Common Factors in Equity Option Returns*

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Abstract

We study the factor structure of delta-hedged equity option returns and propose a parsimonious three-factor model that explains their time-series and cross-sectional variation. Using latent estimation techniques, we find that a model with three latent factors generates a correlation of 93% between the realized return and the predicted return from 1996 to 2019. It also explains 77% of their time-series variation. The latent factors can be captured by three tradable option factors: the equal-weighted portfolio return of the sample, the long-short factors sorted by the difference between implied and historical volatility, and the volatility of implied volatility. The three-factor model explains well the cross-section and time series of 1520 other characteristic-sorted option portfolio returns. Stock return factors are uncorrelated with the delta-hedged option factors.

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1 Introduction

Identifying the factors that drive the co-movement of asset returns is a central question in empirical asset pricing. Existing papers on multifactor asset pricing models mainly focus on common factors in stock and bond returns.[1] To properly describe the stochastic discount factor that can be used to price all assets, higher order risk premiums must be accounted for. Bakshi and Kapadia (2003) show that delta-hedged option returns contain risk premiums beyond the equity premium, such as the variance risk premium. Our goal is to investigate the factor structure in the cross-section of option returns and uncover the factors that drive higher order risk premiums.

To study the factor structure of the equity option returns, we work with option portfolios sorted by firm characteristics that have been shown to have predictive power in the cross-section of option returns. We consider 19 characteristics that predict option returns including 14 characteristics in Zhan, Han, Cao, and Tong (2022), the log difference of realized volatility and implied volatility in Goyal and Saretto (2009), idiosyncratic volatility in Cao and Han (2013), the volatility term structure in Vasquez (2017), volatility of volatility in Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2022), and credit rating in Vasquez and Xiao (Forthcoming). We construct 185 delta-hedged call option portfolios sorted by the 19 characteristics from January 1996 to December 2019.

We use latent estimation techniques to uncover the factor structure of delta-hedged option returns. To estimate the number of factors, we apply multiple methods and find that option returns display a strong factor structure. The results show that the option returns are driven by one strong factor and up to five weak factors. It is difficult to distinguish weak factors from idiosyncratic noise, and principal component analysis (PCA) might fail to estimate them correctly (Onatski (2012)). Therefore, we estimate the factors using the Risk-Premium PCA method (RP-PCA) of Lettau and Pelger (2020b) which works more efficiently in the presence of weak factors.[2]

[1]The literature about common factors in stock returns is vast. Hundreds of papers have proposed hundreds of factors; see, for example, Harvey, Liu, and Zhu (2016). Factors for the cross-section of bond returns are studied in Bai, Bali, and Wen (2019) and Kelly, Palhares, and Pruitt (2020).

[2]PCA focuses on finding factors that minimize the unexplained variation of a linear factor model. In contrast, RP-PCA minimizes the unexplained variation and the pricing error generated by the linear model. Lettau and Pelger (2020b) show that PCA is a particular case of the RP-PCA. Lettau and Pelger (2020a)

We find that three latent factors suffice to fit the time-series and cross-section of delta-hedged option returns. Using more than three RP-PCA factors does not improve the model performance on any of the dimensions we use to evaluate the asset pricing model (Sharpe ratio, correlation between expected and predicted returns, magnitude of the pricing error, and time-series R^2). We also find that a model with RP-PCA factors outperforms the classical PCA factors. The first RP-PCA is the factor that best explains the time-series variation of the delta-hedged option returns, while the second and third RP-PCA factors explain their cross-section. The correlation between the average returns of the 185 characteristic-based delta-hedged portfolios and the predicted returns by the three-factor model is 0.93.

To provide an economic interpretation of the information captured by the model with three RP-PCA factors (henceforth, the *three-RP-PCA-factor model*), we explore which observed and tradable factors capture each of the three RP-PCA factors. We use 21 tradable factors: 19 characteristic-based factors constructed using long-short option strategies of the univariate sorted portfolios, the straddle return of the S&P 500 index, and the equally-weighted portfolio of the 185 characteristic-based delta-hedged portfolios (EWP) constructed with the 19 characteristics.

Empirically, we find that a parsimonious model with three tradable factors (henceforth, the *three-factor model*) is a good proxy of the three-RP-PCA factor model. The first RP-PCA, the factor that fits the time-series of delta-hedged option returns, is perfectly captured by EWP, the equally-weighted portfolio.[3] The second and third RP-PCAs, the factors that explain the cross-section of delta-hedged equity option returns, are most correlated with the long-short strategies of the volatility of implied volatility (VOV) and the log difference between implied and historical volatilities (Voldev).

Our results are consistent with the intuition that factors related to volatility risk and higher-order risks are important factors that help explain the cross-section of option returns. In the paper, we provide a stylized model, in which delta-hedged option returns are driven

show that the SDF could be estimated more efficiently using RP-PCA than PCA, especially in the presence of weak factors. Weak factors are pervasive in asset pricing databases, and recently, more papers investigate alternative estimation methods to address this issue. See, for example, the supervised-PCA of Giglio et al. (2021) and the scaled PCA of Huang et al. (2022).

[3] This is consistent with the results in Ahn and Horenstein (2021) showing that in multifactor models the EWP can explain the time-series of asset returns. EWP cannot explain the cross-section because it has constant factor loadings.

by exposures to volatility risk and volatility-of-volatility risk. We argue that the long-short option return portfolio constructed for Voldev, the difference between implied and historical volatilities, captures the volatility risk factor. The long-short option portfolio sorted by volatility of implied volatility possibly captures the higher order risk factor and the volatility-of-volatility risk factor in the model.

