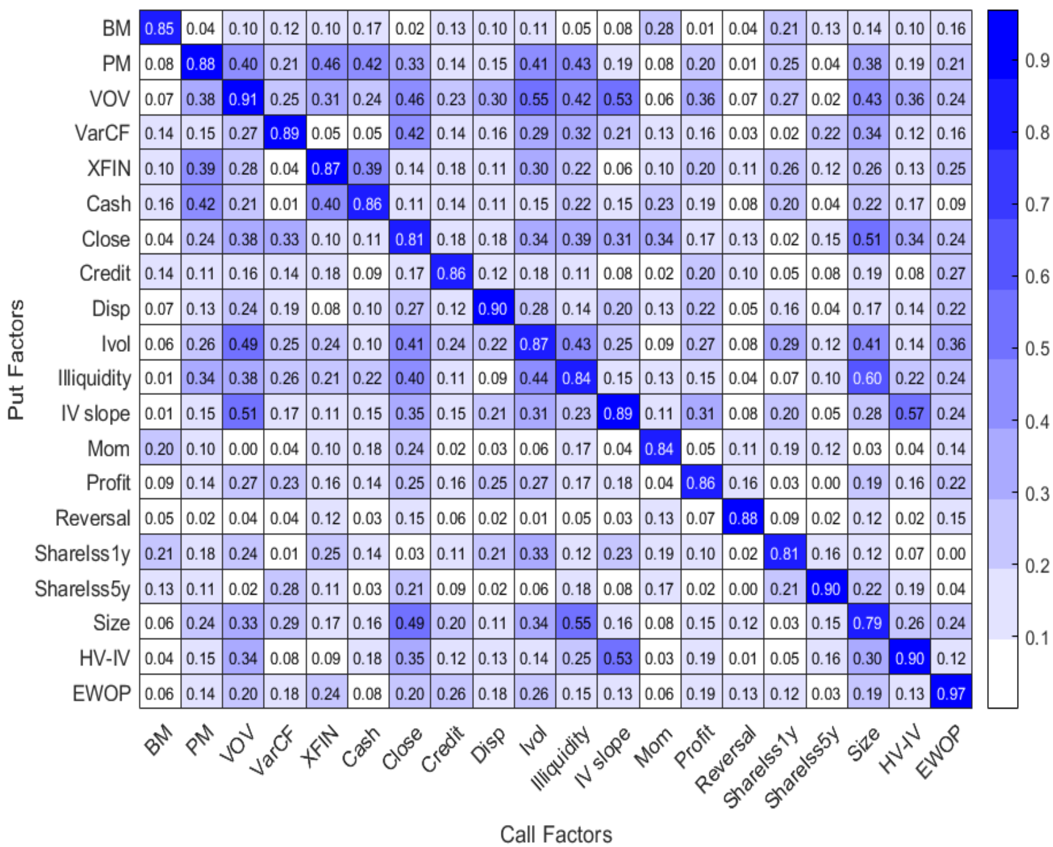
Panel (a) plots the largest fifteen eigenvalues from the sample second-moment matrix of the 370 delta-hedged ATM call and put option portfolio returns. Panel (b) presents the results from the Ahn and Horenstein (2013) Eigenvalue Ratio (ER) and the Growth Ratio (GR) estimators. The 370 option portfolios, 185 delta-hedged call and 185 delta-hedged put option portfolios, are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 2: In-sample and Out-of-Sample Performance of the PCA Factors



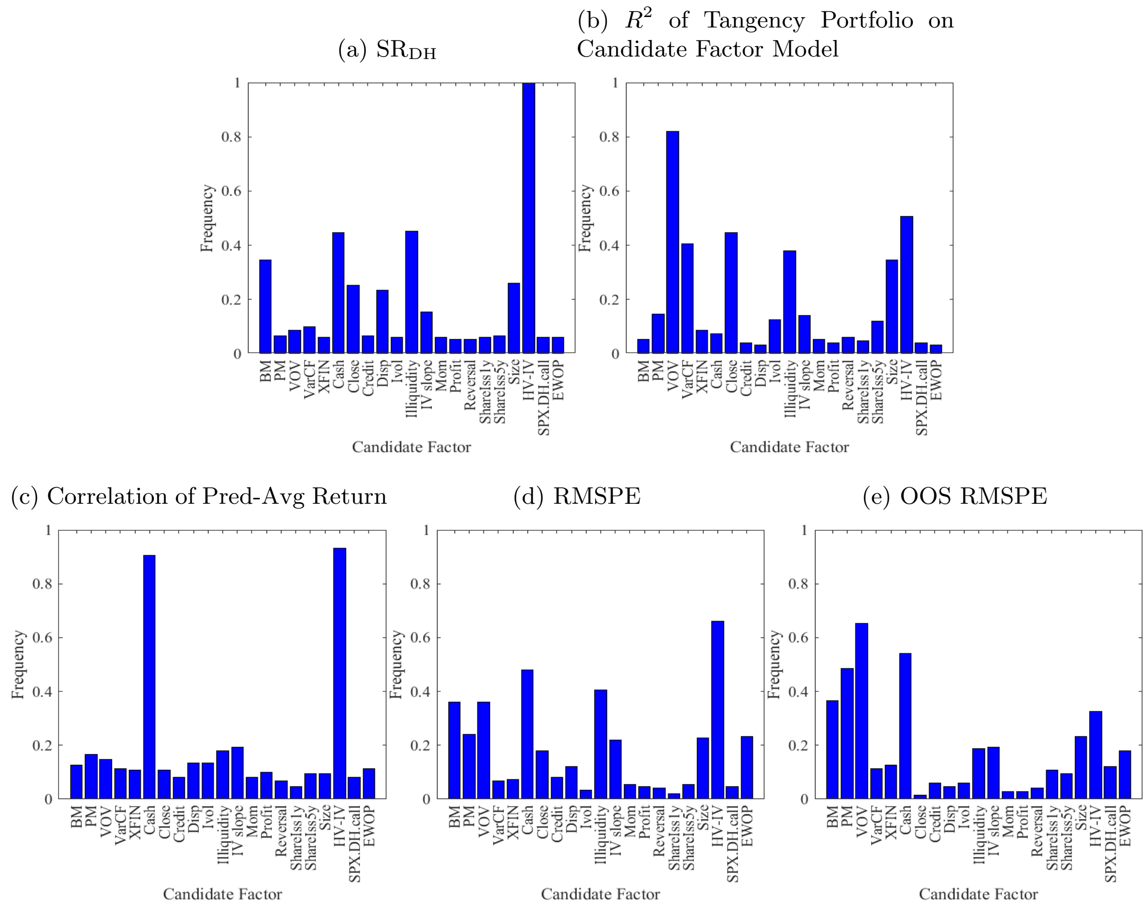
This figure plots in-sample and out-of-sample Sharpe ratios ($\mathrm{SR_{DH}}$) in Panel (a) and root mean square pricing errors (RMSPE) in Panel (b) generated by the PCA factor model when one to six factors are included in the model. For the out-of-sample performance we use a window of 120 months to estimate the factor scores and factor loadings at period t and use those estimations to construct the period t+1 factors and estimate the period t+1 pricing errors. The 370 option portfolios, 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios, are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 3: Correlation Heatmap of At-the-money Call and Put Factors



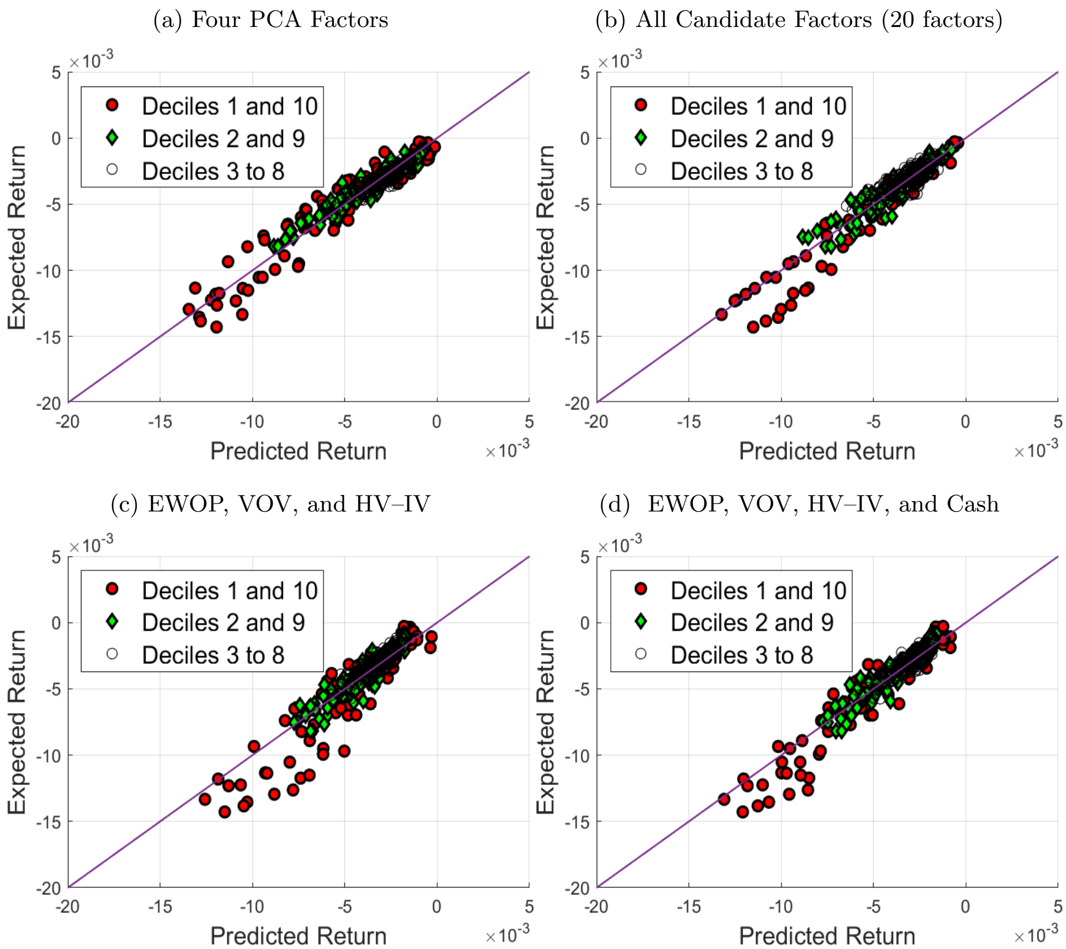
This figure shows the correlation heatmap between candidate factors in ATM call options and put options. The 19 candidate factors in call options and the 19 factors candidate in put options are 10-minus-1 (5-minus-1 for Credit) long-short at-the-money option portfolio returns sorted by the following characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. EWOP is the equal-weighted option portfolio of the 185 delta-hedged portfolios of calls or puts constructed with the 19 characteristics. Correlations are reported in absolute value. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 4: Candidate Factor Selection



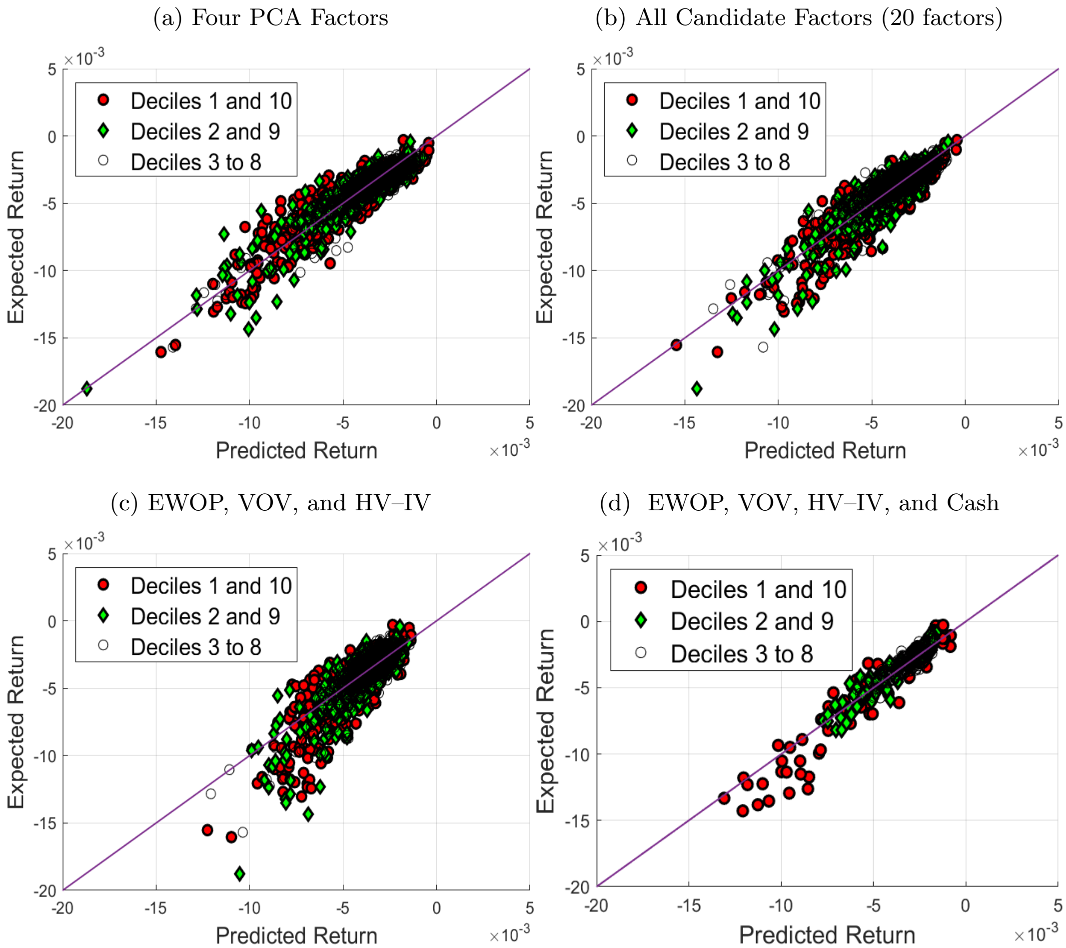
This figure plots the frequency of candidate factors in the top 2.5% of models (150 models) of all possible 4-factor models from the 21 factor candidates based on five criteria. We generate all possible 4-factor models from the 21 candidate factors derived from ATM call options, which include the 19 characteristic-based factors, EWOP, and the S&P 500 option factor. This results in a total of 5,985 distinct models. We then select the top 2.5% of models (150 models) based on the $\mathrm{SR}_{\mathrm{DH}}$ (Panel (a)), and R^2 of regressing tangency portfolio of the PCA factors on the candidate factor model (Panel (b)), the correlation between average returns and model-predicted returns (Panel (c)), as well as the Root Mean Square Error (RMSPE) of the pricing error (Panel (d)), and the average RMSPE of Out-of-Sample (OOS RMSPE) pricing errors (Panel (e)). We report the frequency that each factor appears in the models at the top of the distribution for the different metrics. The 19 characteristics are: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. SPX_DH_call is the one-month delta-hedged ATM call option return of the S&P 500 index and EWOP is the equal-weighted option portfolio of the 370 delta-hedged portfolios of calls and puts constructed with the 19 characteristics. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 5: Pricing Performance of the PCA-factor-model vs. Candidate Factor Models



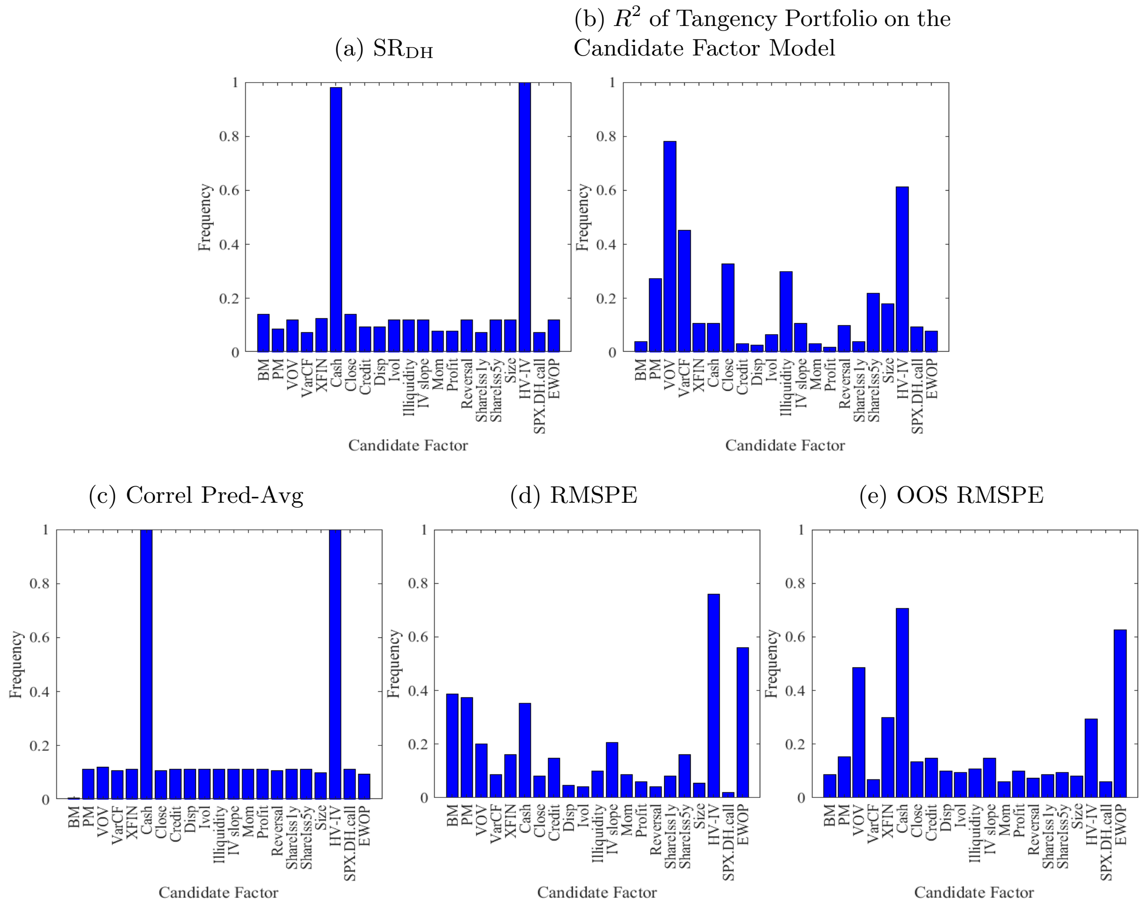
This figure shows the performance of the four-PCA-factor-model and candidate factor models in terms of the relation between average return and predicted return by the factors. The first panel of the figure shows the relation between average returns and predicted returns from models regressing the 370 option portfolios, 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios, onto the first four PCA factors. The other three panels report the relation between average returns and predicted returns using all candidate factors (20 factors), using EWOP, VOV and HV–IV, and using EWOP, VOV, HV–IV, and Cash. EWOP is the equal weighted return of 370 option portfolios. VOV, HV–IV, and Cash are the 10-minus-1 long-short factors sorted by VOV, HV–IV, and Cash. Decile portfolios are displayed in three groups: 1) deciles 1 and 10, 2) deciles 2 and 9, and 3) deciles 3 to 8. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 6: Pricing Performance of the PCA-factor-model vs. Candidate Factor Models: 2978 Portfolios Sorted by 149 Characteristics



This figure shows the performance of the four-PCA-factor-model and candidate factor models in terms of the relation between average return and predicted return by the factors. The test assets are 2,978 portfolios constructed by sorting ATM call and put options on 149 characteristics, which are different from 19 characteristics in the main analysis. Decile portfolios are displayed in three groups: 1) deciles 1 and 10, 2) deciles 2 and 9, and 3) deciles 3 to 8. The first panel of the figure shows the relation between average returns and predicted returns from models regressing the delta-hedged option portfolio returns onto the first four PCA factors. The other three panels of the figure shows the relation between average returns and predicted returns using all candidate factors (20 factors), using EWOP, VOV and HV–IV, and using EWOP, VOV, HV–IV, and Cash. EWOP is the equal weighted return of 370 option portfolios. VOV, HV–IV, and Cash are the 10-minus-1 long-short factors sorted by VOV, HV–IV, and Cash. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure 7: Candidate Factor Selection in Missing-value-treated Dataset



This figure plots the frequency of candidate factors in the top 2.5% of models (150 models) of all possible four-factor models from the 21 factor candidates based on five criteria. The factors and portfolios are constructed using the missing value treated dataset. We generate all possible four-factor models from the 21 candidate factors derived from ATM call options, which include the 19 characteristic-based factors, EWOP, and the S&P 500 option factor. This results in a total of 5,985 distinct models. We then select the top 2.5% of models (150 models) based on SR$_{\text{DH}}$ (Panel (a)), and R^2 of regressing tangency portfolio of the PCA factors on the candidate factor model (Panel (b)), the correlation between average returns and model-predicted returns (Panel (c)), as well as the Root Mean Square Pricing Error (RMSPE) (Panel (d)), and the Out-of-Sample RMSPE (OOS RMSPE) (Panel (e)). We report the frequency that each factor appears in the models at the top of the distribution for the different metrics. The 19 characteristics are: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. SPX_DH_call is the one-month delta-hedged call option return of the S&P 500 index and EWOP is the equal-weighted option portfolio of the 185 delta-hedged portfolios of ATM calls constructed with the 19 characteristics. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 1: Summary Statistics of the Candidate Factors in the Option Market

	Mean	Std. Dev.	10th. Pctl.	25th. Pctl.	50th. Pctl.	75th. Pctl.	90th. Pctl.	Skew	Kurt
Panel A: Call Options									
Size	1.10	0.79	0.29	0.60	1.05	1.45	1.80	0.71	3.1
Ivol	-0.81	0.94	-1.81	-1.22	-0.81	-0.33	0.22	0.26	4.9
HV–IV	1.23	0.79	0.33	0.68	1.07	1.59	2.16	0.78	0.9
IV_slope	0.90	0.77	0.06	0.52	0.84	1.25	1.73	-0.15	3.3
BM	0.24	0.70	-0.45	-0.12	0.23	0.57	0.93	0.50	7.2
Credit	-0.40	0.58	-1.05	-0.72	-0.37	-0.11	0.20	0.57	3.1
VOV	-1.08	0.92	-1.91	-1.42	-1.01	-0.55	-0.07	-0.95	4.5
Illiquidity	-1.02	0.73	-1.81	-1.38	-0.96	-0.57	-0.21	-0.61	3.3
Reversal	0.15	0.82	-0.76	-0.22	0.17	0.61	0.98	-0.91	6.5
Mom	0.23	0.85	-0.64	-0.20	0.24	0.58	1.28	-0.68	4.1
VarCF	-0.58	0.74	-1.37	-0.87	-0.50	-0.10	0.13	-0.77	4.8
Cash	-0.72	0.80	-1.70	-1.12	-0.67	-0.23	0.16	0.28	2.1
Disp	-0.35	0.61	-1.00	-0.68	-0.39	-0.03	0.35	0.65	2.9
ShareIss1y	-0.30	0.77	-1.01	-0.62	-0.21	0.07	0.42	-1.85	21.6
ShareIss5y	0.13	0.59	-0.47	-0.15	0.09	0.40	0.71	-0.39	7.1
PM	0.82	0.77	-0.04	0.41	0.75	1.12	1.56	0.59	3.0
Close	1.16	0.94	0.09	0.62	1.10	1.53	1.95	0.69	4.4
Profit	0.34	0.61	-0.33	-0.01	0.32	0.71	1.02	-0.77	3.1
XFIN	-0.62	0.79	-1.44	-1.02	-0.57	-0.21	0.20	0.33	3.8
SPX_DH_call	-0.06	0.60	-0.63	-0.35	-0.12	0.15	0.52	3.02	22.8
EWOP	0.01	0.16	-0.17	-0.08	0.00	0.11	0.19	0.87	2.9