We use delta-hedged call option returns in the main analysis to test our three-factor model. For robustness purposes, we test the performance of our model on four additional portfolio sets: 1) 185 sorted delta-hedged put portfolios constructed using the same 19 characteristics as the ones used in the main analysis for call options, 2) 1520 sorted delta-hedged call portfolio returns created using 152 characteristics other than the 19 characteristics used in the main analysis, 3) 1517 delta-hedged put equity option returns created from the 152 characteristics (we remove three portfolios with missing data), and 4) long-short stock portfolio returns from 190 stock return predictors.[4] We find that our factor model estimated from delta-hedged call option portfolio returns formed on 19 characteristics works well on the additional portfolio sets of option returns. More precisely, the correlation coefficient between the portfolios' average returns and the expected returns predicted by the three-RP-PCA-factor model (three-factor model) is 0.93 (0.84) for the 185 delta-hedged call option returns, 0.85 (0.78) for the 185 delta-hedged put option returns, 0.84 (0.62) for the 1520 placebo portfolios of call options, and 0.72 (0.50) for the 1517 placebo portfolios of put options. Meanwhile, our option-based model could not explain the 190 stock portfolios. The correlation between average and predicted stock returns is -0.13 for the three-RP-PCA-factor model and -0.09 for the three-factor model. This suggests that factors in the cross-section of delta-hedged option returns contain information about volatility risk premia and higher order risk premia, which are not captured by stock return factors. We also confirm these findings using canonical correlation analysis.

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 (2021), and Büchner and Kelly (2022). On the cross-

[4] We download 152 predictive firm-level characteristics and the 190 long-short portfolio returns from Chen and Zimmerman's webpage at https://www.openassetpricing.com.

section of options, Duan and Wei (2009) and Christoffersen, Fournier, and Jacobs (2017) study the factor structure of the option prices, not option 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 (2020), and Bali, Beckmeyer, Moerke, and Weigert (2021). Different from these studies, our paper uses latent factor techniques to study the factor structure in the cross-section of option returns. Similar to the stock return literature, multiple predictive characteristics have been proposed but they do not necessarily span different dimensions in which option returns co-move. We are the first to address this issue in the options market and find that three factors summarize all the information about the cross-section and time series among the multiple candidate factors proposed in the option return literature.

Lewellen (2022) shows that looking for a parsimonious model is not necessarily beneficial for certain empirical asset pricing objectives like estimating pricing errors. However, in the case of this paper, finding a parsimonious model for higher-order risk premia is the main objective since there is no benchmark available as of today. While we do not rule out the possibility that the proposed model's performance might be improved by using alternative procedures to construct the empirical factors or even by adding more factors, our main result will remain the same. That is, three latent factors suffice to capture the time-series and cross-section of delta-hedged equity call option returns; EWP, VoV, and Voldev can capture these factors, which are unrelated to stock returns' factors

Section 2 presents our main analytical results motivating the factor structure in delta-hedged option returns. Section 3 explains the data used for our empirical analysis. In Section 4, we perform our quantitative studies: Section 4.1 analyzes the factor structure in option returns using latent variable techniques; in Section 4.2, we study which option returns observable factors better explain the factor structure in option returns and conduct some robustness checks. In Section 4.3, we discuss the interpretation of our results and suggest paths to improve the performance of the model with observable factors. We conclude in Section 5.

2 Theoretical motivation: Delta-hedged equity option gains in a multi-factor framework

In this section, we derive expected delta-hedged equity option gains in a multi-factor framework in which stock returns and volatility are driven by multiple factors. The model also allows the existence of higher order risks, where volatility of the 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 risk factors.

We denote the stock price and the volatility of stock return 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:

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

$$V_t^i = \sum_{j=1}^{n} \beta^j V_{f,t}^j + Z_t^i, \tag{2}$$

$$dV_{f,t}^j = \theta^j dt + \eta_t^j dW_{2t}^{i,j}, \tag{3}$$

$$d\eta_t^j = \xi^j dt + q^j dW_{3t}^{i,j}. \tag{4}$$

Equation (3) describes the dynamic of volatility factor j. To incorporate the role of higher order risk components, we use Equation (4) to describe the dynamic of volatility of volatility factor j. η_t^j is the volatility of volatility factor $V_{f,t}^j$, and q^j is 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 leverage effect do not change the main result of the model.

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

$$C^i_{t+\tau} = C^i_t + \int_t^{t+\tau} \Delta^i_u dS^i_u + \int_t^{t+\tau} \sum_{j=1}^n \frac{\partial C^i}{\partial V^j_f} dV^j_{f,u} + \int_t^{t+\tau} \sum_{j=1}^n \frac{\partial C^i}{\partial \eta^j_t} d\eta^j_u + \int_t^{t+\tau} b^i_u du, \quad (5)$$

where $\Delta^i_u = \frac{\partial C^i_u}{\partial S^i_u}$ is the delta of the call option and

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

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

$$\begin{aligned} &\frac{1}{2}(V^i S^i)^2 \frac{\partial^2 C^i}{\partial (S^i)^2} + \frac{1}{2}\sum_{j=1}^n (\eta^j)^2 \frac{\partial^2 C^i}{\partial (V^j_f)^2} + \frac{1}{2}\sum_{j=1}^n (q^j)^2 \frac{\partial^2 C^i}{\partial (\eta^j)^2} + rS_i \frac{\partial C^i}{\partial S_i} + \\ &\qquad \sum_{j=1}^n (\theta^j - \lambda^j_v) \frac{\partial C^i}{\partial V^j_f} + \sum_{j=1}^n (\xi^j - \lambda^j_\eta) \frac{\partial C^i}{\partial \eta^j} + \frac{\partial C^i}{\partial t} - rC^i = 0. \end{aligned} \quad (6)$$