Table 1: continued

	Mean	Std. Dev.	10th. Pctl.	25th. Pctl.	50th. Pctl.	75th. Pctl.	90th. Pctl.	Skew	Kurt
Panel B: Put Options									
Size	1.20	0.83	0.24	0.72	1.15	1.48	2.04	0.65	2.8
Ivol	-0.97	1.00	-1.91	-1.40	-0.97	-0.50	0.15	0.29	4.4
HV–IV	1.24	0.81	0.36	0.69	1.10	1.58	2.30	0.88	1.9
IV_slope	0.96	0.85	0.14	0.50	0.86	1.37	1.86	0.25	3.2
BM	0.22	0.62	-0.46	-0.09	0.25	0.60	0.91	-0.30	4.8
Credit	-0.42	0.61	-1.12	-0.72	-0.41	-0.09	0.23	0.45	2.8
VOV	-1.22	0.93	-2.11	-1.61	-1.14	-0.73	-0.14	-0.71	3.8
Illiquidity	-1.12	0.85	-2.09	-1.41	-1.02	-0.62	-0.30	-0.83	3.6
Reversal	-0.02	0.79	-0.98	-0.42	0.06	0.42	0.85	-0.54	3.2
Mom	0.28	0.75	-0.51	-0.09	0.26	0.70	1.21	-0.40	2.0
VarCF	-0.66	0.75	-1.45	-0.96	-0.55	-0.21	0.10	-1.15	4.7
Cash	-0.68	0.77	-1.56	-1.09	-0.68	-0.27	0.25	0.48	1.6
Disp	-0.40	0.62	-1.02	-0.77	-0.44	-0.08	0.29	0.91	3.4
ShareIss1y	-0.28	0.68	-1.03	-0.68	-0.23	0.12	0.51	0.81	3.9
ShareIss5y	0.22	0.57	-0.38	-0.08	0.18	0.46	0.83	1.07	3.6
PM	0.88	0.78	-0.06	0.44	0.81	1.28	1.68	0.30	1.2
Close	1.18	0.91	0.12	0.69	1.14	1.62	2.01	0.31	2.6
Profit	0.35	0.62	-0.31	0.04	0.36	0.75	1.10	-0.72	2.3
XFIN	-0.70	0.78	-1.55	-1.11	-0.67	-0.24	0.20	0.47	2.1

This table reports summary statistics of the return of the 21 candidate factors in the equity option market (in percentage). The option factors are the long-short return spread of delta-hedged option returns of ATM calls in Panel A and ATM puts in Panel B sorted by the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOV is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. SPX_DH_call is the one-month delta-hedged ATM call option return of the S&P 500 index and EWOP is the equal-weighted option portfolio of the 370 ATM delta-hedged portfolios of calls and puts constructed with the 19 characteristics. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 2: Estimation for the Number of Factors in the Delta-hedged Call and Put Option Portfolios

Common factors used	Number of factors found in the residuals	
	Call Options	Put Options
1	3	3
2	2	2
3	1	1
4	0	0

This table presents results based on the Gagliardini, Ossola, and Scaillet (GOS) estimator proposed by Gagliardini et al. (2019). The GOS estimator scrutinizes the error terms generated by a factor model and tests whether these errors are weakly cross-sectionally correlated or share at least one common factor. This table shows the number of factors found in the residuals of the call and put datasets as we sequentially add one of the common factors estimated from the combined datasets. The factors are simultaneously estimated from the combined datasets of calls and puts. The test assets are 370 option portfolios: 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 3: Performance of PCA Factor Models with Different Number of Factors

Models	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\lvert t_\alpha \rvert > 3$	OOS RMSPE	F_{max}
Factor 1	0.55	77%	0.84	0.21%	68%	0.25%	0.00
Factor 2	1.54	94%	0.87	0.09%	14%	0.08%	0.02
Factor 3	1.54	94%	0.88	0.09%	15%	0.08%	0.01
Factor 4	1.70	96%	0.89	0.07%	9%	0.07%	0.00,0.67
Factor 5	1.74	96%	0.9	0.07%	11%	0.06%	0.00,0.56
Factor 6	1.86	97%	0.9	0.06%	7%	0.06%	0.01,1.00

This table reports the following performance measures for six models that sequentially add the first PCA factor to the sixth PCA factor: Sharpe Ratio for delta-hedged portfolios (SR_{DH}), the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$ where t_α is the heteroskedastic robust t-statistics to test the null hypothesis of $\alpha = 0$, out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq 5\%$ and report the liberal MC p-value when the liberal MC p-value $\geq 5\%$. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. The test assets are 370 option portfolios: 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 4: Performance of Models with VOV and HV-IV

Models	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\|t_\alpha\| > 3$	OOS RMSPE	F_{max}
Four PCA model	1.7	0.96	0.89	0.07%	9%	0.07%	0.00,0.67
Panel A: Factors from ATM call option long-short strategies							
All candidate factors (20)	2.06	0.95	0.9	0.08%	9%	0.10%	0.00,1
EWOP, VOV, HV-IV	1.68	0.93	0.86	0.10%	12%	0.14%	0.00,0.14
EWOP, VOV, HV-IV, Cash	1.79	0.95	0.87	0.08%	7%	0.11%	0.00,0.74
EWOP, VOV, HV-IV, Illiquid	1.79	0.93	0.87	0.09%	9%	0.12%	0.00,0.46
EWOP, VOV, HV-IV, VarCF	1.68	0.93	0.87	0.10%	14%	0.14%	0.00,0.11
EWOP, VOV, HV-IV, Close	1.71	0.92	0.87	0.10%	12%	0.13%	0.00,0.25
Panel B: Factors from ATM put option long-short strategies							
All candidate factors (20)	2.06	0.98	0.9	0.05%	2%	0.06%	0.15
EWOP, VOV, HV-IV	1.7	0.96	0.86	0.08%	7%	0.13%	0.00,0.69
EWOP, VOV, HV-IV , Cash	1.78	0.96	0.87	0.07%	7%	0.09%	0.00,0.97
EWOP, VOV, HV-IV , Illiquid	1.78	0.96	0.87	0.06%	5%	0.10%	0.00,0.99
EWOP, VOV, HV-IV , VarCF	1.7	0.96	0.87	0.08%	7%	0.12%	0.00,0.73
EWOP, VOV, HV-IV , Close	1.76	0.96	0.87	0.07%	4%	0.10%	0.03,1

Panel A (B) reports the following performance measures for six models using factors from ATM call (put) option long-short strategies: Sharpe Ratio for delta-hedged option portfolios (SR_{DH}), the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$, and out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq 5\%$ and report the liberal MC p-value when the liberal MC p-value $\geq 5\%$. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. We calculate t-statistics using heteroskedastic robust standard errors. The test assets are 370 option portfolios: 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. The first three models are: the four PCA factor model, the model with all candidate factors, and the model with EWOP, VOV and HV-IV. The other four models add either Cash, Illiquid, VarCF, or Close to the model with EWOP, VOV and HV-IV. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 5: Summary Statistics of the Long-short Factors

	Delta-Hedged Call options			Delta-Hedged Put options		
	Mean	3-factor Alpha	4-factor Alpha	Mean	3-factor Alpha	4-factor Alpha
Size	1.10%	0.33%	0.27%	1.20%	0.57%	0.48%
	(24.66)	(3.73)	(3.22)	(25.59)	(6.82)	(5.97)
Ivol	-0.81%	0.05%	0.08%	-0.97%	-0.18%	-0.09%
	(-15.11)	(0.71)	(1.13)	(-17.02)	(-2.29)	(-1.05)
IV_slope	0.90%	0.09%	0.10%	0.96%	0.19%	0.14%
	(20.54)	(1.25)	(1.25)	(19.93)	(2.15)	(1.58)
BM	0.24%	0.33%	0.15%	0.22%	0.33%	0.16%
	(5.99)	(3.60)	(2.16)	(6.39)	(3.76)	(2.46)
Credit	-0.40%	-0.09%	-0.07%	-0.42%	-0.15%	-0.12%
	(-12.21)	(-1.36)	(-1.26)	(-12.08)	(-2.14)	(-2.18)
Illiquidity	-1.02%	-0.39%	-0.28%	-1.12%	-0.55%	-0.43%
	(-24.63)	(-4.23)	(-3.22)	(-23.19)	(-5.49)	(-4.39)
Reversal	0.15%	-0.07%	0.02%	-0.02%	-0.13%	-0.06%
	(3.27)	(-0.52)	(0.21)	(-0.35)	(-1.00)	(-0.53)
Mom	0.23%	-0.09%	0.10%	0.28%	0.06%	0.21%
	(4.71)	(-0.90)	(1.16)	(6.66)	(0.71)	(2.58)
VarCF	-0.58%	0.09%	0.02%	-0.66%	-0.08%	-0.09%
	(-13.90)	(1.09)	(0.23)	(-15.55)	(-0.92)	(-0.95)
Cash	-0.72%	-0.46%	NA	-0.68%	-0.54%	NA
	(-15.81)	(-4.48)	NA	(-15.51)	(-5.40)	NA
Disp	-0.35%	-0.18%	-0.20%	-0.40%	-0.31%	-0.32%
	(-10.30)	(-2.52)	(-2.96)	(-11.22)	(-4.06)	(-4.53)
shareiss1	-0.30%	0.04%	0.16%	-0.28%	-0.06%	0.08%
	(-6.84)	(0.46)	(2.13)	(-7.27)	(-0.78)	(1.15)
shareiss5	0.13%	0.00	0.06%	0.22%	0.06%	0.10%
	(3.75)	(0.10)	(0.75)	(6.84)	(0.73)	(1.22)
PM	0.82%	0.24%	0.04%	0.88%	0.42%	0.20%
	(18.61)	(3.17)	(0.69)	(19.91)	(5.02)	(3.02)
Close	1.16%	0.22%	0.23%	1.18%	0.45%	0.41%
	(21.72)	(2.32)	(2.33)	(22.91)	(5.30)	(4.48)
Profit	0.34%	0.08%	0.00%	0.35%	0.11%	0.05%
	(9.72)	(1.61)	(0.09)	(10.06)	(1.99)	(0.80)
XFIN	-0.62%	-0.17%	0.03%	-0.70%	-0.32%	-0.13%
	(-13.91)	(-2.22)	(0.51)	(-15.89)	(-3.99)	(-1.71)

This table reports the average raw return and alphas of long-short strategies with respect to the three- and four-factor models from ATM call options. We also report their corresponding t-statistic in parenthesis. The three-factor model includes EWOP, VOV and HV-IV. The four-factor model adds Cash to the model. We calculate t-statistics using heteroskedastic robust standard errors. The long-short factors for ATM calls and ATM puts are obtained by sorting on the following characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; BM is the book to market; Credit is S&P credit ratings; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 6: Pricing Performance on Out-of-the-money Option Portfolios

Models	N	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\lvert t_\alpha \rvert > 3$	OOS RMSPE	F_{max}
Four PCA factors	364	1.70	0.87	0.61	0.11%	4%	0.21%	0.00, 0.10
EWOP, VOV, HV-IV	364	1.68	0.83	0.60	0.12%	9%	0.18%	0.05,0.98
EWOP, VOV, HV-IV, Cash	364	1.79	0.88	0.60	0.11%	7%	0.20%	0.00,0.80

This table reports the pricing performance of factor models on out-of-the-money (OTM) option portfolios. The factor models constructed using ATM options are: the four PCA-factor model, the model with EWOP, VOV and HV-IV, and the model with EWOP, VOV, HV-IV, and Cash. The performance measures are: Sharpe Ratio for delta-hedged option portfolios (SR_{DH}), the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$, and out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq 5\%$ and report the liberal MC p-value when the liberal MC p-value $\geq 5\%$. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. We calculate t-statistics using heteroskedastic robust standard errors. The test assets are 364 OTM delta-hedged call and put option portfolios sorted on the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOV is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 7: Summary of Long-Short Delta-Hedged Option Returns Sorted on 149 Characteristics

	N	Mean	Median	Std.Dev.	P10	P25	P75	P90	$\|t\| > 3$
|Call Long-Short Returns|	149	0.257	0.139	0.287	0.019	0.057	0.374	0.736	
$\|t - stat\|$		(6.0)	(3.9)	(6.0)	(0.6)	(1.7)	(8.6)	(15.7)	56%
|Put Long-Short Returns|	149	0.283	0.152	0.314	0.019	0.060	0.423	0.792	
$\|t - stat\|$		(6.7)	(4.5)	(6.4)	(0.6)	(2.1)	(9.6)	(16.9)	62%
|All Long-Short Returns|	298	0.270	0.147	0.301	0.019	0.060	0.398	0.774	
$\|t - stat\|$		(6.4)	(4.1)	(6.2)	(0.5)	(1.8)	(9.0)	(15.9)	59%

This table reports summary statistics of the absolute value of the long-short delta-hedged ATM call and ATM put returns obtained by sorting on 149 characteristics along with the absolute value of their t-statistics. We calculate t-statistics using heteroskedastic robust standard errors. The 149 variables are downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com) and are defined in Table A3. In Table A4 we report the delta-hedged call and put option return along with their t-statistics for deciles 1 and 10, and the long-short (10-1) portfolio for each of the 149 variables. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 8: Pricing Performance on Portfolios Sorted on 149 Characteristics

Models	N	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	OOS RMSPE	$\lvert t_\alpha \rvert > 3$	F_{max}
Panel A: Individual Portfolios								
Four PCA factors	2,978	1.70	0.92	0.86	0.07%	0.08%	6%	0.00,0.09
EWOP, VOV, HV-IV	2,978	1.68	0.85	0.84	0.09%	0.13%	7%	0.00,0.61
EWOP, VOV, HV-IV, Cash	2,978	1.79	0.91	0.84	0.07%	0.09%	4%	0.00,0.68
Panel B: Long-short Portfolios								
Four PCA factors	298	1.70	0.91	0.23	0.16%	0.20%	14%	0.01
EWOP, VOV, HV-IV	298	1.68	0.86	0.11	0.21%	0.32%	20%	0.04
EWOP, VOV, HV-IV, Cash	298	1.79	0.93	0.18	0.14%	0.19%	10%	0.00,0.27

Panel A (B) reports the following performance metrics for factor models on individual portfolios (long-short portfolios): Sharpe Ratio, the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$, out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq$ 5% and report the liberal MC p-value when the liberal MC p-value $\geq$ 5%. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. We calculate t-statistics using heteroskedastic robust standard errors. The three models are: the four PCA model, the model with EWOP, VOV and HV-IV, and the model with EWOP, VOV, HV-IV and Cash. The test assets are 2,978 portfolios constructed by sorting ATM call and put options on 149 characteristics, which are different from 19 characteristics in the main analysis. The 149 variables are downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com) and are defined in Table A3. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 9: Correlation Between Option Factors From the Average All Imputation Method and Other Methods

	Mid	BSM	BSM PC-parity	Prior five days	After five days	Intrinsic	Benchmark
Size	1.00	0.99	0.98	0.97	0.97	0.97	0.83
Ivol	1.00	1.00	1.00	0.99	0.99	0.99	0.93
HV-IV	1.00	1.00	1.00	0.99	0.99	0.99	0.86
IV_slope	1.00	1.00	1.00	1.00	0.99	0.99	0.84
BM	1.00	1.00	1.00	0.99	0.99	0.99	0.87
Credit	1.00	1.00	1.00	0.99	0.99	0.99	0.87
VOV	1.00	1.00	1.00	0.99	0.99	0.99	0.90
Illiquidity	1.00	0.99	0.99	0.97	0.97	0.97	0.82
Reversal	1.00	1.00	1.00	0.99	0.99	0.99	0.90
Mom	1.00	1.00	0.99	0.99	0.99	0.99	0.85
VarCF	1.00	1.00	0.99	0.99	0.99	0.99	0.85
Cash	1.00	1.00	1.00	0.99	0.99	0.99	0.88
Disp	1.00	1.00	1.00	0.99	0.99	0.99	0.84
shareiss1	1.00	1.00	1.00	0.99	0.99	0.99	0.90
shareiss5	1.00	1.00	1.00	1.00	0.99	0.99	0.80
PM	1.00	1.00	1.00	0.99	0.99	0.99	0.87
Close	1.00	0.99	0.99	0.98	0.98	0.98	0.88
Profit	1.00	1.00	1.00	1.00	0.99	0.99	0.83
XFIN	1.00	1.00	1.00	0.99	0.99	0.99	0.89
EWOP	1.00	1.00	1.00	1.00	1.00	1.00	0.99

This table reports correlation between option factors from the "Average All" imputation method and other imputation methods. The benchmark dataset is the one used in the main analyses of the paper. The treated dataset includes firms with bid option price equal to zero, or missing option or stock price, or firms that were delisted or acquired. We use the following imputation methods. 1) Mid option price = ask/2. Bid is equal to zero. 2) Black-Scholes-Merton model (BSM) to price the option with an interpolated implied volatility computed from the implied volatility surface (IVS) from Optionmetrics. 3) BSM model with put-call parity (BSM PC-parity): Using the BSM model, we price a call (put) option by finding the corresponding put (call) with valid implied volatility that we add to the interpolated implied volatility put-call spread computed as the difference of the put IVS and call IVS. 4) We find options with valid bid and ask prices in the previous five trading days before the end of the holding period. We choose the one with the closest date to end of the holding period and perform a delta-gamma-vega-theta adjustment. 5) Similar to 4) but in the following five trading days. 6) Intrinsic option price. 7) Average all is the average of all theoretically imputed prices from methodologies 1 to 5. When no theoretical imputed price is available, we use the intrinsic option price. The benchmark dataset is the one used in the main analyses of the paper. The option factors are the long-short return spread of delta-hedged option returns of ATM calls sorted by the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOV is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. EWOP is the equal-weighted option portfolio of the 370 ATM delta-hedged portfolios of calls and puts constructed with the 19 characteristics. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 10: Performance of Models Using Missing-value-treated Dataset as Response Variables

Models	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\|t_\alpha\| > 3$	OOS RMSPE	F_{max}
Four PCA model	1.17	93%	0.88	0.06%	14%	0.05%	0.00
Panel A: Benchmark factors on missing value treated portfolios							
EWOP, VOV, HV-IV	1.69	90%	0.85	0.07%	8%	0.10%	0.00, 0.36
EWOP, VOV, HV-IV , Cash	1.81	92%	0.85	0.07%	8%	0.08%	0.00, 0.54
Panel B: Missing value treated factors on missing value treated portfolios							
EWOP, VOV, HV-IV	1.36	93%	0.85	0.06%	6%	0.09%	0.00
EWOP, VOV, HV-IV , Cash	1.43	96%	0.85	0.04%	4%	0.07%	0.00,0.69

This table presents performance metrics, with the portfolios from the missing-value-treated dataset serving as response variables. Panel A uses factors from the benchmark dataset, while Panel B uses factors from the treated dataset. Both panels report the following performance measures for models that use ATM call option long-short strategies as factors: Sharpe Ratio for delta-hedged option portfolios (SR_{DH}), the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$, and out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq 5\%$ and report the liberal MC p-value when the liberal MC p-value $\geq 5\%$. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. We calculate t-statistics using heteroskedastic robust standard errors. The test assets are 370 option portfolios from the treated dataset: 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. The three models are: the four PCA factor model, the model with EWOP, VOV and HV-IV, and the models that add Cash. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table 11: Summary Statistics of the Missing-value-treated Long-short Factors

	Delta-Hedged Call options					Delta-Hedged Put options				
		Benchmark factor		Missing Value Treated Factors			Benchmark factor		Missing Value Treated Factors	
	Mean	3-factor Alpha	4-factor Alpha	3-factor Alpha	4-factor Alpha	Mean	3-factor Alpha	4-factor Alpha	3-factor Alpha	4-factor Alpha
Size	0.54%	-0.09%	-0.08%	0.08%	0.08%	0.57%	0.09%	0.08%	0.23%	0.19%
	(11.72)	(-1.05)	(-0.86)	(1.17)	(1.09)	(12.01)	(1.03)	(0.81)	(3.24)	(2.66)
Ivol	-0.52%	0.20%	0.24%	-0.06%	-0.02%	-0.67%	-0.04%	0.03%	-0.28%	-0.22%
	(-9.65)	(2.75)	(3.07)	(-1.19)	(-0.43)	(-11.87)	(-0.44)	(0.31)	(-4.49)	(-3.37)
IV_slope	0.65%	-0.04%	-0.03%	0.02%	0.03%	0.73%	0.03%	0.01%	0.14%	0.13%
	(14.50)	(-0.56)	(-0.36)	(0.37)	(0.50)	(15.24)	(0.36)	(0.15)	(2.29)	(2.02)
BM	0.21%	0.22%	0.02%	0.27%	0.11%	0.23%	0.24%	0.05%	0.28%	0.14%
	(5.50)	(2.59)	(0.31)	(4.02)	(1.96)	(5.84)	(3.05)	(0.74)	(4.25)	(2.30)
Credit	-0.17%	0.13%	0.14%	0.04%	0.03%	-0.18%	0.07%	0.07%	-0.03%	-0.03%
	(-5.17)	(2.30)	(2.54)	(0.84)	(0.74)	(-5.27)	(1.26)	(1.39)	(-0.59)	(-0.65)
Illiquidity	-0.52%	0.08%	0.14%	-0.08%	-0.03%	-0.57%	-0.05%	0.01%	-0.20%	-0.13%
	(-11.72)	(0.96)	(1.51)	(-1.16)	(-0.44)	(-11.78)	(-0.50)	(0.11)	(-2.67)	(-1.68)
Reversal	0.07%	-0.02%	0.05%	-0.02%	0.06%	-0.14%	-0.12%	-0.07%	-0.14%	-0.09%
	(1.61)	(-0.20)	(0.45)	(-0.19)	(0.73)	(-2.99)	(-0.97)	(-0.56)	(-1.70)	(-1.07)
Mom	0.04%	-0.20%	-0.01%	-0.15%	-0.00%	0.09%	-0.00%	0.13%	-0.00%	0.00%
	(0.84)	(-2.17)	(-0.16)	(-2.25)	(-0.14)	(2.19)	(-0.11)	(1.55)	(-0.02)	(1.60)
VarCF	-0.37%	0.27%	0.18%	0.08%	0.03%	-0.43%	0.08%	0.04%	-0.05%	-0.07%
	(-8.71)	(3.21)	(1.96)	(1.29)	(0.42)	(-10.12)	(0.97)	(0.41)	(-0.79)	(-1.00)
Cash	-0.54%	-0.24%	NA	-0.37%	NA	-0.48%	-0.33%	NA	-0.42%	NA
	(-11.43)	(-2.60)	NA	(-5.28)	NA	(-10.99)	(-3.70)	NA	(-5.95)	NA
Disp	-0.14%	0.05%	-0.00%	0.01%	-0.00%	-0.17%	-0.09%	-0.12%	-0.10%	-0.00%
	(-4.01)	(0.66)	(-0.02)	(0.28)	(-0.17)	(-4.85)	(-1.23)	(-1.75)	(-1.82)	(-2.03)
shareiss1	-0.21%	0.11%	0.22%	-0.07%	0.02%	-0.20%	-0.01%	0.10%	-0.15%	-0.08%
	(-5.28)	(1.18)	(2.64)	(-1.40)	(0.38)	(-5.27)	(-0.16)	(1.33)	(-2.95)	(-1.39)
shareiss5	0.08%	0.00%	0.06%	0.01%	0.05%	0.15%	0.00%	0.07%	0.02%	0.05%
	(2.25)	(0.11)	(0.80)	(0.23)	(0.97)	(4.76)	(0.54)	(1.12)	(0.50)	(0.99)
PM	0.57%	-0.00%	-0.19%	0.17%	-0.00%	0.61%	0.16%	-0.03%	0.30%	0.00%
	(12.29)	(-0.08)	(-2.38)	(2.71)	(-0.07)	(13.29)	(1.78)	(-0.38)	(4.50)	(2.21)
Close	0.68%	-0.12%	-0.10%	0.09%	0.10%	0.63%	0.08%	0.05%	0.22%	0.19%
	(13.14)	(-1.37)	(-0.99)	(1.36)	(1.53)	(12.42)	(0.85)	(0.48)	(3.20)	(2.63)
Profit	0.20%	0.02%	-0.05%	0.07%	-0.02%	0.22%	0.05%	-0.02%	0.09%	0.01%
	(5.62)	(0.32)	(-0.90)	(1.27)	(-0.37)	(6.05)	(0.71)	(-0.31)	(1.92)	(0.25)
XFIN	-0.40%	-0.00%	0.20%	-0.21%	-0.04%	-0.45%	-0.14%	0.04%	-0.31%	-0.16%
	(-9.09)	(-0.03)	(3.17)	(-3.97)	(-0.81)	(-10.12)	(-1.91)	(0.59)	(-5.44)	(-2.91)

This table presents the average raw return and alphas of the treated dataset's long-short strategies in relation to the three- and four-factor models derived from ATM call options. These models are constructed using both the treated and benchmark datasets. The three-factor model comprises EWOP, VOV, and HV-IV, while the four-factor model additionally incorporates Cash. The option factors are the long-short return spread of delta-hedged option returns of ATM calls and puts sorted by the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOV is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. We also report their corresponding t-statistic in parenthesis. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

A Appendix

A.1 Theoretical motivation: Delta-hedged equity option gains in a multi-factor framework

In this section, we show that the proposed three-option-factor model in Section 3 is consistent with a multi-factor framework, in which stock returns and volatilities are driven by multiple factors. The model also allows the existence of higher order moment risks, where the volatility of volatility factors are time-varying and randomly distributed. The results show that when stock volatility has a factor structure, and when the volatility factors are driven by non-Gaussian processes, delta-hedged stock option gains are driven by the risk premia related to the volatility factors and higher-order moment risk factors.