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

Combining Equation (5) and (6), we have:

$$\begin{aligned} C^i_{t+\tau} - C^i_t = &\int_t^{t+\tau} \Delta^i_u dS^i_u + \int_t^{t+\tau} r(C^i - S_i \frac{\partial C^i}{\partial S_i}) du + \\ &\int_t^{t+\tau} \sum_{j=1}^n \lambda^j_v \frac{\partial C^i}{\partial V^j_f} du + \int_t^{t+\tau} \sum_{j=1}^n \lambda^j_\eta \frac{\partial C^i}{\partial \eta^j} du + \quad (7) \\ &\int_t^{t+\tau} [\sum_{j=1}^n \theta^j \frac{\partial C^i}{\partial V^j_f} dW^{i,j}_2] + \int_t^{t+\tau} [\sum_{j=1}^n \xi^j \frac{\partial C^i}{\partial \eta^j} dW^{i,j}_3]. \quad (8) \end{aligned}$$

With a delta-hedged portfolio, we buy the call option and dynamically delta-hedge the option position with time-varying delta Δ^i_u. The delta-hedged gain $\Pi^i_{t,t+\tau}$ 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 (7), we obtain the expectation of the delta-hedged gain for stock option i:

$$E[\Pi^i_{t,t+\tau}] = \sum_{j=1}^{n} E[\int_t^{t+\tau} \lambda^j_v \frac{\partial C^i}{\partial V^j_f} du] + \sum_{j=1}^{n} E[\int_t^{t+\tau} \lambda^j_\eta \frac{\partial C^i}{\partial \eta^j} du] \tag{9}$$

The 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 ($\frac{\partial C^i}{\partial \eta^j}$).

In the empirical section, we mainly work with the long-short characteristic-based option portfolios as potential proxies of factors. The details of the characteristics and factors are provided in Section 3.

3 Data and variables description

3.1 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 2019. Implied volatility and Greeks are calculated by OptionMetrics using the binomial tree in Cox et al. (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. First, to avoid illiquid options, 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. 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. At the end of each month and for each stock with options, we select a call option that is 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 the majority of options. Our final sample contains ****how many?*** option-month observations for calls. The time to maturity ranges from 43 to 53 days.

3.2 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. In this paper, following the literature, we study the gain of delta-hedged options, such that the portfolio gain is not sensitive to the movement of the underlying stock. Empirical studies find that the average gain of the delta-hedged option portfolios is negative for both indexes and individual stocks (Bakshi and Kapadia (2003), Carr and Wu (2009), and Cao and Han (2013)). Bakshi and Kapadia (2003) show that the sign and the magnitude of delta-hedged gain are related to the variance risk premium and the jump risk premium. 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, $\Delta_t = \frac{\partial C_t}{\partial S_t}$ 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, $n = 0, 1, ...N-1$. As shown by Bakshi and Kapadia (2003) in a simulation setting, 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

$$\Pi_{t,t+\tau} = O_{t+\tau} - O_t - \sum_{n=0}^{N-1} \Delta_{t_n}[S_{t_{n+1}} - S_{t_n}] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}(O_{t_n} - \Delta_{t_n} S_{t_n}), \tag{10}$$

where O_t is the price of the option, 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. To make the delta-hedged gains comparable across stocks we use delta-hedged option returns defined as the delta-hedged option gain $\Pi_{t,t+\tau}$ scaled by the absolute value of the securities involved, i.e. $\Delta_t S_t - O_t$ for call options. We start the position at the beginning of each month and close the position at the end of each month. We work with monthly returns through the empirical analysis.

3.3 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 are constructed with portfolios composed by ranked stocks by certain characteristic, such as the size factor, the value factor or the momentum factor. 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) Book-to-market ratio (BM): the ratio of book equity to market equity.

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

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

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

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

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

(8) 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.

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

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

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

(12) Stock price (Price): The log of stock price at the end of last month.

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

Zhan et al. (2022) find that delta-hedged option returns increase with size, momentum, reversal, profitability, stock price, profit margin, and firm profitability. They also find that delta-hedged option returns decrease with cash holding, cash flow variance, new shares issuance, total external financing, and dispersion of analyst forecasts. In addition to these variables, we also consider the following option return predictors in the literature.

(14) 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). Christoffersen et al. (2018) and Choy and Wei (2020) find the existence of liquidity risk premium in the cross-section of option returns.

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

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

(17) The slope of volatility term structure (Vts): the difference between long-term and short-term implied volatility. Vasquez (2017) finds that straddle portfolios with high slopes

of the volatility term structure outperform straddle portfolios with low slopes by a significant amount.

(18) 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.

(19) Volatility of volatility (VoV): Standard deviation of implied volatility change in the past month. Ruan (2020) and Cao et al. (2022) find that volatility of volatility is negatively related to future equity option returns.

At the end of each month, we sort all stock options into 10 portfolios based on the first 19 characteristics described above.[5] 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 3.2. We consider the 185 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 are the long-short return spreads, 10-1 (5-1 for credit rating), based on the 19 characteristics. We also consider two candidate factors related to common volatility risk:

(20) Straddle return of the S&P 500 index (Strad): a proxy for the market volatility risk in Coval and Shumway (2001) and Carr and Wu (2009).

(21) Equal-weighted portfolio (EWP): equal-weighted portfolio return of all 185 characteristic-based delta-hedged portfolios, used as a measure to capture the average variance risk of the portfolios.

Table 1 reports summary statistics for the average returns of delta-hedged option portfolios sorted by the 19 predictors. The table shows that the long-short returns constructed by buying the top decile (quintile) and selling the bottom decile (quintile) are significantly different from zero for all predictors but one. The average return spreads range from -1.91% to 2.68% with t-statistics ranging from -13.73 to 19.02. We are able to replicate most of the

[5] 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 the portfolio returns.

results from the original papers. The delta-hedged equity option returns increase for nine characteristics (Size, Voldev, Vts, BM, Reversal, ShareIss5y, PM, Profit, and stock Price), while they decrease for nine characteristics (Ivol, Credit rating, VOV, Illiquidity, VarCF, Ch, Disp, ShareIss1y, and Xfin).