We denote the stock price and the volatility of stock returns for firm i as S_t^i and V_t^i. The volatility of stock i is driven by n common factors: $V_{f,t}^j$, $j = 1, ..., n$ and a component of idiosyncratic volatility Z_t^i. The factors are independent of each other. The stock price evolves according to the process:

$$\frac{dS_t^i}{S_t^i} = \mu_t^i(S_t^i, V_t^i)dt + V_t^i dW_{1t}^i, \tag{2}$$

$$V_t^i = \sum_{j=1}^{n} \beta^j V_{f,t}^j + Z_t^i, \tag{3}$$

$$dV_{f,t}^j = \theta^j dt + \eta_t^j dW_{2t}^{i,j}, \tag{4}$$

$$d\eta_t^j = \xi^j dt + q^j dW_{3t}^{i,j}. \tag{5}$$

Equation (4) describes the dynamics of volatility factor j. To incorporate the role of higher order risk components, we use Equation (5) to describe the dynamics of the volatility of volatility factor j where η_t^j is the volatility of volatility factor $V_{f,t}^j$ and q^j is the volatility of η_t^j. To simplify the analysis, we assume that the correlations among the standard Brownian motions W_{1t}^i, $W_{2t}^{i,j}$ and $W_{3t}^{i,j}$ are all 0. Relaxing this assumption and allowing for the leverage effect does not change the main result of the model.

By Ito's lemma, we can write the price of a call option written on the stock as,

$$C_{t+\tau}^i = C_t^i + \int_t^{t+\tau} \Delta_u^i dS_u^i + \int_t^{t+\tau} \sum_{j=1}^n \frac{\partial C^i}{\partial V_f^j} dV_{f,u}^j + \int_t^{t+\tau} \sum_{j=1}^n \frac{\partial C^i}{\partial \eta_t^j} d\eta_u^j + \int_t^{t+\tau} b_u^i du, \tag{6}$$

where $\Delta_u^i = \frac{\partial C_u^i}{\partial S_u^i}$ is the delta of the call option and

$$b_u^i = \frac{\partial C^i}{\partial u} + \frac{1}{2}(V^i S^i)^2 \frac{\partial^2 C^i}{\partial (S^i)^2} + \frac{1}{2}\sum_{j=1}^n (\eta^j)^2 \frac{\partial^2 C^i}{\partial (V_f^j)^2} + \frac{1}{2}\sum_{j=1}^n (q^j)^2 \frac{\partial^2 C^i}{\partial (\eta^j)^2}.$$

The no-arbitrage assumption implies that the valuation equation that determines the call option price is:

$$\begin{aligned} &\frac{1}{2}(V^i S^i)^2 \frac{\partial^2 C^i}{\partial (S^i)^2} + \frac{1}{2}\sum_{j=1}^n (\eta^j)^2 \frac{\partial^2 C^i}{\partial (V_f^j)^2} + \frac{1}{2}\sum_{j=1}^n (q^j)^2 \frac{\partial^2 C^i}{\partial (\eta^j)^2} + rS_i \frac{\partial C^i}{\partial S_i} + \\ &\qquad \sum_{j=1}^n (\theta^j - \lambda_v^j) \frac{\partial C^i}{\partial V_f^j} + \sum_{j=1}^n (\xi^j - \lambda_\eta^j) \frac{\partial C^i}{\partial \eta^j} + \frac{\partial C^i}{\partial t} - rC^i = 0. \end{aligned} \tag{7}$$

Here $\lambda_v^j = -cov_t(\frac{dm_t}{m_t}, dV_{f,t}^j)$ is the risk premium for volatility factor j given a pricing kernel m_t. $\lambda_\eta^j = -cov_t(\frac{dm_t}{m_t}, d\eta_{f,t}^j)$ is the risk premium related to volatility of the volatility factor j given a pricing kernel m_t.

Combining Equation (6) and (7), we have:

$$\begin{aligned} C_{t+\tau}^i - C_t^i = &\int_t^{t+\tau} \Delta_u^i dS_u^i + \int_t^{t+\tau} r(C^i - S_i \frac{\partial C^i}{\partial S_i}) du + \\ &\int_t^{t+\tau} \sum_{j=1}^n \lambda_v^j \frac{\partial C^i}{\partial V_f^j} du + \int_t^{t+\tau} \sum_{j=1}^n \lambda_\eta^j \frac{\partial C^i}{\partial \eta^j} du + \end{aligned} \tag{8}$$

$$\int_t^{t+\tau} [\sum_{j=1}^n \theta^j \frac{\partial C^i}{\partial V_f^j} dW_2^{i,j}] + \int_t^{t+\tau} [\sum_{j=1}^n \xi^j \frac{\partial C^i}{\partial \eta^j} dW_3^{i,j}]. \tag{9}$$

With a delta-hedged portfolio, we buy the call option and dynamically delta-hedge the option position with time-varying delta Δ_u^i. The delta-hedged gain $\Pi_{t,t+\tau}^i$ is the gain or loss on a delta-hedged option portfolio in excess of the risk-free rate earned by this portfolio and is defined as

$$\Pi^i_{t,t+\tau} = C^i_{t+\tau} - C^i_t - \int_t^{t+\tau} \Delta^i_u dS^i_u - \int_t^{t+\tau} r(C^i - S_i \frac{\partial C^i}{\partial S_i})du.$$

From the definition of delta-hedged gain and Equation (8), we obtain the expectation of the delta-hedged gain for stock option i as

$$E[\Pi^i_{t,t+\tau}] = \sum_{j=1}^{n} E[\int_t^{t+\tau} \lambda^j_v \frac{\partial C^i}{\partial V^j_f} du] + \sum_{j=1}^{n} E[\int_t^{t+\tau} \lambda^j_\eta \frac{\partial C^i}{\partial \eta^j} du] \tag{10}$$

This result shows that the expected delta-hedged option gain for stock i is driven by the risk premiums related to volatility factors (λ^j_v, $j = 1, ..., n$), the exposure of stock option i on the volatility factors ($\frac{\partial C^i}{\partial V^j_f}$), the risk premiums related to volatility of volatility factors (λ^j_v, $j = 1, ..., n$), and the exposure of stock option i on the volatility of volatility factors ($\frac{\partial C^i}{\partial \eta^j}$).

The theoretical results of this section are in line with our empirical findings. The long-short delta-hedged option return ranked by HV–IV, the difference between historical and implied volatilities, can be considered as a proxy for volatility risk. The long-short delta-hedged option return sorted by the volatility of implied volatility can be considered as the proxy for volatility of volatility risk.

A.2 The factor structure in out-of-the-money (OTM) delta-hedge option returns

In this section, we focus our analysis on the factor structure of out-of-the-money (OTM) call and put delta-hedged equity option portfolio returns. For OTM calls (puts), we choose the option with moneyness closest but greater (lower) than 1.1 (0.9). A firm is included only when four options are simultaneously available: an ATM call, an ATM put, an OTM call, and an OTM put. Additionally, the moneyness of the OTM call (put) must be strictly higher (lower) than that of the ATM call (put). The robustness sample contains 53,729 firm-month observations with four options for each firm. We apply the same set of analyses for this type of contract as for ATM options in the main body of the paper.

At the end of each month, we sort all OTM stock options into 10 portfolios (5 for credit rating) based on the 19 characteristics described above. We start the position at the end of the month, hedge its delta exposure on a daily basis, and close it at the end of following month. Their corresponding OTM delta-hedged option returns are calculated according to Section 2.2. We consider 364 option portfolios of OTM delta-hedged call and OTM delta-hedged put options sorted by the 19 different characteristics. The 19 candidate factors for either OTM calls or OTM puts are the long-short return spreads, 10-1 (5-1 for credit rating), based on the 19 characteristics. We also consider two additional factors: EWOP which is the average of the 364 portfolios with OTM options and the delta-hedged S&P 500 call option return.

Using these portfolios as test assets, we conduct the Scree test, along with ER and GR tests, and present the results in Figure A2. The figure suggests the presence of two strong factors and possibly a third, weaker one. This is confirmed by both the ER and GR tests, as well as the Scree test. We then explore the relevance of these factors for pricing. Mirroring the methodology in the main body of the paper, we employ standard principal component analysis to extract the factors from the second-moment matrix without subtracting the variables' means.

[Figure A2 around here]

Table A5 presents the number of factors detected in residuals using the GOS test by Gagliardini et al. (2019). This test is applied sequentially, adding one of the common factors to calls and puts separately. These common factors are estimated from the combined datasets.

[Table A5 around here]

The table shows that after estimating three PCA factors from the combined dataset, there are no additional factors in the residual of the individual datasets. The fact that we find a single factor remaining, regardless of whether we use one or two PCAs, suggests the possibility of two strong factors and a weak one, or simply two strong factors with some cross-correlation leftover in the residuals. However, it is clear that once we use three PCAs from the pooled data, there is no evidence of a factor structure in each dataset separately, indicating that both datasets share the same common factors.

Our analysis in the main body of the paper yields a maximum of four factors for ATM options as opposed to a maximum of three factors for OTM options in this Appendix. This discrepancy can be attributed to at least two reasons. First, by construction, delta-hedged option returns are mainly exposed to higher-order moment risks captured by vega and gamma. Vega and gamma are the highest for ATM options and both decrease for OTM options. If ATM and OTM options share the same factor structure, ATM options are better to identify the common factors since they are more sensitive than OTM options to these higher-order moment risks. Second, this discrepancy might also be attributable to the relative weakness of factors beyond the second one, which becomes less discernible in OTM returns due to fewer observations. The ATM return analysis is obtained from a substantial base of 204,376 firm-month observations, while the OTM return analysis relies on a much smaller dataset of just 53,729 observations. The difficulty of distinguishing weak factors from noise increases with a smaller dataset.

We now move to select the relevant candidate factors that best capture the common component estimated via PCA on our set of OTM delta-hedged equity call and put option returns. Similar to the ATM case, the candidate factors from OTM call options and OTM put options are highly correlated, as shown in the diagonal of the correlation heatmap below.

[Figure A3 around here]

Like in the ATM case, we focus on OTM call options to find the best candidate factors that explain both calls and puts simultaneously. Mirroring the situation with ATM options, we discover that OTM put factors slightly outperform OTM call factors. Hence, our results using OTM call factors can again be seen as a conservative estimate for the models' performance.[19] We construct all possible 3-factor models from the 21 factor candidates derived from OTM call options (the 19 characteristic-based factors, plus the EWOP from OTM options and the delta-hedged S&P 500 index option factor). This yields a total of 1,330 distinct models. We then select the top 2.5% of models (33 models) with the highest $\mathrm{SR}_{\mathrm{DH}}$, R^2 regressing the tangency portfolio of the three PCA factor model on the candidate factor model, correlation between average returns and predicted returns by the model, RMSPE, and OOS RMSPE. We report the frequency at which each factor appears in these models at the top of the distribution for the different metrics. The results are presented in Figure A4. Similar to the results for ATM options, VOV, HV–IV, and Cash computed with OTM call options emerge as the key factors in the top-performing models.

[Figure A4 around here]

We also report the correlation between ATM and OTM long-short strategies for both puts and calls. Figure A5 reports the correlation between candidate factors for ATM and OTM calls in Panel (a) and for puts in Panel (b). The diagonal of both panels shows a high correlation close to 0.9 between long-short strategies constructed using the same characteristic from ATM and OTM calls, or puts. The correlation is slightly higher among calls than puts. These high correlations and the fact that we find the same candidate factor model for ATM and OTM options further supports our claim that ATM and OTM call and put options share the same common factors.

[Figure A5 around here]

Finally, Table A6 compares the performance of the model using three PCA factors against

[19] Results with OTM put factors are available from the authors upon request.

models that incorporate candidate factors from OTM call option strategies. In the main body of the paper, we evaluate how well factor models derived from ATM delta-hedged call equity options explain the returns of OTM call and OTM put option portfolios.

[Table A6 around here]

The table shows that the performance of the candidate factor model mirrors that of the model using PCA factors.

Overall, the findings in the main body of the paper for ATM delta-hedged equity call and put option returns also apply to the OTM case in this Appendix. Both OTM call options and OTM put options share the same factor structure, which can be effectively captured using PCA factors. The relevant information in the statistical factors can be captured by EWOP and long-short strategies based on VOV and HV–IV.

A.3 Comparison with Risk-Premium Principal Component (RP-PCA) and Instrumented Principal Component Analysis (IPCA)

In the main analysis of the paper, we use principal component analysis (PCA) to estimate the factors in delta-hedged equity option returns. In this section, we show that risk-premium PCA in Lettau and Pelger (2020b) and instrumented PCA in Kelly et al. (2019) yield comparable pricing performance than standard PCA.

A.3.1 Comparison with Risk-Premium PCA

Standard PCA focuses on finding factors that minimize the unexplained variation of a linear factor model. In contrast, Lettau and Pelger (2020b) propose risk-premium PCA, which minimizes the unexplained variation and the pricing error generated by the linear model. Lettau and Pelger (2020a) show that the stochastic discount factor could be estimated more efficiently using RP-PCA than PCA, especially in the presence of weak factors. Lettau and Pelger (2020b) show that PCA is a particular case of the RP-PCA method.

We estimate the factors using RP-PCA, and show the results in Figure A6 for the at-the-money options and in Figure A7 for the out-of-the-money options. The two figures show in-sample and out-of-sample SR_{DH} and in-sample and out-of-sample RMSPE generated by the factor models using PCA and RP-PCA using one to six estimated factors with four levels of the tunning parameter γ. The test assets are 370 ATM delta-hedged option portfolio returns: 185 for calls and 185 for puts. The out-of-sample statistics are calculated in the same way as in the main analysis using the first 120 months as the initial window.

[Figure A6 around here]

Figure A6 indicates that RP-PCA factors achieve a slightly higher in-sample and out-of-sample SR_{DH} than PCA factors. This is consistent with the results in Lettau and Pelger (2020a), who show that RP-PCA is a superior estimator for the stochastic discount factor, especially in the presence of weak factors. However, the differences between the two methods are within a magnitude of 0.1, suggesting that the two methods achieve comparable levels of SR_{DH} when extracting latent factors from equity option returns. The in-sample and out-of-sample root mean squared pricing errors (RMSPE) are similar for PCA and RP-PCA factors. In the case of out-of-the-money delta-hedged option returns, the differential performance between RP-PCA and PCA is larger, although PCA still performs reasonably well, as seen in Figure A7.

[Figure A7 around here]

A.3.2 Comparison with Instrumented PCA

Another approach to estimate latent factors in asset pricing is the instrumented principal component analysis (IPCA) proposed in Kelly, Pruitt, and Su (2019), which allows conditional factor loadings to be a linear function of asset characteristics. The model specification for IPCA is as follows,

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} F_{t+1} + \epsilon_{i,t+1},$$

$$\alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \mathcal{V}_{\alpha,i,t}, \beta_{i,t} = z'_{i,t}\Gamma_\beta + \mathcal{V}_{\beta,i,t},$$

where $r_{i,t+1}$ is the return of asset i ($i = 1, ..., N$) over time period t ($t = 1, ..., T$), and F is a matrix of K latent factors. $\alpha_{i,t}$ and $\beta_{i,t}$ are asset specific time-varying intercept and factor loadings that are both assumed to be linearly related to L observable characteristics summarized in $z'_{i,t}$.

One of the main differences between IPCA and PCA is that the former allows for time-varying beta coefficient as a function of asset characteristics, while the factor exposures of PCA are constant. IPCA is usually applied to individual assets, whereas we use characteristic-sorted option portfolios instead of individual options. Using portfolios has the advantage that their risk exposures are more stable over time. Under certain conditions, these two approaches could be equivalent and generate similar empirical results. Giglio and Xiu (2021) show in their Appendix III.9 that if individual factor exposures are linear functions of a certain form of characteristic (dummy variables that indicate the characteristic group to which each stock belongs), then the sorted portfolios have constant factor exposures. Kozak and Nagel (2023) also show that under some conditions, instrumented PCA can be implemented as simple PCA on certain portfolio sorts. Therefore, standard PCA can be applied even if risk exposures of individual options are time-varying, as long as test assets are characteristic-sorted portfolios that have constant factor exposures. We empirically estimate the IPCA model on our test assets and find that the two models generate comparable performance in terms of $\mathrm{SR}_{\mathrm{DH}}$, correlation between average and predicted returns, and average adjusted R^2.

We estimate the unrestricted IPCA model ($\Gamma_\alpha \neq 0$) using the same data as in our main analysis: 370 option portfolios (185 ATM call portfolios and 185 ATM put portfolios) sorted on 19 characteristics from January 1996 to December 2021. We calculate the portfolio characteristics as the average of individual characteristics in the portfolio. Following Kelly et al. (2019), we cross-sectionally transform characteristics period-by-period. We calculate portfolios' ranks for each characteristic, and then divide ranks by the number of non-missing observations and subtract 0.5. This maps characteristics into the [-0.5,+0.5] interval and focuses on their ordering as opposed to their magnitude.

[Table A7 around here]

Table A7 reports the following performance measures for six models that sequentially add the first IPCA factor to the sixth IPCA factor: $\mathrm{SR}_{\mathrm{DH}}$ for the tangency portfolios, correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$, out-of-the-sample root mean square pricing error (OOS RMSPE), and p-values on the bootstrap Wald test of no alpha (i.e., $\Gamma_\alpha = 0$), which is obtained by comparing the models fit to their unconstrained equivalents ($\Gamma_\alpha \neq 0$). The Sharpe ratio, $\mathrm{SR}_{\mathrm{DH}}$, for delta-hedged portfolios is calculated for mean-variance efficient portfolio of factors in each model. The predicted return of each portfolio i is $z'_{i,t}(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{f}_{t+1})$. Adjusted R^2 is calculated by running a regression of portfolio returns on the factor model. α is calculated as the difference between realized return and predicted return by the IPCA model, and the t-statistics tests the null hypothesis that $\alpha = 0$.

We now compare the PCA model (Table 3) with the IPCA model (Table A7) in terms of the seven performance metrics. The PCA and the IPCA models generate similar $\mathrm{SR}_{\mathrm{DH}}$ when using 4 or less factors. When the factor number increases to 5 and 6, the IPCA model generates higher $\mathrm{SR}_{\mathrm{DH}}$s than the PCA model. The correlation between average return and predicted return is 0.96 for the four PCA factor model, whereas the maximum correlation reached by the IPCA model is 0.89. The average adjusted R^2 is similar for both models at 0.90. The in-sample and out-of-sample root mean square pricing error is lower for the PCA model than for the IPCA model. The percentage of $|t_\alpha| > 3$ is only 7% for the PCA model with 6 factors, while it is 48% for the IPCA model with 6 factors. The null hypothesis of no alpha is rejected when there are up to 6 factors. Overall, the PCA model and the IPCA model demonstrate similar performance levels for certain metrics, while each presents its own unique advantages in terms of empirical performance in pricing delta-hedged option portfolios.

A.4 Commonalities between option factors and stock return factors

In this section, we examine the extent of information overlap between common factors derived from delta-hedged option returns and those from stock returns. Leveraging the methodology proposed by Pukthuanthong et al. (2019), we perform a canonical correlation analysis between the statistical factors obtained from option portfolios (four PCAs) and the first six PCA factors extracted from a large panel of long-short stock return strategies (six stock-PCAs).

For our option factors, we use the four PCA model derived from our set of 370 delta-hedged ATM call and put option portfolio returns, which are based on 19 distinct firm characteristics. For estimating the stock return factors, we first download 182 long-short stock portfolio returns from Chen and Zimmermann's webpage (refer to Chen and Zimmermann (2022)).[20] Given that the stock return literature using latent estimated factors identifies between one to six common factors (for instance, Brown (1989) identifies one common factor, Lettau and Pelger (2020b) identify five, and Cooper, Ma, Maio, and Philip (2021) identify six), we extract six statistical factors (stock-PCAs) from the aforementioned long-short characteristic-based strategies.

The canonical correlation analysis between the statistical factors extracted from option portfolios and stock portfolios in Table A8 reveals a weak correlation between the two common components. The table shows that the first pair of canonical variates displays a canonical correlation of 0.44, suggesting a moderate positive relationship between them, accounting for approximately 19.36% (0.44^2) of their total variance. Notably, the first PCA derived from option portfolio returns is strongly related to this first component, explaining about 96% of

[20] https://www.openassetpricing.com

its variance. This indicates that the market aggregator (EWOP) from option returns is the option factor most closely correlated with the common component of stock returns.

[Table A8 around here]

The second pair of canonical variates shows a canonical correlation of 0.23, implying a weaker positive relationship and accounting for roughly 5.29% (0.23^2) of their total variance. Here, the fourth PCA from option returns is the most correlated with this second component, explaining approximately 89% of its variance. The third pair of canonical variates, with a canonical correlation of 0.19, indicates an even weaker positive relationship, accounting for only 3.61% (0.19^2) of the total variance. Both the second and third PCAs from option returns are significantly associated with this third component, explaining approximately 62% and 34% of its variance respectively. The fourth pair of canonical variates, with a canonical correlation of just 0.06, points to a negligible relationship between the factors derived from option returns and stock returns, explaining a mere 0.36% (0.06^2) of the total variance.

The primary insight from the canonical correlation analysis is that the second principal component factor from delta-hedged call and put portfolio returns, which plays a key role in explaining the cross-section of equity option returns, is virtually uncorrelated with the common factors in stock returns. This factor is associated with the third pair of canonical variates, which indicate almost no shared information between the common component in delta-hedged option returns and that in stock returns. Hence our option factor model is suitable for option strategies that are exposed to vega and gamma, such as delta-neutral straddles or strangles. Other options trading strategies like bull spreads, spreads or collars that are also exposed to movements in the underlying security (non-zero delta) should simultaneously use our proposed option factor model and a factor model for stock returns.