[Table 1 around here]

Table 2 presents the summary statistics of 21 candidate factors. 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 straddle returns of the the S&P 500 index options, and the EWP. We observe that the straddle 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 EWP is also negative on average. The highest mean option returns in absolute value are observed for Voldev, Vts, and VOV.

[Table 2 around here]

Table 3 shows the correlations among the long-short portfolios of the option return predictors. We observe that the correlation coefficients among the strategies are mostly below 0.60. Only the correlations between the long-short returns of Size and Illiquidity is 0.78, Size and stock Price is 0.65, and XFIN and PM is -0.70. The low correlation among the long-short candidate factors suggests that these variables might capture distinctive information on the cross-section of delta-hedged option returns. But, how many different factors do these 19 candidate factors capture? How many of them are relevant for explaining covariance matrix of option returns? Do they capture similar information than stock returns factors? We address these questions in the next section.

[Table 3 around here]

4 Empirical Procedure and Results

We first study the factor structure of delta-hedged equity option returns using latent estimation techniques. Factors estimated using latent methods are challenging to interpret economically. Therefore, we choose from a set of tradable candidate factors already published for predicting option returns those most correlated with the estimated ones. Finally, we check the robustness of our results across assets and time.

4.1 The factor structure in delta-hedged equity option returns

Section 2 shows that under a stochastic volatility model, the delta-hedged option return is driven by a linear factor model when the stock variance follows a multifactor structure. Therefore, we can use the latest advances for estimating factor models to study if the stochastic discount factor contains specific factors for higher-order risk premia. We first estimate the number of factors and the common factors from a set of delta-hedged equity option returns modeling an approximate linear factor structure as defined in Chamberlain and Rothschild (1983).[6] More precisely, let x_{it} be the response variable for the ith cross-section unit at time t ($i = 1, 2, ..., N$, and $t = 1, 2, ..., T$). Explicitly, x_{it} can be the return on a delta-hedged option portfolio i at time t. The response variables x_{it} depend on K empirical factors $f_t = (f_{1t}, ..., f_{Kt})'$. That is,

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

where $x_t = (x_{1t}, ..., x_{Nt})'$ 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 (beta matrix); 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 delta-hedged portfolios defined in Section 3.3 ($N = 185$ portfolios) during the entire sample period from January 1996 to December 2019 ($T = 288$ months). As a prelimi-

[6] 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.

nary step, we plot in Figure 1 the largest fifteen eigenvalues from the sample second-moment matrix of the "doubly demeaned" delta-hedged portfolio returns.[7] 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.

[Figure 1 around here]

The scree plot is informative, but it is not a proper statistical tool to estimate the number of factors. We now use five different consistent estimators to calculate the number of factors necessary to explain the comovement of option returns: the Eigenvalue Ratio (ER) and Growth Ratio (GR) estimators of Ahn and Horenstein (2013), the Edge Distribution (ED) estimator of Onatski (2010), the BIC3 and IC1 estimators of Bai and Ng (2002), and the Modified Information Criterion estimator (ABC) of Alessi et al. (2010). Intuitively, these methods separate relevant information from noise and exploit the differential convergence rate of the eigenvalues that correspond to the common and idiosyncratic components of the covariance matrix from a factor model.

[Table 4 around here]

Table 4 reports the number of common factors estimated by the six estimators. While ER, GR, ED, and ABC estimate one common factor, BIC3 estimates three common factors, and IC1 estimates six common factors.[8] The factor structure is consistent with having one strong factor and possibly up to five weak factors.

We now move to estimate the factors themselves. Connor and Korajczyk (1986) show that principal component analysis (PCA) can be used to obtain consistent estimators of the factors. Bai and Ng (2002) show that if there are r factors, as the dimension of the panel (N,

[7]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.

[8]For all these estimators, we set the parameter $kmax$, the maximum number of factors to test for, equal to 15.

T) increases, the r eigenvectors of the second moment matrix corresponding to the largest r eigenvalues are consistent estimators of the factors in an approximate linear factor model like the one we are studying. However, in the presence of weak factors, PCA can fail to identify the factors (Onatski, 2012). Lettau and Pelger (2020b) propose a modified version of the PCA estimator called the Risk Premium-PCA (RP-PCA) that is more efficient in estimating the SDF than PCA and works better in the presence of weak factors.[9]

The objective of PCA is to estimate the factors that explains most of the comovement of the response variables, but it is silent about the mean values. In asset pricing, the asset's means play a fundamental role as they are directly link to the risk-premium. RP-PCA address this issue by adding the objective of minimizing the pricing error generated by the factor model. To implement RP-PCA, the econometrician needs to pick a parameter $\gamma \geq -1$ that weights the importance given to the additional constraint.[10] Figure 2 shows the Sharpe Ratio of PCA and RP-PCA models using one to six estimated factors. For the RP-PCA estimation, we select γ ranging from 5 to 20. The PCA model is estimated from the uncentered second-moment matrix (i.e. it is equivalent to the RP-PCA estimator using $\gamma = 0$).

[Figure 2 around here]

Figure 2 shows that the increment in Sharpe Ratio becomes negligible beyond the third estimated factor. The figure also indicates that RP-PCA factors achieve a higher Sharpe Ratio than PCA factors. Notably, the wedge in Sharpe Ratio between the model with two RP-PCA factors and the one with two PCA factors is quite large. This is consistent with the results in Lettau and Pelger (2020a) and Lettau and Pelger (2020b), who show that RP-PCA is a superior estimator for the SDF, especially in the presence of weak factors.