A.5 Treatment to missing values: supplemental material

A.5.1 Detailed description of imputation methods and summary statistics

Below, we provide a more detailed explanation of the imputation methods presented in Section 3.5. When a contract lacks a price at the end of the holding period, we apply seven distinct methodologies to impute the missing data. A theoretical price, once imputed, is deemed valid only if it is lower than the ask price and higher than the bid price (which may be zero). If determining a theoretical price is not feasible, we default to setting the option price at its intrinsic value. In situations where the stock price is unavailable at the end of the holding period, due to the firm's delisting or acquisition, we compute the option price and delta-hedged option return only up until the date of delisting or acquisition. Firms are excluded from our analysis if their delisting or acquisition date aligns with the trading date. The specific imputation methods are:

(1) Mid option price (Mid): since bid is equal to zero, the option price is equal to mid=ask/2.

(2) Black Scholes Merton (BSM) model. We use the implied volatility surface for calls (puts) from Optionmetrics to find the interpolated implied volatility of the call (put) with the corresponding strike price and time-to-maturity. With the interpolated implied volatility, we price the option using the BSM model with S, K, r, T where S is the stock price at the end of the holding period, K is the strike price, r is the interest rate, and T is the time to maturity. This price is valid only if it is lower than the ask price.

(3) BSM model with put-call parity (BSM PC-parity). To price a call (put) option, we find the corresponding put (call) option at the end of the holding period with same underlying, strike price and time-to-maturity with a valid mid price (bid>0, ask>0 and ask>bid) and implied volatility. To account for the put-call spread, we compute the implied put-call spread surface as the difference of the call IVS minus the put IVS to find the interpolated put-call spread. We add the put (call) implied volatility of the valid put (call) option to the interpolated put-call spread to obtain the new implied volatility for the call (put). With this

new implied volatility, we price the call (put) option using the BSM model with S, K, r, T where S is the stock price, K is the strike price, r is the interest rate, and T is the time to maturity at the end of the holding period. This price is valid only if it is lower than the ask price.

(4) Prior five days' availability: We look for valid option prices (bid>0, ask>0 and ask>bid) in the previous five trading days before the end of the holding period. We select the price from the option with the closest date to the end of the holding period date. Since the underlying stock price, implied volatility, and time-to-maturity change during the t days until the end of the holding period T, we perform a Delta (δ), Gamma (γ), Theta (θ), and Vega (ν) adjustment of the valid mid option price to obtain a theoretical mid price at the end of the holding period as follows:

$$Mid_T = Mid_{T-t} + \delta_{T-t}(S_T - S_{T-t}) + \frac{1}{2}\gamma_{T-t}(S_T - S_{T-t})^2 + \frac{\theta_{T-t}}{365}t + \frac{\nu_{T-t}}{100}(\sigma_T - \sigma_{T-t})$$

where mid price (Mid_{T-t}), implied volatility (σ_{T-t}) and Greeks—Delta: δ_{T-t}, Gamma: γ_{T-t} , Theta: θ_{T-t}, and Vega: ν_{T-t}—are obtained for the valid option at $T-t$, S_T is the stock price at the end of the holding period, and σ_T is the interpolated implied volatility obtained in methodology (2). We obtain the Greeks from OptionMetrics. This price is valid only if it is lower than the ask price at the end of the holding period.

(5) After five days' availability: We look for valid option prices (bid>0, ask>0 and ask>bid) in the next five trading days after the end of the holding period. When available, we select the option price with the date closest to date of the end of the holding period. Since the underlying stock price, implied volatility, and time-to-maturity change during the t days after the end of the holding period T, we perform a Delta (δ), Gamma (γ), Theta (θ), and Vega(ν) adjustment of the valid mid option price to obtain a theoretical mid price at the end of the holding period T as follows:

$$Mid_T = Mid_{T+t} + \delta_{T+t}(S_T - S_{T+t}) + \frac{1}{2}\gamma_{T+t}(S_T - S_{T+t})^2 - \frac{\theta_{T+t}}{365}t + \frac{\nu_{T+t}}{100}(\sigma_T - \sigma_{T+t})$$

where the mid price (Mid_{T+t}), implied volatility (σ_{T+t}) and Greeks—Delta: δ_{T+t}, Gamma: γ_{T+t} , Theta: θ_{T+t}, and Vega: ν_{T+t}—are obtained for the valid option at $T+t$, S_T is the stock price at the end of the holding period, and σ_T is the interpolated implied volatility obtained in methodology (2). We obtain the Greeks from OptionMetrics. This price is valid only if it is lower than the ask price at the end of the holding period.

(6) Intrinsic option price. Equity options are American. Intrinsic price is the option price that would result from exercising the option. For a call option the intrinsic price is equal to $max(S-K,0)$ and for a put option it is $max(K-S,0)$, where S is the stock price at the end of the holding period and K is the strike price. Intrinsic price is the option value that results from exercising the option and it excludes the time value or extrinsic price. This price is valid only if it is lower than the ask price.

(7) Average all. This method imputes the option price as the average of all the theoretically imputed prices from methodologies 1 to 5.

[Table A10 and A11 around here]

Tables A10 and A11 report the long-short delta-hedged option returns for calls and for puts, respectively, for firms sorted by the 19 characteristics for each of the imputation methods.

A.5.2 Number of factors in the treated dataset

To estimate the number of factors, K, in delta-hedged option returns, we utilize delta-hedged call and put option portfolios as response variables. These portfolios are constructed based on 19 characteristics outlined in Section 2.3, using the treated dataset created with the "Average All" imputation method for a total of 370 portfolios ($N=370$). The sample period spans from January 1996 to December 2021 for a total of 312 months ($T=312$ months). As a preliminary step, Figure A8 Panel A displays the largest fifteen eigenvalues from the sample second-moment matrix. This Scree plot suggests the presence of at most five common factors, with one factor exhibiting significantly stronger explanatory power than the other four. The Eigenvalue Ratio (ER) and Growth Ratio (GR) estimators, as proposed by Ahn and Horenstein (2013) and illustrated in Panel B, peak at the first factor and show a secondary peak at the fourth, indicating the presence of one dominant factor, similar to the Scree test results, but suggesting a total of at most four common factors.

Given the slight discrepancies between the results from the Scree tests and the Eigenvalue Ratio tests, we also present results from the Gagliardini et al. (2019) (GOS) estimator used in the main body of the paper. The GOS estimator examines the error terms generated by a factor model to determine whether these errors are weakly cross-sectionally correlated or exhibit at least one common factor. This analysis is crucial to determine whether the common factors estimated from the combined dataset capture all common factors present in the individual datasets. Such an assessment helps us determine if there are distinct factors in call or put options and provides a second reference point for the total number of factors. Table A12 reports the number of factors found in the residuals of the missing-value-treated call and put databases as we sequentially add one of the common factors estimated from the two datasets together.

[Table A12 around here]

The table shows that, after removing the first and second factors, two factors remain detectable in the residuals of delta-hedged call and put options, considered separately. However, even upon the removal of three factors, the GOS estimator identifies one factor persisting in the residuals. When four or more factors are removed, the GOS estimator stops finding any additional factor in the residuals. These findings provide supporting evidence for the results obtained from the Eigenvalue Ratio tests, which suggest the presence of one dominant factor and a total of up to four common factors.

Finally, we present the correlation heatmap between delta-hedged call and put option factors constructed using the treated database in Figure A9. The diagonal of the correlation heatmap reveals that call and put option candidate factors of the same characteristic are highly correlated. The high correlation suggests that either call or put option returns could be used as factor candidates, as they essentially contain very similar information. The results are consistent with our findings for the benchmark dataset reported in Figure 3.

[Figure A9 around here]

In conclusion, our analyses reveal that four common factors account for the co-movement in delta-hedged call and put options within the treated dataset. These findings align with the results presented in Section 3 based on our benchmark dataset.

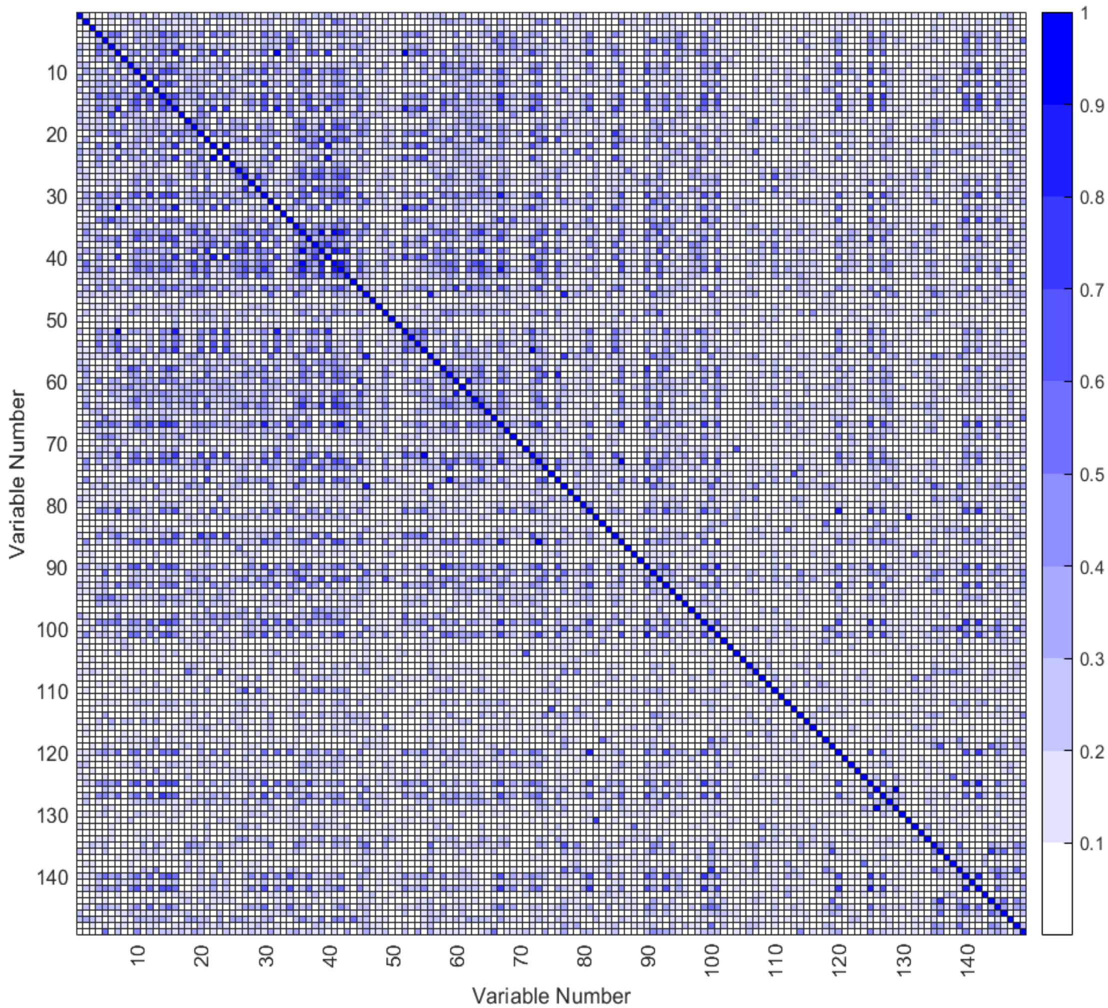
A.5.3 Pricing extreme portfolios in the treated dataset

In the final section of this Appendix, we reproduce Figure 5 from the paper, illustrating the case where the response variables are from the treated dataset, while the VOV, HV-IV, and Cash factors are from the benchmark dataset.

[Figure A10 around here]

The figure shows that the benchmark factors provide an excellent fit for the extreme portfolios of the treated dataset.

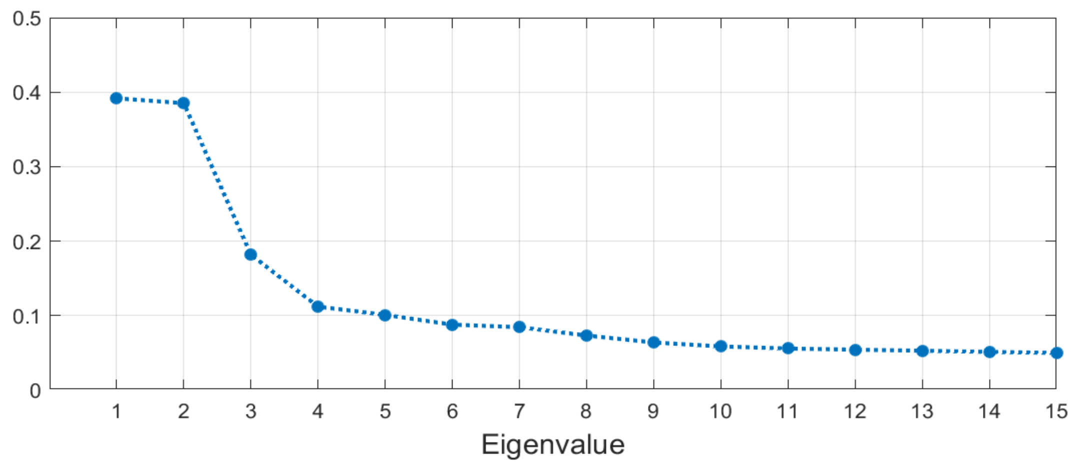
Figure A1: Correlation Heatmap of Long-Short Call Option Factors Constructed from 149 Other Characteristics



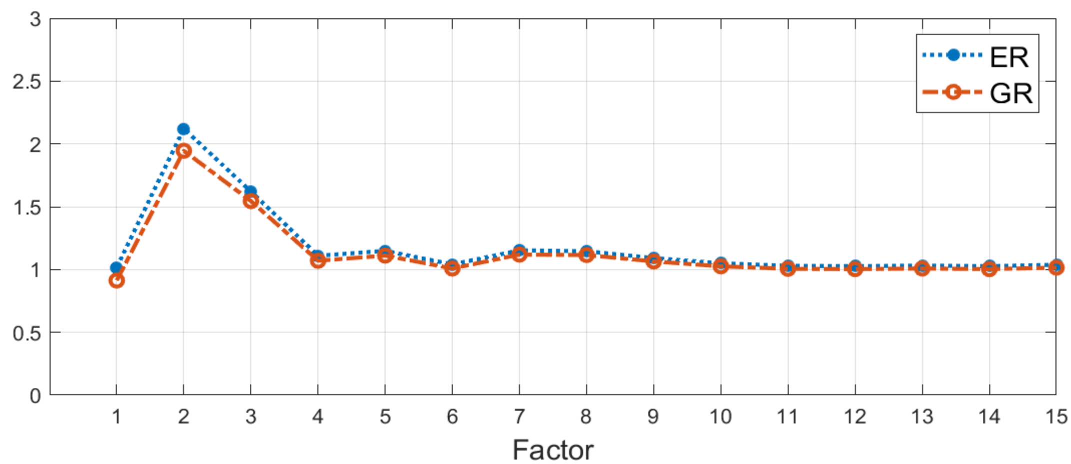
This figure shows the correlation heatmap between long-short at-the-money call option factors constructed from 149 characteristics other than the 19 characteristics in the main analysis. The 149 variables are downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com) and are defined in Table A3. In Table A4 we report the delta-hedged call and put option return along with their t-statistics for deciles 1 and 10, and the long-short (10-1) portfolio for each of the 149 variables. Correlations are reported in absolute value. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A2: Scree Test for Out-of-the-money Call and Put Option Returns

(a) The Scree Plot

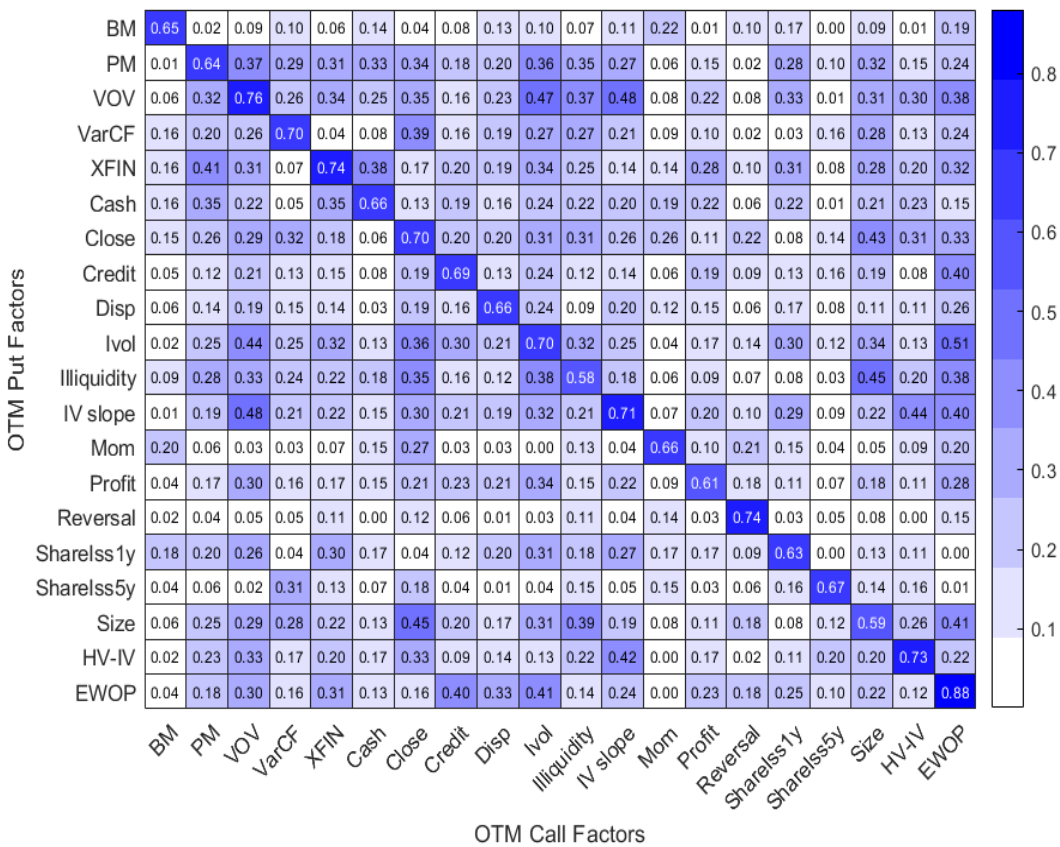


(b) GR and ER Values



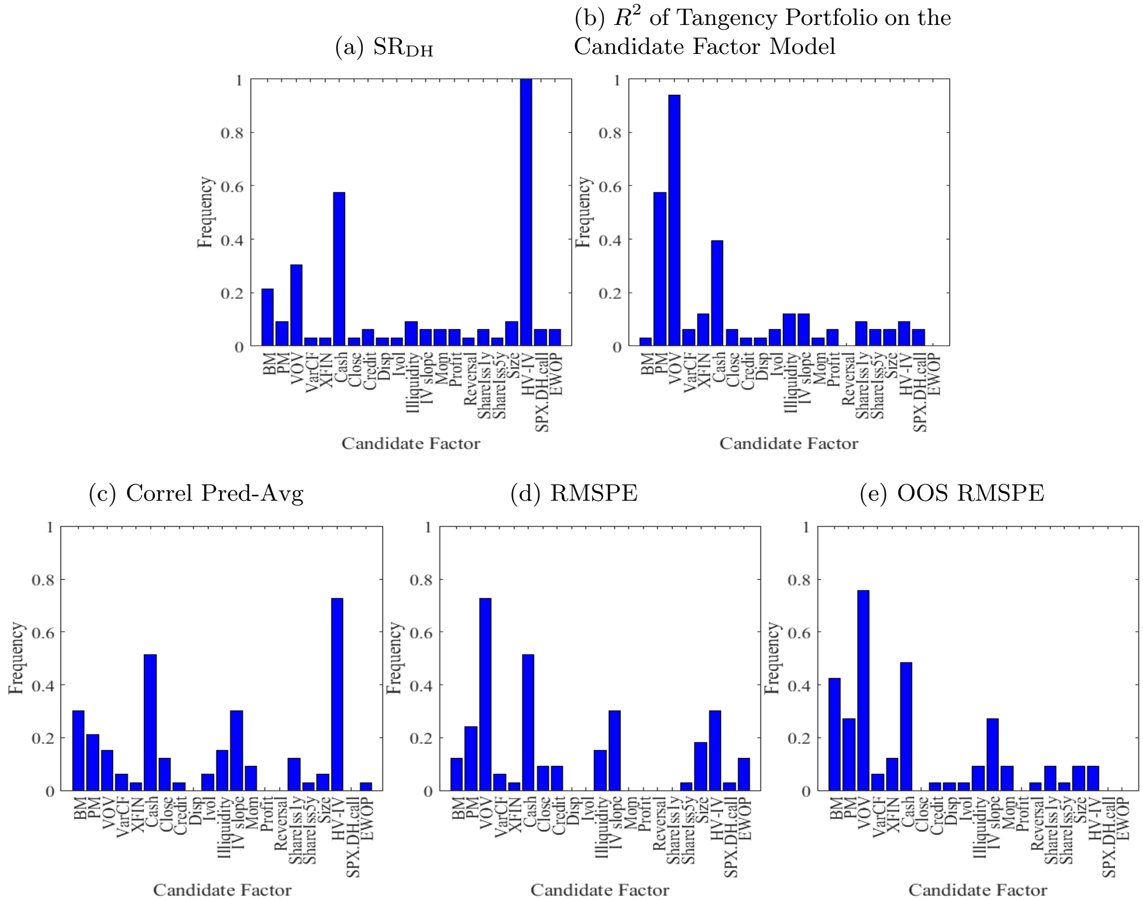
Panel (a) plots the largest fifteen eigenvalues from the sample second-moment matrix of the 370 delta-hedged out-of-the-money call and put option portfolio returns. Panel (b) presents the results from the Ahn and Horenstein (2013) Eigenvalue Ratio (ER) and the Growth Ratio (GR) estimators. The 364 OTM delta-hedged call and put option portfolios are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, illiquidity, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A3: Correlation Heatmap of Out-of-the-money Call and Put Factors



This figure shows the correlation heatmap between factor candidates in out-of-the-money (OTM) call options and OTM put options. The 19 candidate factors in call options and the 19 candidate factors in put options are 10-minus-1 (5-minus-1 for Credit) long-short out-of-the-money option portfolio returns sorted by the following characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. EWOP is the equal-weighted option portfolio of the 185 OTM delta-hedged portfolios of calls or puts constructed with the 19 characteristics. Correlations are reported in absolute value. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

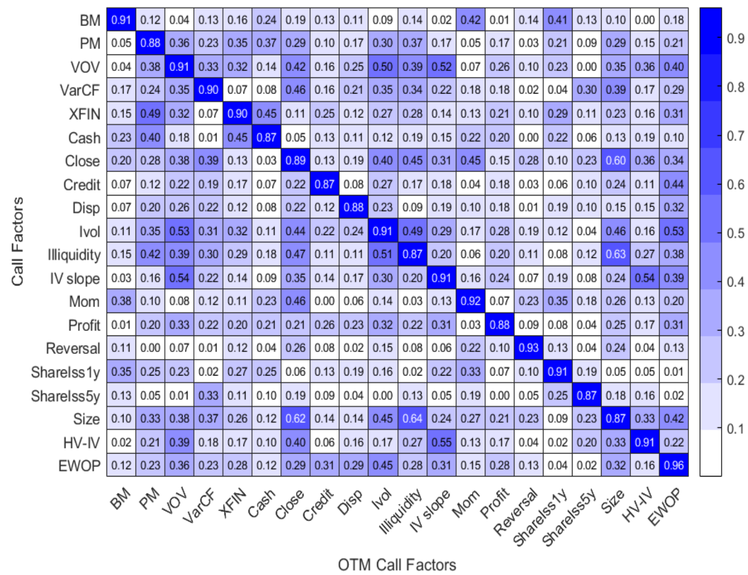
Figure A4: Candidate Factor Selection - OTM Options



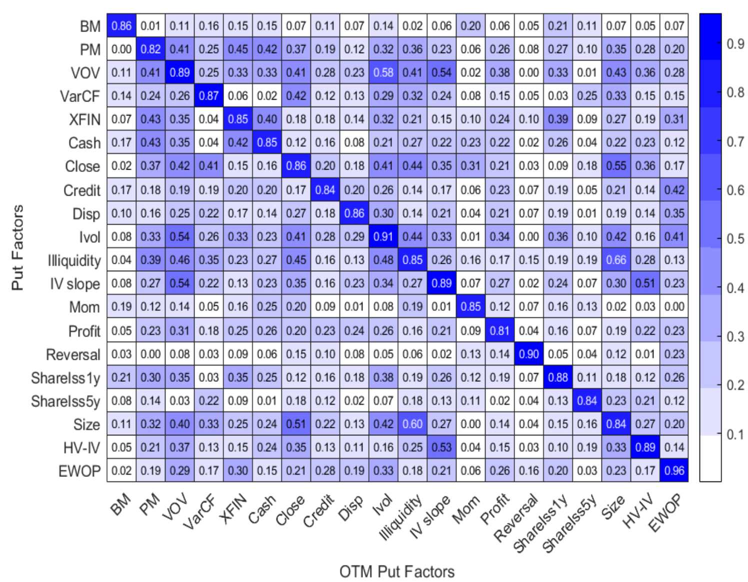
This figure plots the frequency of candidate factors in the top 2.5% of models (33 models) of all possible 4-factor models from the 21 factor candidates based on five criteria. We generate all possible 3-factor models from the 21 candidate factors derived from OTM call options, which include the 19 characteristic-based factors, EWOP, and the S&P 500 option factor. This results in a total of 1,330 distinct models. We then select the top 2.5% of models (33 models) based on $\mathrm{SR_{DH}}$ (Panel (a)), and R^2 of regressing tangency portfolio of the PCA factors on the candidate factor model (Panel (b)), the correlation between average returns and model-predicted returns (Panel (c)), as well as the Root Mean Square Pricing Error (RMSPE) (Panel (d)), and the Out-of-Sample RMSPE (OOS RMSPE) (Panel (e)). We report the frequency that each factor appears in the models at the top of the distribution for the different metrics. The 19 characteristics are: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. SPX_DH_call is the one-month delta-hedged call option return of the S&P 500 index and EWOP is the equal-weighted option portfolio of the 364 delta-hedged portfolios of OTM calls and OTM puts constructed with the 19 characteristics. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A5: Correlation Heatmap of ATM and OTM Call (Put) Factors

(a) Correlation Between ATM and OTM Call Factors

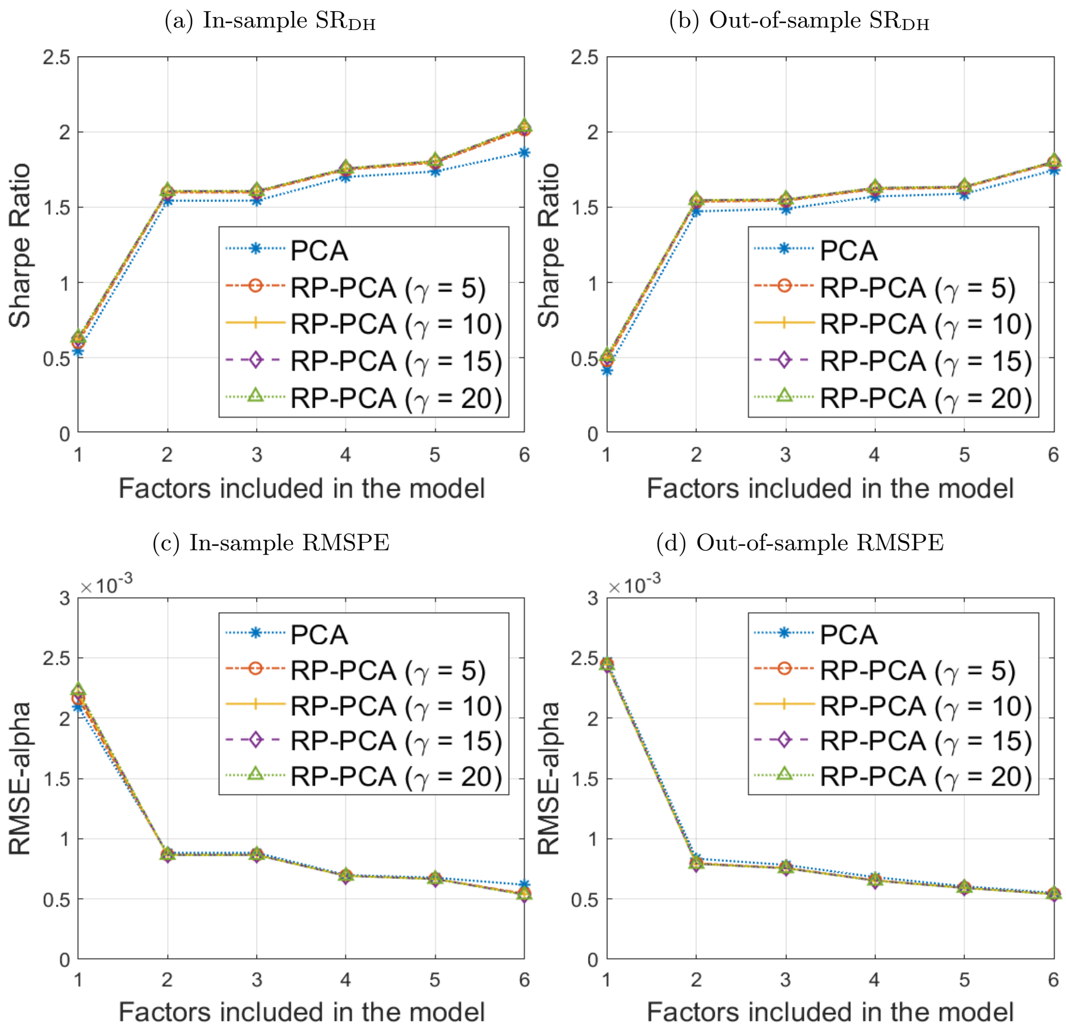


(b) Correlation Between ATM and OTM Put Factors



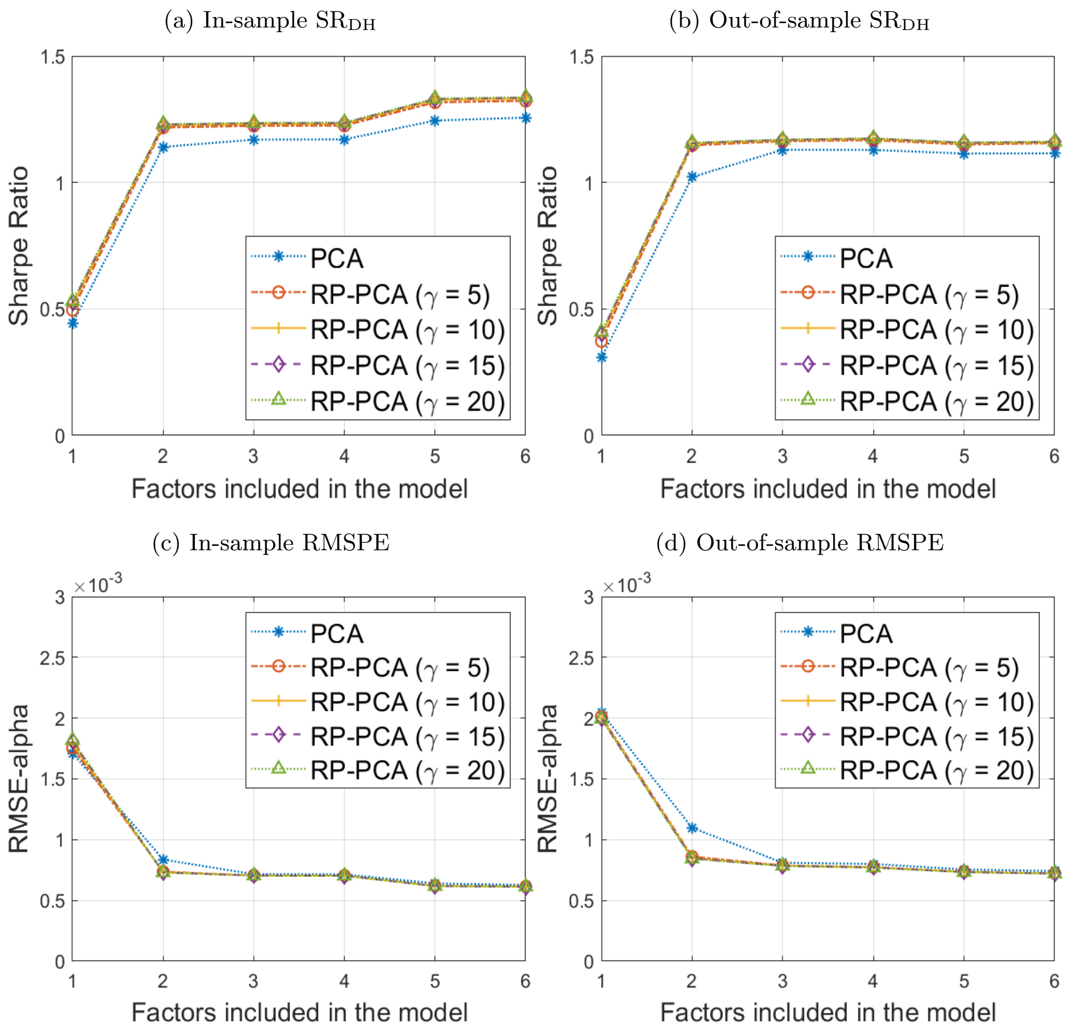
Panel (a) in this figure shows the correlation heatmap between factor candidates in ATM and OTM call factors. Panel (b) shows the correlation heatmap between factor candidates in ATM and OTM put factors. The 19 candidate factors in call options and the 19 candidate factors in put options are the 10-minus-1 (5-minus-1 for Credit) long-short ATM and OTM option portfolio returns sorted by the following characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. EWOP is the equal-weighted option portfolio of the 185 ATM or OTM delta-hedged portfolios of calls or puts constructed with the 19 characteristics. Correlations are reported in absolute value. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A6: PCA vs. RP-PCA (ATM Options)



This figure shows in-sample SR_{DH} (Panel (a)), out-of-sample SR_{DH} (Panel (b)), in-sample RMSPE (Panel (c)), and out-of-sample RMSPE (Panel (d)) generated by the factor models using PCA and Risk-Premium PCA (RPPCA) of the 370 delta-hedged ATM call and put option portfolio returns with four levels of γ. The RP-PCA method is proposed by Lettau and Pelger (2020a). The 370 delta-hedged call and put option portfolios are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

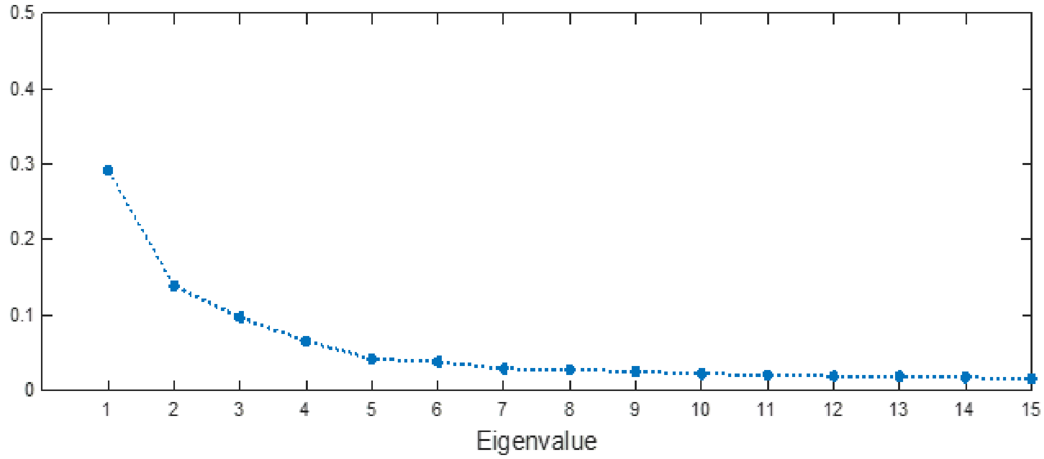
Figure A7: PCA vs. RP-PCA (OTM Options)



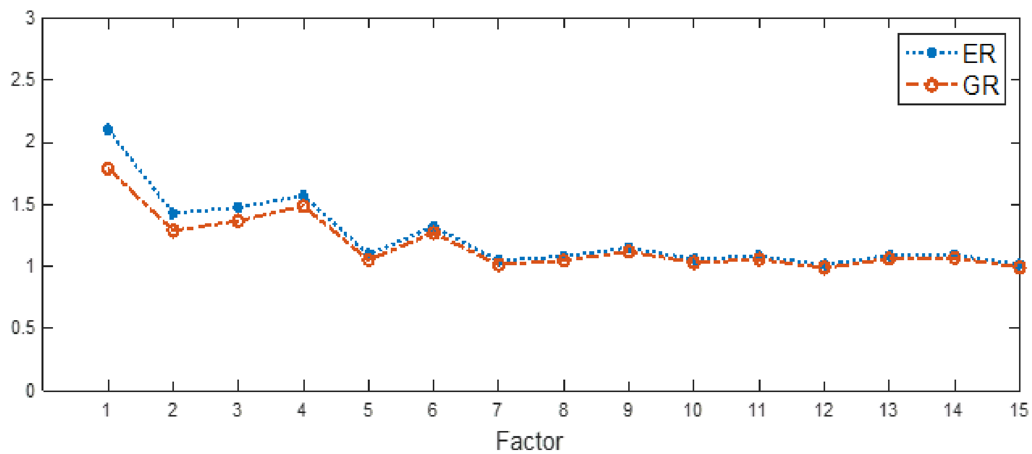
This figure shows in-sample SR_{DH} (Panel (a)), out-of-sample SR_{DH} (Panel (b)), in-sample RMSPE (Panel (c)), and out-of-sample RMSPE (Panel (d)) generated by the factor models using PCA and Risk-Premium PCA (RPPCA) of the 364 delta-hedged out-of-the-money (OTM) call and put option portfolio returns with four levels of γ. The RP-PCA method is proposed by Lettau and Pelger (2020a). The 364 OTM delta-hedged call and put option portfolios are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A8: Scree Test for Missing Value Treated Dataset

(a) The Scree Plot

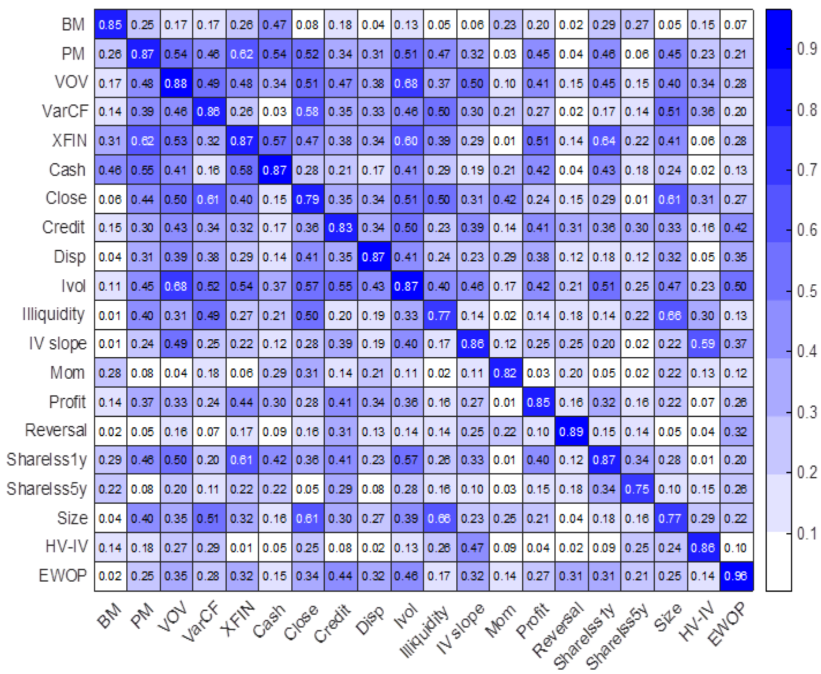


(b) GR and ER Values



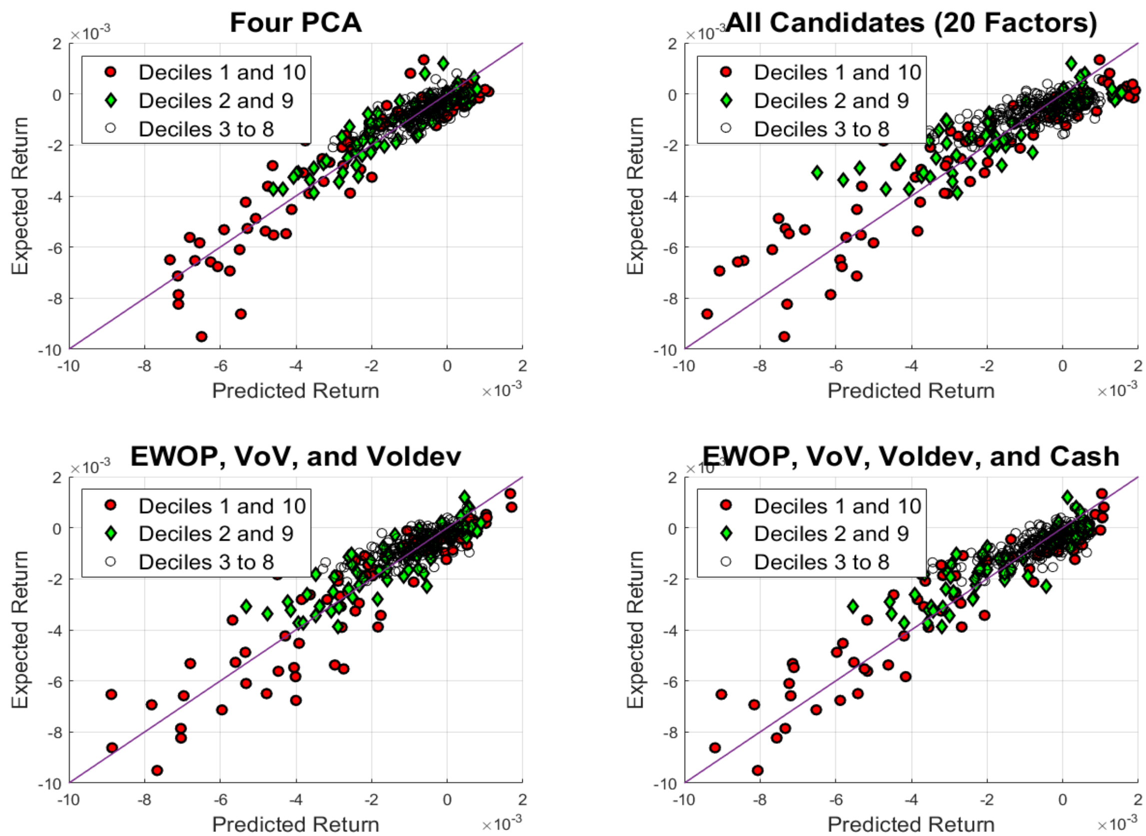
This figure shows the scree plot and GR and ER values for the missing value treated dataset. Panel (a) plots the largest fifteen eigenvalues from the sample second-moment matrix of the 370 delta-hedged at-the-money call and put option portfolio returns. Panel (b) presents the results from the Ahn and Horenstein (2013) Eigenvalue Ratio (ER) and the Growth Ratio (GR) estimators. The 370 ATM delta-hedged call and put option portfolios are obtained by sorting in deciles (quintiles for Credit) by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, illiquidity, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A9: Correlation Heatmap of at-the-money Call and Put Factors from the Treated Dataset



This figure shows the correlation heatmap between candidate factors in ATM call options and put options in the missing value treated dataset. Horizontal axis represents call options and vertical axis represents put options. The 19 candidate factors in call options and the 19 factors candidate in put options are 10-minus-1 (5-minus-1 for Credit) long-short at-the-money option portfolio returns sorted by the following characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. EWOP is the equal-weighted option portfolio of the 185 delta-hedged portfolios of calls or puts constructed with the 19 characteristics. Correlations are reported in absolute value. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Figure A10: Pricing Performance of Benchmark Factor Models on Treated Dataset



This figure shows the performance of the benchmark four-PCA-factor-model and benchmark candidate factor models in terms of the relation between average return of the treated dataset and predicted return by the benchmark factors. The first panel of the figure shows the relation between treated average returns and benchmark predicted returns from models regressing the 370 option portfolios of the treated dateset, 185 delta-hedged ATM call and 185 delta-hedged ATM put option treated portfolios, onto the first four PCA benchmark factors. The other three panels report the relation between average treated returns and predicted benchmark returns using all candidate factors (20 factors), using EWOP, VOV and HV–IV, and using EWOP, VOV, HV–IV, and Cash. EWOP is the equal weighted return of 370 option treated portfolios. VOV, HV–IV, and Cash are the 10-minus-1 long-short factors sorted by VOV, HV–IV, and Cash from the benchmark dataset. Decile portfolios for the treated dateset are displayed in three groups: 1) deciles 1 and 10, 2) deciles 2 and 9, and 3) deciles 3 to 8. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A1: Delta-hedged ATM Call Option Return Sorted by 19 Characteristics