Capturing the second factor with precision is paramount as it is the most important factor in explaining the cross-section of delta-hedged call option returns. Figure 3 shows this explicitly. The first three panels of the figure show the relation between average returns and

[9] Other recent methodologies developed to estimate the factors when some of them are weak are the Supervised-PCA of Giglio et al. (2021) and the Scaled PCA of Huang et al. (2022).

[10] RP-PCA can be considered a generalization of PCA. When $gamma = -1$, the RP-PCA estimator is the standard PCA estimator obtained from the centered second moment matrix. When $\gamma = 0$, the RP-PCA estimator is the PCA estimator from the uncentered second moment. When $gamma > 0$, the RP-PCA estimator differs from PCA because the restriction for minimizing the pricing error is binding. Lettau and Pelger (2020b) suggests using $\gamma = 10$.

predicted returns from univariate models regressing the test assets onto each of the first three RP-PCA factors. The last panel of the figure shows the relation between average returns and predicted returns using a model with the first three RP-PCA factors together (henceforth, the three-RP-PCA-factor model). The figure clearly shows that the second RP-PCA factor (RP-PCA2) is the critical factor for explaining the cross-section of our test assets. The fourth panel shows that using the three RP-PCA factors in tandem improves the cross-sectional fit of the model.

[Figure 3 around here]

Next, we explore the relative importance of RP-PCA1 and RP-PCA3 in explaining the cross-sectional fit. Ahn and Horenstein (2021) show under general assumptions that, if a multifactor linear asset pricing model generates the pricing kernel, then all assets have the same loading with respect to the equally-weighted portfolio (EWP). This portfolio explains the time-series of returns, but it adds little to no information about the cross-section. Consistent with these findings, in our sample, the correlation between EWP and the first RP-PCA is 0.99 and EWP has little to no power for explaining the cross-section. The first panel of Figure 4 shows how much the correlation between average return and predicted return improves when adding RP-PCA1 to a model containing RP-PCA2, and then adding RP-PCA3 to the other two factors. The figure shows that most of the information about the cross-section is contained in RP-PCA2, some in RP-PCA3, but there is no additional information captured by RP-PCA1. More precisely, the correlation between expected return and predicted returns is 0.85 for a model containing only RP-PCA2, or RP-PCA2 and RP-PCA1. That correlation increases to 0.93 when we add RP-PCA3.

The second panel of Figure 4 shows the relative importance of each factor in explaining the time-series of delta-hedged call option returns. We first regress each observation onto RP-PCA1 and compute the Average Adjusted R^2. Then we augment RP-PCA1 with RP-PCA2, and finally, we add RP-PCA3. Overall, RP-PCA1 is the factor that best fits the time-series of delta-hedged call option returns.

[Figure 4 around here]

Lastly, we check if there is any useful information for pricing delta-hedged option returns beyond RP-PCA3. For that purpose, we create six models that sequentially add RP-PCA1 to RP-PCA6 and report four relevant asset pricing metrics in Table 5: Sharpe Ratio, the correlation between expected return and predicted return, average adjusted R^2 (time-series), and the Average Annualized Absolute Alpha. Table 5 shows that all metrics increase from RP-PCA1 to RP-PCA3 and remain at almost the same level from RP-PCA3 onwards. Therefore, we conclude that the three-RP-PCA-factor model suffices to fit the time-series and cross-section of delta-hedged call option returns.

[Table 5 around here]

In the next section, we explore the economic interpretation of the three-RP-PCA-factor model by studying which of the 21 candidate factors explain the three latent factors. Given that there are three common factors, many of the 21 candidate factors proposed as predictors might contain redundant information. Therefore, it is crucial to identify the candidate factors that can best capture the information in the latent factors.

4.2 Relevant candidate factors of the cross-section of delta-hedged option returns

In the previous section, we find that the three-RP-PCA-factor model is capable of explaining the time-series and cross-section of delta-hedged call option returns. However, we do not know which observed variables drive the common risks across the test portfolios. To answer this question, we run univariate regressions of each of the three RP-PCA factors on the 21 factor candidates discussed in Section 3.3 and report the R^2's in Table 6.

[Table 6 around here]

Table 6 shows that RP-PCA1 is perfectly captured by EWP ($R^2 = 0.99$). The factor that best captures RP-PCA2 is VoV ($R^2 = 0.47$) and the factor that best captures RP-PCA3 is

Voldev ($R^2 = 0.51$). Other factors correlate with RP-PCA2 and RP-PCA3, but none come close to VoV and Voldev. Therefore, we now test if a parsimonious model with observable (and tradable) factors containing EWP, VoV, and Voldev is a good proxy for the Three RP-PCA model. We call this model the *three-factor model*.

Figure 5 shows the relationship between expected returns and predicted returns by each candidate factors compared to the RP-PCA factors. The last tile of the figure compares the three-factor model with the three-RP-PCA-factor model.

[Figure 5 around here]

Figure 5 shows that the observable factors perform similarly to the RP-PCA factors in explaining the cross-section of delta-hedged call option returns. Table 7 further compares the performance of the models using the same metrics asset pricing as in Table 7: Sharpe Ratio, the correlation between expected return and predicted return, average adjusted R^2 (time-series), and average annualized absolute alpha.

[Table 7 around here]

The three-RP-PCA-factor model outperforms the three-factor model in all dimensions but not by a large margin. Results from this table confirm that a parsimonious model with three observable factors (EWP, VoV, and Voldev) captures most of the information in the SDF that the three-RP-PCA-factor model captures.

We now perform some robustness checks across time for the proposed models. Using a window of 60 months, we perform a rolling regression of both factor models on the 185 delta-hedged call portfolio returns used as test assets. Figure 6 reports the results of the correlation between expected return and predicted return (cross-sectional fit) in the top panel and the Average Adjusted R^2 (time-series fit) in the bottom panel.