	1	2	3	4	5	6	7	8	9	10	L-S
Size	-1.14	-0.75	-0.51	-0.38	-0.30	-0.25	-0.19	-0.13	-0.09	-0.04	1.1***
	(-19.1)	(-13.5)	(-10.0)	(-8.0)	(-6.7)	(-5.6)	(-4.3)	(-3.0)	(-2.1)	(-0.9)	(24.7)
Ivol	-0.13	-0.15	-0.20	-0.24	-0.28	-0.31	-0.41	-0.46	-0.63	-0.93	-0.81***
	(-3.8)	(-4.1)	(-5.1)	(-5.7)	(-6.7)	(-6.6)	(-8.3)	(-8.8)	(-11.0)	(-13.2)	(-15.1)
HV-IV	-1.33	-0.63	-0.43	-0.32	-0.27	-0.22	-0.18	-0.15	-0.11	-0.11	1.23***
	(-23.1)	(-12.5)	(-9.2)	(-6.6)	(-6.0)	(-5.0)	(-4.1)	(-3.4)	(-2.4)	(-2.3)	(27.3)
IV_slope	-1.23	-0.55	-0.38	-0.29	-0.25	-0.19	-0.20	-0.17	-0.17	-0.33	0.9***
	(-18.5)	(-10.1)	(-8.0)	(-6.2)	(-5.7)	(-4.4)	(-4.8)	(-4.2)	(-4.2)	(-7.5)	(20.5)
BM	-0.62	-0.41	-0.38	-0.32	-0.36	-0.33	-0.31	-0.32	-0.29	-0.38	0.24***
	(-12.1)	(-8.8)	(-8.1)	(-7.4)	(-8.3)	(-7.3)	(-6.8)	(-7.2)	(-6.1)	(-6.8)	(6.0)
Credit	-0.03	-0.12	-0.21	-0.29	-0.43						-0.4***
	(-0.7)	(-3.0)	(-4.8)	(-6.3)	(-7.7)						(-12.2)
VOV	-0.10	-0.12	-0.17	-0.20	-0.24	-0.30	-0.35	-0.45	-0.64	-1.18	-1.08***
	(-2.8)	(-3.0)	(-4.2)	(-4.4)	(-5.4)	(-6.3)	(-7.3)	(-8.8)	(-11.0)	(-18.8)	(-20.7)
Illiquidity	-0.03	-0.09	-0.13	-0.21	-0.27	-0.31	-0.41	-0.55	-0.70	-1.05	-1.02***
	(-0.8)	(-2.1)	(-3.1)	(-4.8)	(-5.9)	(-6.6)	(-8.7)	(-10.6)	(-13.3)	(-18.3)	(-24.6)
Reversal	-0.64	-0.42	-0.35	-0.31	-0.31	-0.28	-0.28	-0.31	-0.38	-0.49	0.15***
	(-9.7)	(-7.9)	(-7.4)	(-7.0)	(-7.8)	(-6.8)	(-6.8)	(-7.3)	(-8.7)	(-9.2)	(3.3)
Mom	-0.65	-0.46	-0.40	-0.36	-0.31	-0.29	-0.28	-0.28	-0.31	-0.42	0.23***
	(-10.0)	(-9.3)	(-9.2)	(-8.4)	(-7.6)	(-6.8)	(-6.7)	(-6.2)	(-6.4)	(-7.6)	(4.7)
VarCF	-0.16	-0.20	-0.23	-0.24	-0.25	-0.32	-0.44	-0.49	-0.61	-0.74	-0.58***
	(-3.9)	(-4.8)	(-5.9)	(-5.7)	(-5.7)	(-7.0)	(-9.5)	(-10.2)	(-11.5)	(-12.8)	(-13.9)
Cash	-0.23	-0.21	-0.25	-0.27	-0.26	-0.26	-0.31	-0.37	-0.47	-0.95	-0.72***
	(-5.2)	(-4.7)	(-5.5)	(-6.2)	(-4.9)	(-5.5)	(-6.5)	(-7.5)	(-9.4)	(-15.7)	(-15.8)
Disp	-0.19	-0.21	-0.22	-0.23	-0.26	-0.32	-0.41	-0.41	-0.51	-0.54	-0.35***
	(-4.7)	(-4.9)	(-4.6)	(-5.2)	(-5.6)	(-6.5)	(-8.6)	(-6.6)	(-9.7)	(-9.9)	(-10.3)
ShareIss1y	-0.24	-0.22	-0.27	-0.31	-0.35	-0.38	-0.42	-0.47	-0.55	-0.54	-0.3***
	(-5.1)	(-5.2)	(-6.5)	(-6.9)	(-7.2)	(-7.8)	(-9.0)	(-9.9)	(-11.0)	(-9.4)	(-6.8)
ShareIss5y	-0.44	-0.24	-0.32	-0.35	-0.33	-0.31	-0.34	-0.39	-0.42	-0.32	0.13**
	(-9.8)	(-5.7)	(-6.9)	(-7.4)	(-7.2)	(-7.1)	(-7.3)	(-9.0)	(-8.2)	(-6.1)	(3.8)
PM	-1.05	-0.50	-0.34	-0.31	-0.28	-0.25	-0.22	-0.21	-0.17	-0.24	0.82***
	(-16.4)	(-9.3)	(-6.2)	(-7.0)	(-6.8)	(-5.9)	(-5.2)	(-4.9)	(-3.9)	(-5.5)	(18.6)
Close	-1.22	-0.76	-0.53	-0.37	-0.25	-0.19	-0.15	-0.12	-0.10	-0.07	1.16***
	(-17.4)	(-14.3)	(-10.7)	(-7.9)	(-5.7)	(-4.5)	(-3.5)	(-2.9)	(-2.6)	(-1.5)	(21.7)
Profit	-0.65	-0.42	-0.32	-0.29	-0.24	-0.22	-0.23	-0.22	-0.20	-0.31	0.34***
	(-11.4)	(-8.2)	(-6.6)	(-6.2)	(-5.2)	(-5.4)	(-5.5)	(-5.4)	(-4.9)	(-7.2)	(9.7)
XFIN	-0.27	-0.24	-0.25	-0.29	-0.31	-0.34	-0.37	-0.39	-0.47	-0.89	-0.62***
	(-6.4)	(-5.2)	(-5.8)	(-6.3)	(-6.4)	(-7.3)	(-8.4)	(-7.9)	(-8.9)	(-14.6)	(-13.9)

At the end of each month, we group delta-hedged ATM call options in deciles (quintiles for Credit) by sorting on the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOC is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. We report equal-weighted returns and the long-short (10-1) returns along with their t-statistics in parentheses based on Newey-West standard errors with optimal lag length. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A2: Delta-hedged ATM Put Option Return Sorted by 19 Characteristics

	1	2	3	4	5	6	7	8	9	10	L-S
Size	-1.26	-0.82	-0.56	-0.41	-0.33	-0.28	-0.21	-0.16	-0.13	-0.06	1.2***
	(-20.8)	(-14.5)	(-10.9)	(-8.4)	(-7.0)	(-6.2)	(-4.6)	(-3.6)	(-2.9)	(-1.5)	(25.6)
Ivol	-0.17	-0.19	-0.22	-0.25	-0.30	-0.33	-0.41	-0.51	-0.70	-1.13	-0.97***
	(-4.7)	(-4.9)	(-5.4)	(-5.6)	(-6.8)	(-6.8)	(-8.2)	(-9.4)	(-11.8)	(-16.0)	(-17.0)
HV-IV	-1.43	-0.66	-0.46	-0.36	-0.30	-0.25	-0.22	-0.18	-0.16	-0.19	1.24***
	(-23.4)	(-13.0)	(-9.7)	(-7.7)	(-6.4)	(-5.5)	(-4.9)	(-3.9)	(-3.4)	(-3.9)	(27.0)
IV_slope	-1.38	-0.58	-0.38	-0.30	-0.27	-0.22	-0.23	-0.20	-0.22	-0.42	0.96***
	(-20.2)	(-10.3)	(-7.7)	(-6.3)	(-6.2)	(-4.9)	(-5.3)	(-4.9)	(-5.1)	(-8.9)	(19.9)
BM	-0.70	-0.42	-0.39	-0.34	-0.37	-0.36	-0.34	-0.33	-0.34	-0.47	0.22***
	(-13.2)	(-8.9)	(-7.9)	(-7.5)	(-8.2)	(-7.9)	(-7.1)	(-7.3)	(-7.1)	(-9.0)	(6.4)
Credit	-0.08	-0.15	-0.22	-0.30	-0.50						-0.42***
	(-1.9)	(-3.7)	(-4.7)	(-6.5)	(-8.7)						(-12.1)
VOV	-0.13	-0.14	-0.19	-0.21	-0.26	-0.32	-0.37	-0.49	-0.73	-1.35	-1.22***
	(-3.4)	(-3.4)	(-4.7)	(-4.6)	(-5.6)	(-6.4)	(-7.5)	(-9.6)	(-12.6)	(-21.0)	(-23.2)
Illiquidity	-0.05	-0.12	-0.15	-0.23	-0.29	-0.35	-0.44	-0.57	-0.77	-1.17	-1.12***
	(-1.3)	(-2.8)	(-3.5)	(-5.1)	(-6.2)	(-7.1)	(-9.1)	(-11.2)	(-14.0)	(-18.9)	(-23.2)
Reversal	-0.66	-0.40	-0.34	-0.33	-0.34	-0.31	-0.33	-0.37	-0.46	-0.68	-0.02
	(-10.4)	(-7.5)	(-6.9)	(-7.3)	(-8.2)	(-7.3)	(-7.7)	(-8.2)	(-10.2)	(-12.1)	(-0.3)
Mom	-0.77	-0.50	-0.43	-0.38	-0.33	-0.31	-0.31	-0.29	-0.33	-0.49	0.28***
	(-12.3)	(-10.0)	(-9.7)	(-8.8)	(-7.9)	(-7.1)	(-7.3)	(-6.2)	(-6.5)	(-8.5)	(6.7)
VarCF	-0.16	-0.21	-0.24	-0.28	-0.29	-0.37	-0.45	-0.51	-0.64	-0.82	-0.66***
	(-3.8)	(-4.9)	(-5.9)	(-6.3)	(-6.5)	(-7.8)	(-9.4)	(-10.0)	(-11.9)	(-14.0)	(-15.6)
Cash	-0.29	-0.27	-0.29	-0.32	-0.31	-0.32	-0.32	-0.39	-0.48	-0.97	-0.68***
	(-6.4)	(-6.0)	(-6.3)	(-7.0)	(-6.3)	(-6.4)	(-6.4)	(-8.0)	(-9.3)	(-15.8)	(-15.5)
Disp	-0.22	-0.22	-0.21	-0.26	-0.29	-0.35	-0.44	-0.47	-0.59	-0.61	-0.4***
	(-5.2)	(-5.1)	(-4.2)	(-5.9)	(-6.1)	(-7.0)	(-9.3)	(-8.4)	(-11.0)	(-11.0)	(-11.2)
ShareIss1y	-0.32	-0.25	-0.28	-0.33	-0.38	-0.40	-0.44	-0.50	-0.60	-0.60	-0.28***
	(-7.5)	(-5.8)	(-6.5)	(-7.3)	(-7.7)	(-7.9)	(-9.3)	(-10.3)	(-11.3)	(-10.0)	(-7.3)
ShareIss5y	-0.54	-0.27	-0.32	-0.35	-0.35	-0.32	-0.36	-0.42	-0.45	-0.32	0.22**
	(-11.6)	(-6.1)	(-6.9)	(-7.5)	(-7.6)	(-7.0)	(-7.3)	(-9.2)	(-8.6)	(-6.1)	(6.8)
PM	-1.15	-0.54	-0.39	-0.33	-0.30	-0.27	-0.26	-0.24	-0.19	-0.27	0.88***
	(-17.5)	(-9.9)	(-7.9)	(-7.3)	(-7.3)	(-6.0)	(-6.0)	(-5.4)	(-4.2)	(-5.9)	(19.9)
Close	-1.29	-0.82	-0.57	-0.41	-0.29	-0.23	-0.19	-0.15	-0.15	-0.11	1.18***
	(-18.6)	(-15.6)	(-11.0)	(-8.6)	(-6.5)	(-5.4)	(-4.2)	(-3.5)	(-3.5)	(-2.4)	(22.9)
Profit	-0.70	-0.47	-0.34	-0.30	-0.25	-0.23	-0.24	-0.24	-0.26	-0.34	0.35***
	(-11.8)	(-9.0)	(-6.7)	(-6.3)	(-5.3)	(-5.1)	(-5.6)	(-5.8)	(-6.1)	(-7.7)	(10.1)
XFIN	-0.30	-0.27	-0.28	-0.31	-0.33	-0.37	-0.40	-0.42	-0.50	-0.99	-0.7***
	(-7.0)	(-6.7)	(-6.5)	(-6.6)	(-6.7)	(-7.7)	(-8.7)	(-8.2)	(-9.4)	(-16.1)	(-15.9)

At the end of each month, we group delta-hedged ATM put options in deciles (quintiles for Credit) by sorting on the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOC is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. We report equal-weighted returns and the long-short (10-1) returns along with their t-statistics in parentheses based on Newey-West standard errors with optimal lag length. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A3: Definition of Variables in the Robustness Check

	Description	Reference
1	Change in capital investment (ChInvIA)	Abarbanell and Bushee (1998)
2	Effective Tax Rate (ETR)	Abarbanell and Bushee (1998)
3	Gross margin growth to sales growth (GrGMToGrSales)	Abarbanell and Bushee (1998)
4	Sales growth over inventory growth (GrSaleToGrInv)	Abarbanell and Bushee (1998)
5	Sales growth over overhead growth (GrSaleToGrOverhead)	Abarbanell and Bushee (1998)
6	Change in sales vs change in receivables (GrSaleToGrReceivables)	Abarbanell and Bushee (1998)
7	Laborforce efficiency (LaborforceEfficiency)	Abarbanell and Bushee (1998)
8	Change in gross margin vs sales (pchgm_pchsale)	Abarbanell and Bushee (1998)
9	Broker-Dealer leverage beta (BetaBDLeverage)	Adrian, Etula, and Muir (2014)
10	Idiosyncratic risk (IdioVolAHT)	Ali, Hwang, and Trombley (2003)
11	Earnings consistency (EarningsConsistency)	Alwathainani (2009)
12	Change in capex-2Y (grcapx)	Anderson and Garcia-Feijoo (2006)
13	Change in capex-3Y (grcapx3y)	Anderson and Garcia-Feijoo (2006)
14	Idiosyncratic risk-3 factors (IdioVol3F)	Ang, Hodrick, Xing, and Zhang (2006b)
15	Downside beta (DownsideBeta)	Ang, Chen, and Xing (2006a)
16	Change in Return on assets (ChangeRoA)	Balakrishnan, Bartov, and Faurel (2010)
17	Change in Return on equity (ChangeRoE)	Balakrishnan, Bartov, and Faurel (2010)
18	Return on assets quarterly (roaq)	Balakrishnan, Bartov, and Faurel (2010)
19	Maximum return over month (MaxRet)	Bali et al. (2011) & Chen et al. (2021)
20	Return skewness (ReturnSkew)	Bali, Engle, and Murray (2016)
21	Idiosyncratic skewness-3 factors (ReturnSkew3F)	Bali, Engle, and Murray (2016)
22	Cash-based operating profitability (CBOperProf)	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)
23	Operating profitability R&D (OperProfRD)	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)
24	Sales-to-price (SP)	Barbee Jr, Mukherji, and Raines (1996)
25	Firm age based on CRSP (FirmAge)	Barry and Brown (1984)
26	Earnings-to-Price Ratio (EP)	Basu (1977)
27	Employment growth (hire)	Belo, Lin, and Bazdresch (2014a)
28	Inventory growth (InvGrowth)	Belo and Lin (2012)
29	Brand capital to assets (BrandCapital)	Belo, Lin, and Vitorino (2014b)
30	Market leverage (Leverage)	Bhandari (1988)
31	Momentum based on FF3 residuals (ResidualMomentum)	Blitz, Huij, and Martens (2011)
32	Net Payout Yield (NetPayoutYield)	Boudoukh et al. (2007)
33	Payout Yield (PayoutYield)	Boudoukh et al. (2007)
34	Net debt financing (NetDebtFinance)	Bradshaw, Richardson, and Sloan (2006)
35	Net equity financing (netequityfinance)	Bradshaw, Richardson, and Sloan (2006)
36	Past trading volume (DolVol)	Brennan, Chordia, and Subrahmanyam (1998)

37	Return on invested capital (roic)	Brown and Rowe (2007)
38	Failure probability (FailureProbability)	Campbell, Hilscher, and Szilagyi (2008)
39	Earnings announcement return (AnnouncementReturn)	Chan, Jegadeesh, and Lakonishok (1996)
40	Advertising Expense (AdExp)	Chan, Lakonishok, and Sougiannis (2001)
41	R&D to sales (rd_sale)	Chan, Lakonishok, and Sougiannis (2001)
42	Cash Productivity (CashProd)	Chandrashekar and Rao (2009)
43	Share turnover volatility (std_turn)	Chordia, Subrahmanyam, and Anshuman (2001)
44	Volume variance (VolSD)	Chordia, Subrahmanyam, and Anshuman (2001)
45	R&D ability (RDAbility)	Cohen, Diether, and Malloy (2013)
46	Asset growth (AssetGrowth)	Cooper, Gulen, and Schill (2008)
47	Long-vs-short EPS forecasts (EarningsForecastDisparity)	Da and Warachka (2011)
48	Composite equity issuance (CompEquIss)	Daniel and Titman (2006)
49	Intangible return using BM (IntanBM)	Daniel and Titman (2006)
50	Intangible return using CFtoP (IntanCFP)	Daniel and Titman (2006)
51	Intangible return using EP (IntanEP)	Daniel and Titman (2006)
52	Intangible return using Sale2P (IntanSP)	Daniel and Titman (2006)
53	Long-run reversal (LRreversal)	De Bondt and Thaler (1985)
54	Medium-run reversal (MRreversal)	De Bondt and Thaler (1985)
55	Short Interest (ShortInterest)	Dechow, Hutton, Meulbroek, and Sloan (2001)
56	Equity Duration (EquityDuration)	Dechow, Sloan, and Soliman (2004)
57	Operating cash flows to price (cfp)	Desai, Rajgopal, and Venkatachalam (2004)
58	Altman Z-Score (zscore)	Dimson (1979)
59	Dimson beta (BetaDimson)	Eisfeldt and Papanikolaou (2013)
60	Organizational capital (OrgCap)	Elgers, Lo, and Pfeiffer Jr (2001)
61	Earnings Forecast to price (sfe)	Fairfield, Whisenant, and Yohn (2003)
62	Growth in long term operating assets (GrLTNOA)	Fama and French (1992)
63	Total assets to market (AM)	Fama and French (1992)
64	Book leverage annual (BookLeverage)	Fama and French (1992)
65	CAPM beta (Beta)	Fama and MacBeth (1973)
66	CAPM beta squared (BetaSquared)	Fama and MacBeth (1973)
67	Earnings surprise (EarningsSurprise)	Foster, Olsen, and Shevlin (1984)
68	Accrual quality (AccrualQuality)	Francis, LaFond, Olsson, and Schipper (2005)
69	Analyst value (AnalystValue)	Francis, LaFond, Olsson, and Schipper (2005)
70	Analyst optimism (AOP)	Francis, LaFond, Olsson, and Schipper (2005)
71	Pension funding status (FR)	Franzoni and Marin (2006)
72	Frazzini-Pedersen beta (BetaFP)	Frazzini and Pedersen (2014)
73	52 week high (High52)	George and Hwang (2004)
74	Percent Operating Accruals (PctAcc)	Hafzalla et al. (2011)
75	Percent Total Accruals (PctTotAcc)	Hafzalla et al. (2011)
76	Tangibility (tang)	Hahn and Lee (2009)
77	Coskewness (Coskewness)	Harvey and Siddique (2000)
78	Capital turnover (CapTurnover)	Haugen and Baker (1996)
79	Net income / book equity (RoE)	Haugen and Baker (1996)
80	Volume to market equity (VolMkt)	Haugen and Baker (1996)

81	Volume Trend (VolumeTrend)	Haugen and Baker (1996)
82	Momentum without the seasonal part (Mom12mOffSeason)	Heston and Sadka (2008)
83	Off season long-term reversal (MomOffSeason)	Heston and Sadka (2008)
84	Off season reversal years 6 to 10 (MomOffSeason06YrPlus)	Heston and Sadka (2008)
85	Off season reversal years 11 to 15 (MomOffSeason11YrPlus)	Heston and Sadka (2008)
86	Off season reversal years 16 to 20 (MomOffSeason16YrPlus)	Heston and Sadka (2008)
87	Return seasonality years 2 to 5 (MomSeason)	Heston and Sadka (2008)
88	Return seasonality last year (MomSeasonShort)	Heston and Sadka (2008)
89	Net Operating Assets (NOA)	Hirshleifer, Hou, Teoh, and Zhang (2004)
90	change in net operating assets (dNoa)	Hirshleifer, Hou, Teoh, and Zhang (2004)
91	Depreciation to PPE (depr)	Holthausen and Larcker (1992)
92	Bid-ask spread (TAQ) (bidask)	Hou and Robinson (2006)
93	Industry concentration (sales) (Herf)	Hou and Robinson (2006)
94	Industry concentration (assets) (HerfAsset)	Hou and Robinson (2006)
95	Industry concentration (equity) (HerfBE)	Jegadeesh and Livnat (2006)
96	Revenue Surprise (RevenueSurprise)	Jegadeesh and Titman (1993)
97	Momentum 6-month (Mom6m)	Jegadeesh and Titman (1993)
98	Change in recommendation (ChangeInRecommendation)	Jegadeesh, Kim, Krische, and Lee (2004)
99	Tail risk beta (BetaTailRisk)	Kelly and Jiang (2014)
100	Cash flow to market (CF)	Lakonishok, Shleifer, and Vishny (1994)
101	Revenue Growth Rank (MeanRankRevGrowth)	Lakonishok, Shleifer, and Vishny (1994)
102	Real dirty surplus (RDS)	Landsman, Miller, Peasnell, and Yeh (2011)
103	Days with zero trades 6 months (zerotrade)	Liu (2006)
104	Days with zero trades 1 month (zerotradeAlt1)	Liu (2006)
105	Growth in book equity (ChEQ)	Lockwood and Prombutr (2010)
106	Earnings surprise streak (EarningsStreak)	Loh and Warachka (2012)
107	Growth in advertising expenses (GrAdExp)	Lou (2014)
108	Enterprise Multiple (EntMult)	Loughran and Wellman (2011)
109	Composite debt issuance (CompositeDebtIssuance)	Lyandres, Sun, and Zhang (2008)
110	change in ppe and inv/assets (InvestPPEInv)	Lyandres, Sun, and Zhang (2008)
111	Efficient frontier index (Frontier)	Nguyen and Swanson (2009)
112	Operating leverage (OPLeverage)	Novy-Marx (2011)
113	Intermediate Momentum (IntMom)	Novy-Marx (2012)
114	Gross profits / total assets (GP)	Novy-Marx (2013)
115	Asset liquidity over book assets (AssetLiquidityBook)	Ortiz-Molina and Phillips (2014)
116	CF to debt (cashdebt)	Ou and Penman (1989)
117	Current Ratio (currat)	Ou and Penman (1989)
118	Change in Current Ratio (pchcurrat)	Ou and Penman (1989)
119	Change in quick ratio (pchquick)	Ou and Penman (1989)
120	Change in sales to inventory (pchsaleinv)	Ou and Penman (1989)

121	Quick ratio (quick)	Ou and Penman (1989)
122	Sales to cash ratio (salecash)	Ou and Penman (1989)
123	Sales to inventory (saleinv)	Ou and Penman (1989)
124	Sales to receivables (salerec)	Ou and Penman (1989)
125	Leverage component of BM (BPEBM)	Penman, Richardson, and Tuna (2007)
126	Enterprise component of BM (EBM)	Penman, Richardson, and Tuna (2007)
127	Net debt to price (NetDebtPrice)	Penman, Richardson, and Tuna (2007)
128	Order backlog (OrderBacklog)	Rajgopal, Shevlin, and Venkatachalam (2003)
129	Change in current operating assets (DelCOA)	Richardson, Sloan, Soliman, and Tuna (2005)
130	Change in current operating liabilities (DelCOL)	Richardson, Sloan, Soliman, and Tuna (2005)
131	Change in equity to assets (DelEqu)	Richardson, Sloan, Soliman, and Tuna (2005)
132	Change in financial liabilities (DelFINL)	Richardson, Sloan, Soliman, and Tuna (2005)
133	Change in net financial assets (DelNetFin)	Richardson, Sloan, Soliman, and Tuna (2005)
134	Total accruals (TotalAccruals)	Richardson, Sloan, Soliman, and Tuna (2005)
135	Book to market using most recent ME (BM)	Barr Rosenberg and Lanstein (1985)
136	Accruals (Accruals)	Sloan (1996)
137	Asset Turnover (AssetTurnover)	Soliman (2008)
138	Change in Asset Turnover (ChAssetTurnover)	Soliman (2008)
139	Change in Noncurrent Operating Assets (ChNCOA)	Soliman (2008)
140	Change in Net Noncurrent Op Assets (ChNNCOA)	Soliman (2008)
141	Change in Net Working Capital (ChNWC)	Soliman (2008)
142	Change in Profit Margin (ChPM)	Soliman (2008)
143	Return on Net Operating Assets (RetNOA)	Soliman (2008)
144	Inventory Growth (ChInv)	Thomas and Zhang (2002)
145	Change in Taxes (ChTax)	Thomas and Zhang (2011)
146	Investment to revenue (Investment)	Titman, Wei, and Xie (2004)
147	Real estate holdings (realestate)	Tuzel (2010)
148	Whited-Wu index (WW)	Whited and Wu (2006)
149	Abnormal Accruals (AbnormalAccruals)	Xie (2001)

This table reports the definition of 149 variables used to construct test assets. The variables are downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com). The sample period is from January 1996 to December 2021.