[Figure 6 around here]

The top panel of Figure 6 shows that the two models have a similar cross-sectional fit on the data until 2009. After that, the three-RP-PCA-factor model outperforms the three-factor model. More precisely, the correlation between expected returns and predicted returns by the three-RP-PCA-factor model fluctuates between 0.70 and 0.90 while for the three-factor model fluctuates between 0.50 and 0.80. The bottom panel shows that both models have similar time-series performance. This is expected since EWP is perfectly correlated with RP-PCA1, the factor that best fits the time-series dimension (see Figure 4).

4.3 Model Performance across Multiple Test Assets

In the previous subsections we propose the three-RP-PCA-factor model and the three-factor model using 185 delta-hedged call option portfolios from 19 characteristics that predict returns. In this section, we analyze the performance of both models across multiple test assets. In particular, we study the performance of the models for four different groups of test assets. First, we test the model on 185 portfolios of delta-hedged *put* option returns constructed using the same 19 option-return predictors used for call portfolios.

For the second and third groups of test assets, we construct placebo portfolios of call and put options based on 152 characteristics that are different from the original 19 characteristics used to derive the main models. The definition and reference of the characteristics are listed in Table A in the Appendix. Note that the predictability of these characteristics has been studied in the stock market, while it has not been studied in the cross-section of option returns. Hence, they are suitable as test assets in the placebo tests. We test the models on 1520 and 1517 portfolios of delta-hedged call option returns and delta-hedged put option returns based on these 152 characteristics. These 152 characteristics can potentially predict option returns, but our main factor models should have strong commonalities with the factor structure of the placebo portfolios.

Finally, we also explore whether the factors from delta-hedged option returns span dimensions missed by stock return factors. We use as test assets for uncovering the equity risk-premium the long-short stock portfolio returns of 190 stock return predictors used by Chen and Zimmermann (2022). If delta-hedged option returns capture higher-order risk premia beyond the equity risk premium, then we should expect our option factor models to be uncorrelated with the factor structure of stock returns. For this purpose, we add a canonical correlation study in addition to the asset pricing metrics and figures already reported.

Figure 7 shows the relationship between expected and predicted returns for the previously developed three-RP-PCA-factor model and three-factor model across test assets. Table 8 shows the performance metrics of both models across the four groups of test assets.

[Figure 7 around here]

[Table 8 around here]

Figure 7 shows visually that both models perform similarly in the cross-section of portfolio option returns, whether we use call options or put options and different characteristics to construct the univariate sorted portfolios. The figure also shows that the models cannot explain the cross-section of stock returns.

Table 8 shows that the Three RP-PCA model and the Three Observable factor model constructed from 185 delta-hedged call option returns work well across option portfolio returns built using a different set of characteristics to group assets and also for pricing put option returns. Both models fail when stock returns are used as test assets.

These results suggest that there exists commonalities in the factor structure of the different sets of option returns portfolios. In addition, there might be no commonalities between delta-hedged options and stock return portfolios. To confirm this hypothesis, we calculate the sample canonical correlations between the first three RP-PCA factors estimated from each group of test assets. We also include in the comparison the first five RP-PCA factors estimated from stock returns since Lettau and Pelger (2020b) find that five RP-PCA are necessary to fit the time-series and cross-section of stock returns. The results are shown in Table 9.

[Table 9 around here]

The table shows that the three RP-PCA factors extracted from the 185 delta-hedged call option portfolios and those from the 1520 delta-hedged call option portfolios share a very similar factor structure. Two canonical correlations are above 0.90 suggesting that two factors are the same. The third canonical correlation is 0.73, suggesting that a third factor is not fully shared. Similar results are observed for the two sets of delta-hedged option put portfolios. We also find that puts and calls share one factor's information almost perfectly (first canonical correlation is 0.93), share some information on a second factor (second canonical correlation is 0.60), but do not share the third factor. This might happen because put option portfolios are less populated than call portfolios, containing more noise in the estimated factor structure (there are 50% more ATM call contracts than put contracts). Given that the second and third factors are relatively weak, it might be harder to capture them from the set of put portfolios. Finally, the table shows no commonalities between the factor structure of delta-hedged option returns and that of stock returns. Whether we use three RP-PCA or five RP-PCA to estimate the stock returns' stochastic discount factor, the canonical correlations are quite low. This last result confirms that stock return factors cannot span higher-order risk premia.

Overall, our parsimonious model constructed with three observable factors to price delta-hedged option returns works well across test assets and time periods. We also find that option and stock return factors share negligible common information.

5 Conclusion

Despite the extensive and still growing literature on common factors in stock returns developed to understand the drivers of the equity risk premium, there is limited understanding of the factor structure in the cross section of option returns and higher-order risk premia. For this purpose, understanding what drives the comovement of delta-hedged option returns is crucial. We motivate our empirical analysis by showing that in a stochastic volatility model, in which volatility has a factor structure, the expected delta-hedged option returns are possibly driven by factors related to volatility risk and volatility-of-volatility risk.

We construct 185 option portfolios sorted by 19 characteristics using monthly portfolios of delta-hedged options from January 1996 to December 2019. We use the characteristics that predict future option returns according to the current literature. Given that we find that the factor structure of the portfolios contains strong and weak factors, we use the RP-PCA method by Lettau and Pelger (2020b) that outperforms standard PCA in this context and find that three RP-PCA factors explain the time-series and the cross-section of option returns.

We explore which observable factors capture the three RP-PCA latent factors. We consider 19 characteristic-based factors constructed based on long-short strategies of univariate sorted portfolios, the straddle return of the S&P 500 index and average delta-hedged returns of the 185 option portfolios (EWP) as candidate factors. We find that three of them suffice to capture the relevant latent factors and, therefore, to explain the time series and cross-section of delta-hedged equity option returns. The three factors are the EWP, the long-short option portfolio returns constructed based on volatility of implied volatility, and volatility deviation, which is the difference between historical and implied volatilities. The last two factors fit the cross-section while EWP only fits the time-series.