Table A4: Portfolio Sorts for the 149 Characteristics in the Robustness Check

	Call						Put					
	P1	t-stat	P10	t-stat	P10-P1	t-stat	P1	t-stat	P10	t-stat	P10-P1	t-stat
AbnormalAccruals	-0.59	(-11.5)	-0.52	(-10.4)	0.08	(2.70)	-0.66	(-12.4)	-0.55	(-10.4)	0.12	(3.80)
AccrualQuality	-0.17	(-4.4)	-0.78	(-14.2)	-0.60	(-14.5)	-0.21	(-5.0)	-0.82	(-14.0)	-0.61	(-13.6)
Accruals	-0.54	(-10.8)	-0.50	(-10.1)	0.05	(1.80)	-0.63	(-12.2)	-0.57	(-11.2)	0.06	(2.10)
AdExp	-0.28	(-4.9)	-0.43	(-6.3)	-0.15	(-2.6)	-0.31	(-5.5)	-0.61	(-11.7)	-0.30	(-5.7)
AM	-0.50	(-9.1)	-0.31	(-4.9)	0.19	(3.40)	-0.59	(-10.5)	-0.44	(-7.6)	0.14	(3.00)
AnalystValue	-0.79	(-11.6)	-0.32	(-6.4)	0.46	(9.50)	-0.86	(-13.7)	-0.37	(-7.1)	0.48	(10.30)
AnnouncementReturn	-0.53	(-9.6)	-0.37	(-7.0)	0.16	(5.00)	-0.58	(-10.3)	-0.45	(-8.4)	0.13	(4.20)
AOP	-0.32	(-7.1)	-0.35	(-7.2)	-0.03	(-0.9)	-0.37	(-7.5)	-0.36	(-7.2)	0.01	(0.20)
AssetGrowth	-0.70	(-12.3)	-0.53	(-10.1)	0.17	(4.80)	-0.79	(-14.5)	-0.60	(-10.9)	0.19	(5.30)
AssetLiquidityBook	-0.32	(-7.6)	-0.94	(-16.1)	-0.62	(-14.3)	-0.35	(-8.4)	-0.97	(-16.4)	-0.62	(-15.8)
AssetTurnover	-0.59	(-10.5)	-0.38	(-8.3)	0.21	(5.80)	-0.67	(-11.3)	-0.41	(-8.8)	0.26	(7.50)
Beta	-0.29	(-7.8)	-0.66	(-10.4)	-0.37	(-8.2)	-0.33	(-8.7)	-0.72	(-10.9)	-0.38	(-8.0)
BetaBDLeverage	-0.57	(-10.8)	-0.58	(-11.8)	-0.01	(-0.2)	-0.61	(-11.1)	-0.63	(-12.4)	-0.02	(-0.4)
BetaDimson	-0.57	(-12.0)	-0.56	(-8.7)	0.01	(0.20)	-0.64	(-13.3)	-0.66	(-10.3)	-0.02	(-0.4)
BetaFP	-0.34	(-8.9)	-0.43	(-6.3)	-0.10	(-1.8)	-0.37	(-9.8)	-0.54	(-7.9)	-0.17	(-3.2)
BetaSquared	-0.66	(-10.5)	-0.27	(-7.3)	0.40	(8.60)	-0.72	(-11.0)	-0.30	(-7.8)	0.42	(8.70)
BetaTailRisk	-0.37	(-7.3)	-0.62	(-12.2)	-0.25	(-7.0)	-0.42	(-8.0)	-0.65	(-12.6)	-0.23	(-6.3)
bidask	-0.18	(-3.8)	-0.64	(-13.4)	-0.46	(-12.7)	-0.21	(-4.4)	-0.66	(-13.2)	-0.45	(-12.3)
BM	-0.44	(-8.3)	-0.44	(-6.9)	0.01	(0.10)	-0.51	(-9.3)	-0.52	(-9.2)	0.00	(-0.1)
BookLeverage	-0.70	(-13.4)	-0.28	(-5.5)	0.41	(11.00)	-0.76	(-14.3)	-0.36	(-6.9)	0.40	(10.80)
BPEBM	-0.54	(-10.7)	-0.34	(-6.2)	0.19	(6.60)	-0.59	(-11.7)	-0.44	(-8.5)	0.16	(6.10)
BrandCapital	-0.24	(-4.5)	-0.24	(-3.8)	0.00	(0.10)	-0.31	(-5.6)	-0.39	(-8.0)	-0.08	(-1.8)
CapTurnover	-0.75	(-13.0)	-0.29	(-6.5)	0.46	(11.30)	-0.83	(-13.6)	-0.32	(-7.3)	0.51	(12.70)
cashdebt	-1.17	(-18.8)	-0.27	(-6.1)	0.90	(20.50)	-1.23	(-19.3)	-0.29	(-6.2)	0.95	(21.50)
CashProd	-0.28	(-5.7)	-0.28	(-6.1)	0.00	(-0.0)	-0.37	(-7.3)	-0.35	(-7.4)	0.01	(0.40)
CBOperProf	-0.94	(-14.7)	-0.29	(-6.7)	0.65	(15.90)	-1.09	(-16.7)	-0.30	(-6.7)	0.79	(18.10)

CF	-1.09	(-16.6)	-0.35	(-6.9)	0.74	(15.70)	-1.18	(-18.4)	-0.42	(-8.4)	0.76	(16.30)
cfp	-1.09	(-16.7)	-0.35	(-6.8)	0.73	(15.90)	-1.20	(-18.8)	-0.43	(-8.3)	0.77	(16.80)
ChangeInRecommendation_ra	-0.36	(-7.7)	-0.35	(-7.6)	0.01	(0.30)	-0.38	(-7.9)	-0.39	(-7.8)	-0.01	(-0.3)
ChangeRoA	-0.72	(-13.0)	-0.69	(-13.3)	0.03	(0.80)	-0.80	(-14.4)	-0.73	(-13.4)	0.07	(2.40)
ChangeRoE	-0.71	(-13.5)	-0.64	(-12.5)	0.07	(2.30)	-0.81	(-15.2)	-0.69	(-12.8)	0.12	(4.00)
ChAssetTurnover	-0.41	(-8.5)	-0.39	(-8.2)	0.02	(0.80)	-0.42	(-8.8)	-0.41	(-8.4)	0.01	(0.50)
ChEQ	-0.68	(-11.7)	-0.54	(-10.4)	0.14	(4.10)	-0.75	(-13.4)	-0.59	(-11.1)	0.15	(4.50)
ChInv	-0.39	(-7.2)	-0.32	(-6.9)	0.07	(2.40)	-0.46	(-9.2)	-0.38	(-7.9)	0.08	(3.30)
ChInvIA	-0.61	(-12.0)	-0.50	(-10.1)	0.11	(3.50)	-0.66	(-12.9)	-0.57	(-10.9)	0.09	(2.90)
ChNCOA	-0.50	(-10.0)	-0.33	(-6.6)	0.17	(6.70)	-0.57	(-11.2)	-0.40	(-7.8)	0.17	(6.20)
ChNNCOA	-0.60	(-12.1)	-0.53	(-10.8)	0.08	(3.00)	-0.65	(-12.3)	-0.58	(-11.2)	0.08	(2.80)
ChNWC	-0.59	(-11.5)	-0.57	(-11.2)	0.02	(0.70)	-0.65	(-12.2)	-0.63	(-11.7)	0.02	(0.80)
ChPM	-0.74	(-13.3)	-0.71	(-12.8)	0.04	(1.20)	-0.81	(-14.3)	-0.74	(-13.1)	0.07	(2.20)
ChTax	-0.36	(-7.2)	-0.32	(-6.6)	0.04	(1.40)	-0.39	(-7.5)	-0.36	(-7.1)	0.03	(1.40)
CompEquIss	-0.20	(-4.0)	-0.84	(-14.5)	-0.64	(-13.5)	-0.24	(-4.8)	-0.88	(-14.8)	-0.64	(-14.1)
CompositeDebtIssuance_ran	-0.43	(-9.0)	-0.44	(-9.3)	0.00	(-0.1)	-0.46	(-9.5)	-0.48	(-9.8)	-0.01	(-0.4)
Coskewness	-0.26	(-5.2)	-0.48	(-9.8)	-0.22	(-6.8)	-0.30	(-5.9)	-0.55	(-11.3)	-0.25	(-7.7)
currat	-0.36	(-8.3)	-0.80	(-14.2)	-0.44	(-11.4)	-0.44	(-9.4)	-0.83	(-14.4)	-0.39	(-10.4)
DelCOA	-0.45	(-8.8)	-0.41	(-8.7)	0.04	(1.40)	-0.52	(-9.9)	-0.47	(-9.7)	0.04	(1.70)
DelCOL	-0.50	(-9.0)	-0.48	(-9.8)	0.02	(0.80)	-0.60	(-11.2)	-0.55	(-11.1)	0.04	(1.50)
DelEqu	-0.79	(-13.4)	-0.62	(-11.5)	0.17	(4.80)	-0.87	(-15.1)	-0.67	(-12.2)	0.20	(5.30)
DelFINL	-0.42	(-7.8)	-0.41	(-8.7)	0.01	(0.40)	-0.48	(-9.7)	-0.48	(-9.8)	0.00	(0.10)
DelNetFin	-0.54	(-10.9)	-0.58	(-11.4)	-0.04	(-1.5)	-0.61	(-11.8)	-0.62	(-12.0)	-0.01	(-0.4)
depr	-0.35	(-7.6)	-0.54	(-10.5)	-0.19	(-5.8)	-0.46	(-9.6)	-0.55	(-10.5)	-0.09	(-3.0)
dNoa	-0.60	(-11.6)	-0.41	(-8.2)	0.19	(6.80)	-0.67	(-12.6)	-0.49	(-9.5)	0.18	(6.40)
DolVol	-0.94	(-17.9)	-0.04	(-0.9)	0.90	(22.60)	-1.02	(-19.4)	-0.08	(-1.7)	0.94	(23.10)
DownsideBeta	-0.37	(-8.0)	-0.53	(-8.0)	-0.16	(-3.1)	-0.45	(-10.7)	-0.64	(-9.5)	-0.19	(-3.8)
EarningsConsistency	-0.63	(-11.4)	-0.34	(-7.6)	0.28	(7.20)	-0.66	(-11.3)	-0.36	(-7.6)	0.30	(7.10)
EarningsForecastDisparity	-0.31	(-5.8)	-0.41	(-7.5)	-0.11	(-3.0)	-0.36	(-6.7)	-0.46	(-7.9)	-0.10	(-2.9)
EarningsStreak	-0.72	(-11.6)	-0.63	(-12.4)	0.09	(2.60)	-0.84	(-14.3)	-0.69	(-13.5)	0.15	(4.40)

EarningsSurprise	-0.35	(-7.2)	-0.37	(-8.3)	-0.02	(-0.8)	-0.39	(-7.9)	-0.41	(-8.8)	-0.02	(-0.9)
EBM	-0.35	(-7.0)	-0.42	(-8.3)	-0.07	(-2.8)	-0.41	(-8.9)	-0.48	(-9.9)	-0.08	(-3.5)
EntMult	-0.37	(-7.2)	-0.27	(-5.0)	0.09	(2.30)	-0.38	(-7.7)	-0.30	(-5.5)	0.08	(2.20)
EP	-0.31	(-6.2)	-0.32	(-7.0)	-0.02	(-0.5)	-0.33	(-6.5)	-0.41	(-8.8)	-0.07	(-2.2)
EquityDuration	-0.33	(-7.0)	-0.89	(-14.6)	-0.55	(-14.8)	-0.40	(-8.0)	-1.00	(-16.7)	-0.61	(-15.7)
ETR	-0.48	(-9.2)	-0.41	(-8.6)	0.08	(3.00)	-0.53	(-9.8)	-0.46	(-9.4)	0.08	(3.00)
FailureProbability	-0.95	(-13.3)	-0.16	(-4.5)	0.80	(15.30)	-1.10	(-15.7)	-0.19	(-5.1)	0.91	(17.40)
FirmAge	-0.31	(-6.4)	-0.12	(-3.2)	0.18	(6.50)	-0.44	(-9.2)	-0.21	(-5.4)	0.23	(8.10)
FR	-0.31	(-6.0)	-0.15	(-2.9)	0.16	(3.90)	-0.44	(-8.0)	-0.21	(-3.8)	0.23	(5.30)
Frontier	-0.36	(-6.7)	-0.64	(-11.4)	-0.28	(-5.9)	-0.43	(-7.9)	-0.66	(-12.2)	-0.23	(-5.5)
GP	-1.13	(-17.9)	-0.34	(-7.7)	0.79	(18.70)	-1.21	(-18.8)	-0.36	(-8.3)	0.85	(20.50)
GrAdExp	-0.38	(-6.5)	-0.38	(-6.7)	0.00	-	-0.41	(-7.3)	-0.41	(-7.0)	0.00	(0.10)
grcapx	-0.65	(-13.2)	-0.57	(-11.5)	0.08	(2.50)	-0.71	(-13.6)	-0.62	(-11.9)	0.09	(2.60)
grcapx3y	-0.71	(-13.3)	-0.52	(-10.7)	0.19	(5.60)	-0.77	(-14.1)	-0.54	(-10.5)	0.23	(6.60)
GrGMToGrSales	-0.68	(-12.2)	-0.60	(-11.4)	0.08	(2.90)	-0.77	(-13.5)	-0.64	(-11.6)	0.13	(4.60)
GrLTNOA	-0.50	(-9.9)	-0.49	(-9.6)	0.01	(0.40)	-0.57	(-10.8)	-0.55	(-10.5)	0.02	(0.60)
GrSaleToGrInv	-0.40	(-8.1)	-0.49	(-9.6)	-0.09	(-3.3)	-0.45	(-8.7)	-0.54	(-9.9)	-0.08	(-2.9)
GrSaleToGrOverhead	-0.48	(-9.2)	-0.42	(-7.8)	0.06	(2.00)	-0.54	(-10.1)	-0.49	(-9.0)	0.05	(1.60)
GrSaleToGrReceivables_ran	-0.56	(-10.8)	-0.57	(-10.2)	-0.02	(-0.5)	-0.61	(-11.8)	-0.67	(-12.9)	-0.06	(-2.2)
Herf	-0.43	(-7.9)	-0.31	(-7.4)	0.13	(3.50)	-0.49	(-8.5)	-0.36	(-8.6)	0.13	(3.50)
HerfAsset	-0.51	(-9.8)	-0.26	(-6.1)	0.25	(7.60)	-0.55	(-10.0)	-0.32	(-7.3)	0.23	(6.70)
HerfBE	-0.51	(-9.7)	-0.33	(-7.4)	0.18	(5.30)	-0.55	(-10.0)	-0.39	(-8.7)	0.16	(4.60)
High52	-0.75	(-10.4)	-0.17	(-3.6)	0.58	(11.10)	-0.88	(-12.6)	-0.25	(-5.1)	0.64	(13.50)
hire	-0.52	(-10.6)	-0.48	(-9.6)	0.05	(1.70)	-0.61	(-11.8)	-0.56	(-10.9)	0.05	(1.70)
IdioVol3F	-0.11	(-3.1)	-0.96	(-13.6)	-0.86	(-16.2)	-0.15	(-3.9)	-1.18	(-16.9)	-1.04	(-18.7)
IdioVolAHT	-0.05	(-1.5)	-1.04	(-14.4)	-0.99	(-17.6)	-0.10	(-2.8)	-1.29	(-17.5)	-1.18	(-19.8)
IntanBM	-0.48	(-7.8)	-0.49	(-10.1)	-0.01	(-0.1)	-0.53	(-9.0)	-0.50	(-10.2)	0.03	(0.60)
IntanCFP	-0.36	(-6.5)	-0.39	(-7.6)	-0.03	(-0.8)	-0.41	(-7.9)	-0.41	(-7.7)	0.01	(0.10)
IntanEP	-0.38	(-7.4)	-0.36	(-7.1)	0.02	(0.60)	-0.43	(-8.4)	-0.38	(-7.4)	0.05	(1.20)
IntanSP	-0.64	(-10.8)	-0.25	(-5.3)	0.39	(9.30)	-0.70	(-11.8)	-0.26	(-5.4)	0.45	(11.20)

IntMom	-0.64	(-10.7)	-0.51	(-9.8)	0.12	(3.10)	-0.77	(-13.4)	-0.55	(-10.1)	0.23	(6.20)
Investment	-0.63	(-12.6)	-0.40	(-8.8)	0.22	(8.60)	-0.64	(-12.3)	-0.43	(-8.9)	0.22	(8.10)
InvestPPEInv	-0.50	(-10.7)	-0.28	(-5.6)	0.21	(8.00)	-0.56	(-11.5)	-0.38	(-7.3)	0.18	(6.50)
InvGrowth	-0.52	(-9.4)	-0.44	(-8.9)	0.08	(2.30)	-0.57	(-10.0)	-0.51	(-9.6)	0.06	(1.90)
LaborforceEfficiency	-0.65	(-12.1)	-0.62	(-11.6)	0.02	(0.80)	-0.72	(-13.2)	-0.68	(-12.3)	0.04	(1.40)
Leverage	-0.55	(-10.3)	-0.30	(-4.8)	0.25	(4.40)	-0.63	(-11.6)	-0.44	(-7.6)	0.19	(3.90)
LRreversal	-0.73	(-12.7)	-0.41	(-8.3)	0.32	(7.70)	-0.83	(-14.1)	-0.43	(-8.3)	0.40	(10.00)
MaxRet	-0.18	(-5.3)	-0.78	(-11.4)	-0.59	(-12.0)	-0.21	(-5.8)	-0.98	(-14.6)	-0.77	(-14.8)
MeanRankRevGrowth	-0.31	(-7.1)	-0.44	(-9.4)	-0.13	(-4.3)	-0.34	(-7.2)	-0.48	(-9.9)	-0.14	(-4.9)
Mom12mOffSeason	-0.57	(-9.1)	-0.53	(-8.6)	0.04	(0.90)	-0.64	(-10.9)	-0.63	(-9.9)	0.01	(0.30)
Mom6m	-0.67	(-10.5)	-0.46	(-7.9)	0.22	(4.40)	-0.76	(-12.3)	-0.53	(-8.9)	0.22	(5.00)
MomOffSeason	-0.59	(-10.2)	-0.53	(-9.8)	0.07	(1.70)	-0.70	(-12.5)	-0.60	(-10.8)	0.10	(2.60)
MomOffSeason06YrPlus	-0.60	(-11.6)	-0.47	(-9.5)	0.13	(3.90)	-0.63	(-12.0)	-0.50	(-9.9)	0.13	(4.00)
MomOffSeason11YrPlus	-0.48	(-9.3)	-0.43	(-10.4)	0.05	(1.40)	-0.52	(-9.8)	-0.44	(-10.1)	0.07	(2.30)
MomOffSeason16YrPlus	-0.29	(-6.3)	-0.38	(-8.0)	-0.09	(-2.4)	-0.35	(-7.5)	-0.38	(-8.2)	-0.03	(-0.8)
MomSeason	-0.61	(-11.1)	-0.54	(-10.2)	0.07	(2.20)	-0.70	(-13.1)	-0.57	(-10.3)	0.12	(4.10)
MomSeasonShort	-0.58	(-10.5)	-0.52	(-10.0)	0.06	(1.70)	-0.70	(-12.2)	-0.56	(-10.6)	0.13	(4.10)
MRreversal	-0.65	(-11.2)	-0.56	(-10.3)	0.09	(2.20)	-0.75	(-13.6)	-0.60	(-11.0)	0.15	(3.90)
NetDebtFinance	-0.37	(-7.0)	-0.41	(-8.9)	-0.04	(-1.4)	-0.45	(-9.0)	-0.47	(-9.7)	-0.02	(-0.8)
NetDebtPrice	-0.88	(-12.5)	-0.51	(-6.9)	0.37	(5.10)	-0.87	(-13.4)	-0.70	(-9.7)	0.17	(2.40)
netequityfinance	-0.42	(-10.3)	-1.64	(-29.1)	-1.22	(-30.2)	-0.47	(-11.2)	-1.74	(-29.7)	-1.27	(-32.7)
NetPayoutYield	-0.92	(-15.4)	-0.22	(-5.3)	0.71	(15.90)	-0.97	(-15.8)	-0.30	(-7.4)	0.67	(15.20)
NOA	-0.83	(-14.8)	-0.34	(-6.8)	0.49	(13.50)	-0.88	(-15.7)	-0.41	(-8.1)	0.47	(13.60)
OperProfRD	-0.80	(-12.2)	-0.25	(-5.8)	0.55	(13.30)	-0.95	(-14.8)	-0.26	(-5.9)	0.69	(16.40)
OPLeverage	-0.22	(-4.0)	-0.37	(-7.5)	-0.15	(-4.8)	-0.30	(-5.4)	-0.44	(-10.0)	-0.15	(-4.8)
OrderBacklog	-0.44	(-8.4)	-0.24	(-4.7)	0.19	(4.00)	-0.44	(-8.0)	-0.29	(-5.5)	0.15	(3.00)
OrgCap	-0.33	(-7.1)	-0.56	(-9.2)	-0.23	(-5.6)	-0.43	(-9.2)	-0.64	(-11.3)	-0.21	(-5.2)
PayoutYield	-0.42	(-8.7)	-0.36	(-7.8)	0.06	(1.60)	-0.41	(-8.0)	-0.45	(-9.6)	-0.04	(-1.1)
pchcurrat	-0.63	(-12.5)	-0.58	(-11.6)	0.05	(1.80)	-0.66	(-12.2)	-0.63	(-12.3)	0.03	(1.10)
pchgm_pchsale	-0.68	(-12.4)	-0.57	(-11.0)	0.11	(4.10)	-0.76	(-13.6)	-0.61	(-11.3)	0.15	(5.50)