The explanatory power of our proposed factor model extends to delta-hedged put option portfolios based on the 19 characteristics and 1520 (1517) placebo portfolios of delta-hedged call (put) option portfolios based on 152 firm characteristics. Finally, the three factors we find are uncorrelated with stock returns factors. Therefore, volatility risk premium and higher-order risk premia are driven by a different set of factors than the equity risk premium.

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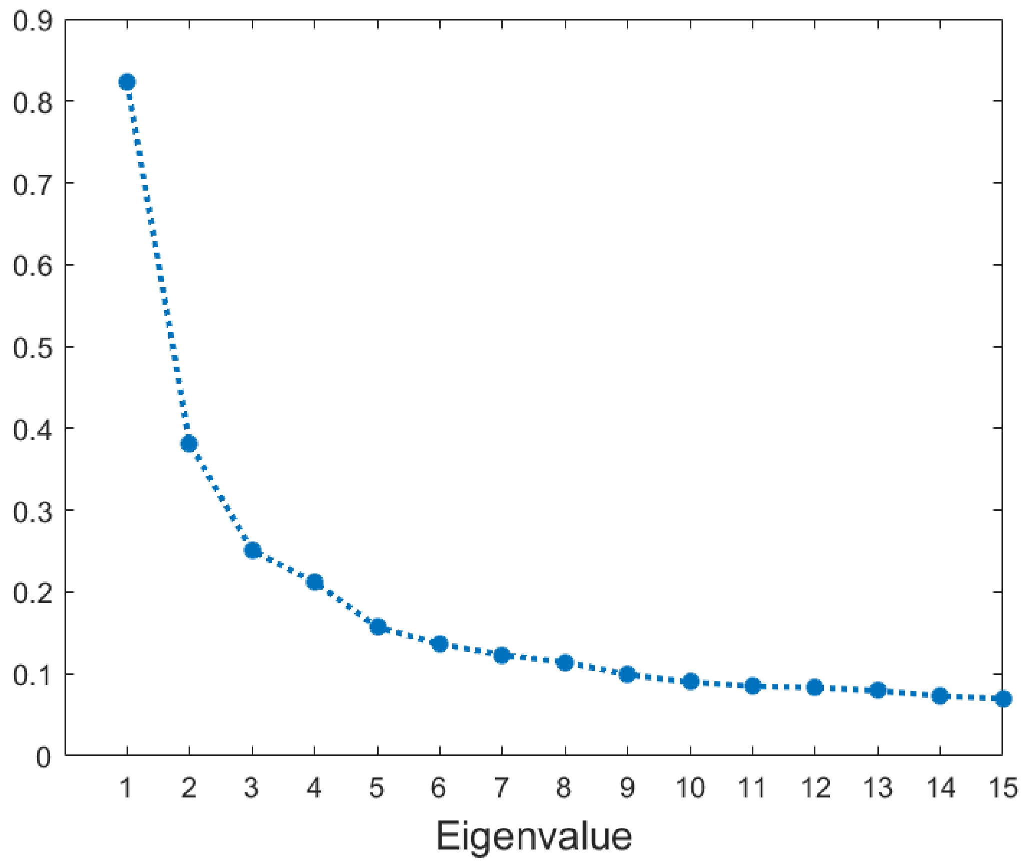
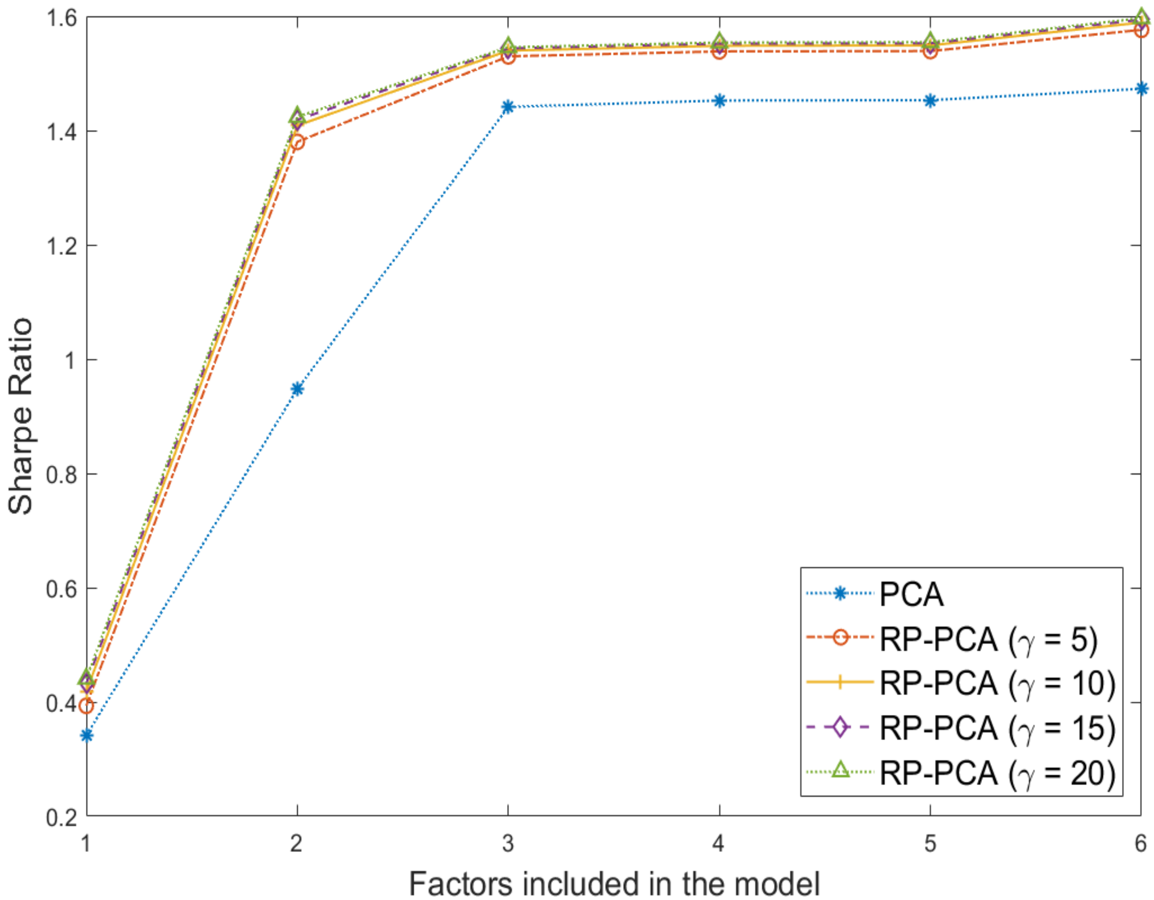
Figure 1: Scree Test