pchquick	-0.61	(-12.2)	-0.55	(-11.0)	0.06	(2.20)	-0.66	(-12.2)	-0.60	(-11.4)	0.06	(2.20)
pchsaleinv	-0.42	(-8.2)	-0.48	(-9.5)	-0.07	(-2.4)	-0.49	(-9.2)	-0.52	(-10.0)	-0.04	(-1.4)
PctAcc	-0.32	(-7.1)	-0.41	(-8.2)	-0.09	(-3.9)	-0.35	(-7.6)	-0.48	(-9.5)	-0.13	(-5.8)
PctTotAcc	-0.40	(-8.3)	-0.38	(-7.4)	0.02	(0.90)	-0.46	(-9.6)	-0.41	(-7.8)	0.05	(2.00)
quick	-0.33	(-7.9)	-0.84	(-15.0)	-0.51	(-13.2)	-0.41	(-9.4)	-0.86	(-14.9)	-0.46	(-12.1)
rd_sale	-0.29	(-6.7)	-1.35	(-19.6)	-1.06	(-18.6)	-0.32	(-7.3)	-1.43	(-19.9)	-1.11	(-18.7)
RDAbility	-0.40	(-6.6)	-0.35	(-5.6)	0.05	(0.80)	-0.39	(-6.2)	-0.33	(-5.1)	0.06	(0.90)
RDS	-0.12	(-2.7)	-0.29	(-6.1)	-0.17	(-7.5)	-0.15	(-3.1)	-0.35	(-7.2)	-0.20	(-8.7)
realestate	-0.68	(-13.1)	-0.62	(-12.5)	0.06	(1.60)	-0.74	(-13.7)	-0.69	(-13.7)	0.04	(1.30)
ResidualMomentum	-0.37	(-7.7)	-0.30	(-6.3)	0.07	(2.20)	-0.41	(-8.1)	-0.33	(-6.7)	0.08	(2.30)
RetNOA	-0.74	(-13.9)	-0.68	(-13.2)	0.06	(1.80)	-0.80	(-14.3)	-0.70	(-13.3)	0.10	(2.70)
ReturnSkew	-0.52	(-11.7)	-0.59	(-11.7)	-0.07	(-2.5)	-0.53	(-11.4)	-0.67	(-13.2)	-0.14	(-5.0)
ReturnSkew3F	-0.52	(-11.5)	-0.53	(-10.9)	-0.01	(-0.4)	-0.53	(-11.3)	-0.58	(-11.7)	-0.05	(-2.1)
RevenueSurprise	-0.34	(-7.3)	-0.34	(-7.7)	0.00	(-0.2)	-0.38	(-8.1)	-0.39	(-8.4)	-0.01	(-0.3)
roaq	-1.16	(-18.1)	-0.27	(-6.3)	0.89	(19.50)	-1.27	(-19.2)	-0.29	(-6.3)	0.98	(21.20)
RoE	-0.93	(-14.6)	-0.41	(-9.1)	0.53	(14.30)	-1.02	(-16.4)	-0.47	(-10.3)	0.54	(14.80)
roic	-1.18	(-18.5)	-0.29	(-6.3)	0.89	(20.70)	-1.24	(-19.1)	-0.33	(-7.1)	0.91	(21.20)
salecash	-1.05	(-17.0)	-0.26	(-5.9)	0.80	(16.00)	-1.13	(-17.8)	-0.31	(-7.2)	0.81	(17.60)
saleinv	-0.40	(-7.8)	-0.34	(-7.6)	0.06	(2.20)	-0.51	(-9.8)	-0.38	(-8.2)	0.13	(4.50)
salerec	-0.42	(-7.6)	-0.36	(-6.9)	0.07	(1.70)	-0.52	(-9.1)	-0.43	(-9.3)	0.09	(2.70)
sfe	-1.55	(-16.6)	-0.56	(-8.7)	0.99	(10.90)	-1.60	(-16.7)	-0.59	(-8.6)	1.01	(10.70)
ShortInterest	-0.22	(-5.4)	-0.55	(-9.6)	-0.33	(-9.7)	-0.24	(-5.6)	-0.82	(-16.2)	-0.59	(-17.7)
SP	-0.96	(-15.4)	-0.41	(-6.9)	0.56	(9.10)	-1.06	(-16.7)	-0.51	(-9.8)	0.55	(10.70)
std_turn	-0.68	(-8.5)	-1.32	(-9.6)	-0.64	(-4.5)	-0.56	(-6.4)	-1.88	(-15.0)	-1.32	(-9.6)
tang	-0.31	(-7.0)	-1.24	(-19.1)	-0.93	(-17.4)	-0.36	(-8.3)	-1.23	(-19.3)	-0.87	(-18.3)
TotalAccruals	-0.78	(-14.8)	-0.51	(-9.8)	0.27	(9.30)	-0.83	(-15.0)	-0.56	(-10.8)	0.27	(8.70)
VolMkt	-0.24	(-6.2)	-0.56	(-7.9)	-0.32	(-5.9)	-0.29	(-6.9)	-0.73	(-10.7)	-0.44	(-8.3)
VolSD	-0.36	(-8.2)	-0.33	(-6.0)	0.03	(0.70)	-0.39	(-8.4)	-0.41	(-7.3)	-0.02	(-0.5)
VolumeTrend	-0.38	(-7.6)	-0.64	(-10.7)	-0.27	(-6.0)	-0.40	(-9.1)	-0.75	(-12.3)	-0.35	(-8.8)
WW	-0.03	(-0.7)	-1.08	(-18.6)	-1.05	(-21.6)	-0.10	(-2.2)	-1.18	(-19.7)	-1.08	(-22.1)

zerotrade	-0.44	(-6.5)	-0.33	(-8.2)	0.10	(2.20)	-0.62	(-9.5)	-0.39	(-9.1)	0.23	(4.80)
zerotradeAlt1	-0.48	(-7.2)	-0.34	(-8.5)	0.15	(3.10)	-0.68	(-10.1)	-0.38	(-8.9)	0.30	(5.90)
zscore	-0.56	(-10.8)	-0.94	(-13.2)	-0.37	(-6.7)	-0.61	(-11.6)	-1.03	(-15.3)	-0.42	(-8.5)

This table reports average return and t-statistics of deciles portfolios of delta-hedged ATM call and ATM put option returns sorted on 149 characteristics. The 149 variables are downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com) and are defined in Table A3. We report deciles 1 and 10, and the long-short (10-1) portfolio along with their t-statistics in parentheses based on Newey-West standard errors with optimal lag length. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A5: Estimation for the Number of Factors in the Delta-hedged Call and Put Option Portfolios (OTM Options)

Common factors used	Number of factors found in the residuals	
	Call Options	Put Options
1	1	1
2	1	1
3	0	0
4	0	0

This table presents results based on the Gagliardini, Ossola, and Scaillet (GOS) estimator proposed by Gagliardini et al. (2019). The GOS estimator scrutinizes the error terms generated by a factor model and tests whether these errors are weakly cross-sectionally correlated or share at least one common factor. This table shows the number of factors found in the residuals of the OTM call and OTM put datasets as we sequentially add one of the common factors estimated from the combined datasets. The factors are simultaneously estimated from the combined datasets of OTM calls and OTM puts. The test assets are 364 option portfolios from OTM delta-hedged call and OTM delta-hedged put options sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A6: Pricing Performance on Out-of-the-money Option Portfolios

Models	N	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\lvert t_\alpha \rvert > 3$	OOS RMSPE	F_{max}
Three PCA factors	364	1.17	0.93	0.68	0.07%	3%	0.08%	0.002
EWOP, VOV, HV-IV	364	0.95	0.88	0.63	0.10%	10%	0.14%	0.002,0.83
EWOP, VOV, HV-IV, Cash	364	1.03	0.92	0.64	0.08%	7%	0.12%	0.002,0.948

This table reports the pricing performance of factor models on out-of-the-money (OTM) option portfolios. The factor models constructed using OTM options are: the three PCA-factor model, the model with EWOP, VOV and HV-IV, and the model with EWOP, VOV, HV-IV, and Cash. The performance measures are: Sharpe Ratio for delta-hedged option portfolios, the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $\lvert t_\alpha \rvert > 3$, and out-of-the-sample root mean square pricing error (OOS RMSPE), and p-value of a mean-variance efficiency test statistics F_{max} in Gungor and Luger (2016). Following the decision rule in Gungor and Luger (2016), we report the conservative MC p-value when the conservative MC p-value $\leq$ 5% and report the liberal MC p-value when the liberal MC p-value $\geq$ 5%. When the MC tests yield an inconclusive outcome, we report both the conservative and liberal MC p-values. The test assets are 364 OTM delta-hedged call and put option portfolios sorted on the following 19 characteristics: Size is the market value of the firm; Ivol is idiosyncratic volatility; HV–IV is the log difference between historical and implied volatilities; IV_slope is the slope of volatility term structure; BM is the book to market; Credit is S&P credit ratings; VOV is volatility of implied volatility; Illiquidity is the Amihud (2002) liquidity measure; Reversal is the lagged one-month return; Mom is momentum over the 11 months prior to the previous month; VarCF is cash flow variance; Cash is cash-to-assets ratio; Disp is analyst earnings forecast dispersion; ShareIss1Y (ShareIss5Y) is one (five) year new issues; PM is profit margin; Close is stock price; Profit is profitability; Xfin is total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A7: Instrumented PCA Factor Models with Different Number of Factors

Models	SR_{DH}	Corr Avg(r)-Pred(r)	Average Adj R^2	RMSPE	$\|t_\alpha\| > 3$	OOS RMSPE	W_α p-value
Factor 1	0.53	0.87	0.85	0.17%	75%	0.20%	0.00
Factor 2	1.47	0.88	0.89	0.11%	53%	0.14%	0.00
Factor 3	1.59	0.88	0.90	0.11%	53%	0.14%	0.00
Factor 4	1.91	0.88	0.90	0.11%	52%	0.14%	0.00
Factor 5	2.13	0.89	0.90	0.11%	49%	0.14%	0.02
Factor 6	2.09	0.89	0.90	0.10%	48%	0.14%	0.02

This table reports the following performance measures for six models that sequentially add the first IPCA factor to the sixth IPCA factor: Sharpe Ratio for delta-hedged portfolios, the correlation between average return and predicted return, average adjusted R^2 (time-series), in-sample root mean square pricing error (RMSPE), percentage of $|t_\alpha| > 3$ where t_α is the t-statistics to test the null hypothesis of $\alpha = 0$, out-of-the-sample root mean square pricing error (OOS RMSPE), and p-values of the bootstrap Wald test of no alpha (i.e., $\Gamma_\alpha = 0$), which is obtained by comparing the models fit to their unconstrained equivalents ($\Gamma_\alpha \neq 0$). The test assets are 370 characteristic-sorted delta-hedged ATM call and put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A8: Canonical Correlation Between Option Factors and Stock Factors

Canonical Variates	Canonical Correlation	Explained Variance (%)	Most Correlated PCA from Option Returns	Explained Variance in Option PCA (%)
1st Pair	0.44	19.36	1st PCA	96
2nd Pair	0.23	5.29	4th PCA	89
3rd Pair	0.19	3.61	2nd PCA, 3rd PCA	62, 34
4th Pair	0.06	0.36	2nd PCA, 3rd PCA	53, 37

This table shows the canonical correlation analysis between the statistical factors extracted from option and stock portfolios. For the option factors, we utilize the PCA factors obtained from the pool of 370 delta-hedged ATM call and put option returns, which are based on 19 distinct firm characteristics. We extract 6 PCA factors from 182 long-short stock portfolio returns, downloaded from Chen and Zimmermann's webpage (https://www.openassetpricing.com). The sample period is from January 1996 to December 2021.

Table A9: Firm-Month Observations in Benchmark and Missing Value Treated Datasets

	Firm-Month Observations	Calls	Puts
Total firm-month obs. in the benchmark dataset	204,376	204,376	204,376
Total firm-month obs. in the treated dataset	264,864	264,864	264,864
Firm-month obs. with missing prices (Average all)	60,488	32,281	30,377
Firm-month obs. with no bid and no ask option price	1,605	598	1,176
Firm-month obs. with mid price	59,835	31,295	28,842
Firm-month obs. with intrinsic option price	60,488	32,281	30,377
Firm-month obs. with BSM model price	44,669	22,797	22,006
Firm-month obs. with BSM PC-parity price	30,024	15,286	14,746
Firm-month obs. with prior five days availability	16,547	7,677	8,881
Firm-month obs. with after five days availability	1,096	576	521
Delisted or Acquired	403	403	403

This table reports firm-month observations in the benchmark dataset and the treated dataset for each imputation method. The benchmark dataset is the one used in the main analyses of the paper. The treated dataset includes firms with bid option price equal to zero, or missing option or stock price, or firms that were delisted or acquired. We use the following imputation methods. 1) Mid option price = ask/2. Bid is equal to zero. 2) Black-Scholes-Merton model (BSM) to price the option with an interpolated implied volatility computed from the implied volatility surface (IVS) from Optionmetrics. 3) BSM model with put-call parity (BSM PC-parity): Using the BSM model, we price a call (put) option by finding the corresponding put (call) with valid implied volatility that we add to the interpolated implied volatility put-call spread computed as the difference of the put IVS and call IVS. 4) We find options with valid bid and ask prices in the previous five trading days before the end of the holding period. We choose the one with the closest date to end of the holding period and perform a delta-gamma-vega-theta adjustment. 5) Similar to 4) but in the following five trading days. 6) Intrinsic option price. 7) Average all is the average of all theoretically imputed prices from methodologies 1 to 5. When no theoretical imputed price is available, we use the intrinsic option price. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A10: Mean of Long-short Delta-hedged Call Option Returns for 19 Characteristics using Seven Imputation Methods

	Mid	Intrinsic	BSM	BSM PC-parity	Prior five days	After five days	Avg All	Benchmark
Size	0.50	0.86	0.65	0.71	0.80	0.85	0.54	1.10
	(10.66)	(18.68)	(14.08)	(15.06)	(17.43)	(18.38)	(11.72)	(24.66)
Ivol	-0.50	-0.64	-0.56	-0.57	-0.61	-0.63	-0.52	-0.81
	(-9.19)	(-11.93)	(-10.55)	(-10.66)	(-11.45)	(-11.87)	(-9.65)	(-15.11)
HV-IV	0.99	1.06	1.01	1.03	1.05	1.06	1.00	1.23
	(21.30)	(23.15)	(21.89)	(22.30)	(22.84)	(23.08)	(21.50)	(27.27)
IV_slope	0.64	0.65	0.65	0.65	0.65	0.65	0.65	0.90
	(14.35)	(14.28)	(14.48)	(14.46)	(14.32)	(14.32)	(14.50)	(20.54)
BM	0.22	0.17	0.20	0.19	0.18	0.17	0.21	0.24
	(5.62)	(4.33)	(5.18)	(4.86)	(4.58)	(4.39)	(5.50)	(5.99)
Credit	-0.15	-0.26	-0.20	-0.21	-0.24	-0.26	-0.17	-0.40
	(-4.68)	(-8.25)	(-6.21)	(-6.59)	(-7.55)	(-8.18)	(-5.17)	(-12.21)
VoV	-0.69	-0.86	-0.75	-0.79	-0.83	-0.85	-0.71	-1.08
	(-13.32)	(-16.67)	(-14.80)	(-15.24)	(-16.12)	(-16.53)	(-13.82)	(-20.71)
Illiquidity	-0.48	-0.83	-0.62	-0.68	-0.77	-0.82	-0.52	-1.02
	(-10.68)	(-18.51)	(-13.94)	(-14.99)	(-17.35)	(-18.22)	(-11.72)	(-24.63)
Reversal	0.07	0.10	0.09	0.09	0.10	0.10	0.07	0.15
	(1.50)	(2.32)	(1.93)	(1.97)	(2.16)	(2.31)	(1.61)	(3.27)
Mom	0.02	0.15	0.09	0.10	0.13	0.15	0.04	0.23
	(0.40)	(3.40)	(1.92)	(2.20)	(2.88)	(3.31)	(0.84)	(4.71)
VarCF	-0.35	-0.50	-0.42	-0.44	-0.48	-0.50	-0.37	-0.58
	(-8.21)	(-11.72)	(-9.82)	(-10.18)	(-11.11)	(-11.61)	(-8.71)	(-13.90)
Cash	-0.53	-0.58	-0.55	-0.55	-0.57	-0.58	-0.54	-0.72
	(-11.25)	(-12.33)	(-11.75)	(-11.71)	(-12.21)	(-12.29)	(-11.43)	(-15.81)
Disp	-0.12	-0.22	-0.16	-0.17	-0.20	-0.22	-0.14	-0.35
	(-3.62)	(-6.50)	(-4.79)	(-5.08)	(-5.98)	(-6.40)	(-4.01)	(-10.30)
shareiss1	-0.21	-0.25	-0.23	-0.23	-0.24	-0.25	-0.21	-0.30
	(-5.20)	(-5.91)	(-5.60)	(-5.51)	(-5.81)	(-5.92)	(-5.28)	(-6.84)
shareiss5	0.07	0.11	0.08	0.09	0.10	0.10	0.08	0.13
	(2.12)	(3.03)	(2.36)	(2.66)	(2.94)	(2.98)	(2.25)	(3.75)
PM	0.55	0.68	0.61	0.62	0.66	0.68	0.57	0.82
	(11.79)	(14.76)	(13.28)	(13.43)	(14.20)	(14.69)	(12.29)	(18.61)
Close	0.63	0.99	0.79	0.83	0.92	0.97	0.68	1.16
	(12.09)	(19.24)	(15.51)	(15.92)	(18.06)	(19.02)	(13.13)	(21.72)
Profit	0.19	0.26	0.22	0.22	0.24	0.25	0.20	0.34
	(5.23)	(7.24)	(6.18)	(6.23)	(6.76)	(7.19)	(5.62)	(9.72)
XFIN	-0.39	-0.48	-0.43	-0.43	-0.46	-0.48	-0.40	-0.62
	(-8.75)	(-10.52)	(-9.71)	(-9.59)	(-10.16)	(-10.48)	(-9.09)	(-13.91)

This table shows mean and t-statistics of long-short delta-hedged call option returns from the treated dataset for 19 characteristics using seven imputation methods. The treated dataset includes firms with bid option price equal to zero, or missing option or stock price, or firms that were delisted or acquired. We use the following imputation methods. 1) Mid option price = ask/2. Bid is equal to zero. 2) Black-Scholes-Merton model (BSM) to price the option with an interpolated implied volatility computed from the implied volatility surface (IVS) from Optionmetrics. 3) BSM model with put-call parity (BSM PC-parity): Using the BSM model, we price a call (put) option by finding the corresponding put (call) with valid implied volatility that we add to the interpolated implied volatility put-call spread computed as the difference of the put IVS and call IVS. 4) We find options with valid bid and ask prices in the previous five trading days before the end of the holding period. We choose the one with the closest date to end of the holding period and perform a delta-gamma-vega-theta adjustment. 5) Similar to 4) but in the following five trading days. 6) Intrinsic option price. 7) Average all is the average of all theoretically imputed prices from methodologies 1 to 5. When no theoretical imputed price is available, we use the intrinsic option price. The benchmark dataset is the one used in the main analyses of the paper. The option factors are the long-short return spread of delta-hedged option returns of ATM calls sorted by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A11: Mean of Long-short Delta-hedged Put Option Returns for 19 Characteristics using Seven Imputation Methods

	Mid	Intrinsic	BSM	BSM PC-parity	Prior five days	After five days	Avg All	Benchmark
Size	0.51	0.87	0.65	0.71	0.80	0.86	0.57	1.20
	(10.76)	(17.83)	(13.67)	(14.67)	(16.42)	(17.61)	(12.01)	(25.59)
Ivol	-0.65	-0.77	-0.70	-0.71	-0.74	-0.77	-0.67	-0.97
	(-11.50)	(-13.40)	(-12.27)	(-12.49)	(-13.01)	(-13.33)	(-11.87)	(-17.02)
HV-IV	1.02	1.12	1.05	1.07	1.10	1.12	1.03	1.24
	(21.79)	(24.05)	(22.61)	(23.04)	(23.65)	(23.94)	(22.14)	(26.96)
IV_slope	0.72	0.74	0.73	0.74	0.74	0.74	0.73	0.96
	(14.97)	(15.63)	(15.47)	(15.52)	(15.65)	(15.63)	(15.24)	(19.93)
BM	0.23	0.19	0.22	0.20	0.20	0.19	0.23	0.22
	(6.01)	(4.72)	(5.57)	(5.25)	(5.04)	(4.72)	(5.84)	(6.39)
Credit	-0.16	-0.27	-0.21	-0.22	-0.25	-0.27	-0.18	-0.42
	(-4.73)	(-7.87)	(-6.05)	(-6.32)	(-7.15)	(-7.74)	(-5.27)	(-12.08)
VoV	-0.80	-0.98	-0.86	-0.91	-0.95	-0.97	-0.83	-1.22
	(-15.94)	(-18.57)	(-16.82)	(-17.52)	(-18.22)	(-18.45)	(-16.37)	(-23.15)
Illiquidity	-0.52	-0.88	-0.64	-0.71	-0.80	-0.86	-0.57	-1.12
	(-10.62)	(-17.54)	(-13.33)	(-14.46)	(-16.14)	(-17.33)	(-11.78)	(-23.19)
Reversal	-0.14	-0.11	-0.13	-0.13	-0.12	-0.11	-0.14	-0.02
	(-3.12)	(-2.40)	(-2.88)	(-2.80)	(-2.55)	(-2.42)	(-2.99)	(-0.35)
Mom	0.07	0.20	0.13	0.14	0.17	0.19	0.09	0.28
	(1.64)	(4.61)	(3.07)	(3.24)	(4.00)	(4.52)	(2.19)	(6.66)
VarCF	-0.40	-0.56	-0.47	-0.48	-0.52	-0.55	-0.43	-0.66
	(-9.52)	(-12.92)	(-10.93)	(-11.37)	(-12.18)	(-12.81)	(-10.12)	(-15.55)
Cash	-0.47	-0.53	-0.49	-0.50	-0.52	-0.53	-0.48	-0.68
	(-10.76)	(-11.72)	(-11.20)	(-11.19)	(-11.54)	(-11.63)	(-10.99)	(-15.51)
Disp	-0.15	-0.26	-0.19	-0.20	-0.23	-0.25	-0.17	-0.40
	(-4.20)	(-7.43)	(-5.56)	(-5.85)	(-6.78)	(-7.32)	(-4.85)	(-11.22)
shareiss1	-0.20	-0.23	-0.20	-0.21	-0.22	-0.23	-0.20	-0.28
	(-5.17)	(-5.83)	(-5.32)	(-5.48)	(-5.71)	(-5.77)	(-5.27)	(-7.27)
shareiss5	0.15	0.18	0.16	0.17	0.18	0.18	0.15	0.22
	(4.61)	(5.77)	(4.95)	(5.31)	(5.49)	(5.73)	(4.76)	(6.84)
PM	0.59	0.71	0.63	0.65	0.69	0.71	0.61	0.88
	(12.88)	(15.37)	(13.84)	(14.09)	(14.88)	(15.24)	(13.29)	(19.91)
Close	0.57	0.94	0.72	0.76	0.86	0.93	0.63	1.18
	(11.09)	(17.67)	(14.04)	(14.63)	(16.27)	(17.48)	(12.42)	(22.91)
Profit	0.21	0.27	0.23	0.24	0.25	0.27	0.22	0.35
	(5.74)	(7.43)	(6.38)	(6.58)	(6.97)	(7.37)	(6.05)	(10.06)
XFIN	-0.44	-0.51	-0.46	-0.48	-0.50	-0.51	-0.45	-0.70
	(-9.91)	(-11.28)	(-10.35)	(-10.59)	(-11.02)	(-11.22)	(-10.12)	(-15.89)

This table shows mean and t-statistics of long-short delta-hedged put option returns from the treated dataset for 19 characteristics using seven imputation methods. The treated dataset includes firms with bid option price equal to zero, or missing option or stock price, or firms that were delisted or acquired. We use the following imputation methods. 1) Mid option price = ask/2. Bid is equal to zero. 2) Black-Scholes-Merton model (BSM) to price the option with an interpolated implied volatility computed from the implied volatility surface (IVS) from Optionmetrics. 3) BSM model with put-call parity (BSM PC-parity): Using the BSM model, we price a call (put) option by finding the corresponding put (call) with valid implied volatility that we add to the interpolated implied volatility put-call spread computed as the difference of the put IVS and call IVS. 4) We find options with valid bid and ask prices in the previous five trading days before the end of the holding period. We choose the one with the closest date to end of the holding period and perform a delta-gamma-vega-theta adjustment. 5) Similar to 4) but in the following five trading days. 6) Intrinsic option price. 7) Average all is the average of all theoretically imputed prices from methodologies 1 to 5. When no theoretical imputed price is available, we use the intrinsic option price. The benchmark dataset is the one used in the main analyses of the paper. The option factors are the long-short return spread of delta-hedged option returns of ATM calls sorted by the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.

Table A12: Estimation for the Number of Factors: Missing-value-treated Dataset

Common factors used	Number of factors found in the residuals	
	Call Options	Put Options
1	2	1
2	2	2
3	1	1
4	0	0

This table presents results using the missing value treated dataset based on the Gagliardini, Ossola, and Scaillet (GOS) estimator proposed by Gagliardini et al. (2019). The GOS estimator scrutinizes the error terms generated by a factor model and tests whether these errors are weakly cross-sectionally correlated or share at least one common factor. This table shows the number of factors found in the residuals of the call and put datasets as we sequentially add one of the common factors estimated from the combined datasets. The factors are simultaneously estimated from the combined datasets of calls and puts. The test assets are 370 option portfolios: 185 delta-hedged ATM call and 185 delta-hedged ATM put option portfolios sorted on the following 19 characteristics: firm size, idiosyncratic volatility, HV–IV, the slope of volatility term structure, book to market, S&P credit rating, VOV, Amihud (2002) illiquidity measure, return reversal, return momentum, cash flow variance, cash-to-assets ratio, analyst earnings forecast dispersion, one-year and five-year new issues, profit margin, stock price, profitability, and total external financing. Sample period is from January 1996 to December 2021 for stocks in the OptionMetrics database.