This figure shows the results for scree test. We plot the largest fifteen eigenvalues from the sample second-moment matrix of the delta-hedged portfolio returns. The sample period is from January 1996 to December 2019.

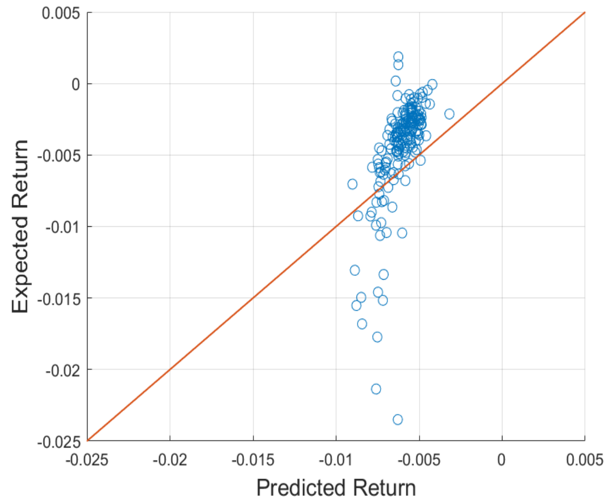
Figure 2: Sharpe Ratio and the Number of Factors in the Model



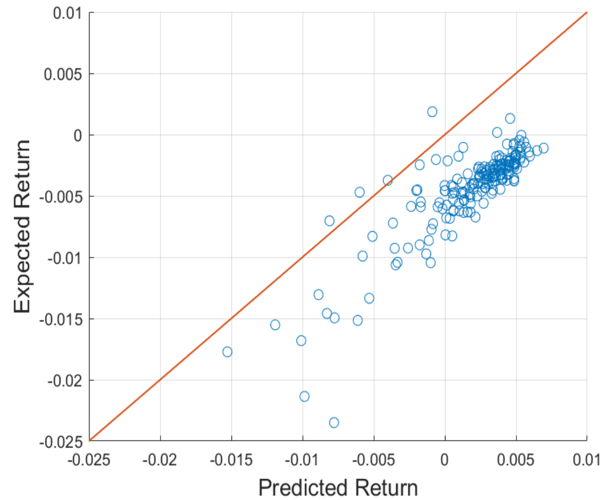
This figure shows the Sharpe ratios generated by the factor model using PCA and risk premium PCA (RP-PCA) with four levels of risk aversion (γ). The sample period is from January 1996 to December 2019 for stocks in the OptionMetrics database.

Figure 3: Performance of the First Three RP-PCA Factors

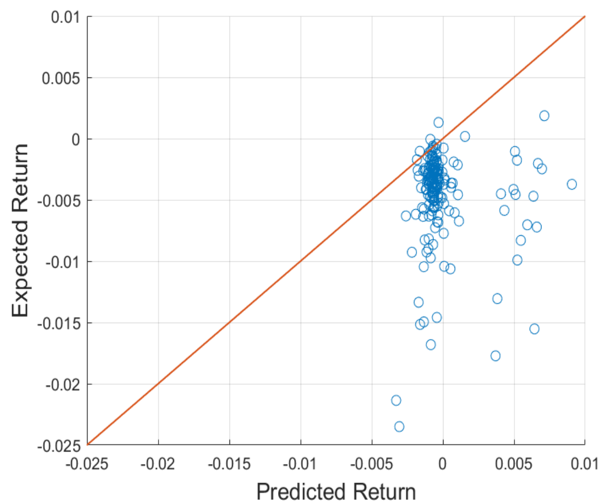
(a) The First RP-PCA Factor



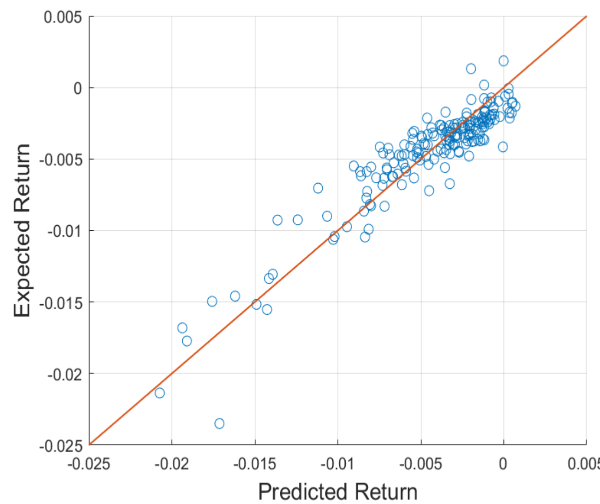
(b) The Second RP-PCA Factor



(c) The Third RP-PCA Factor



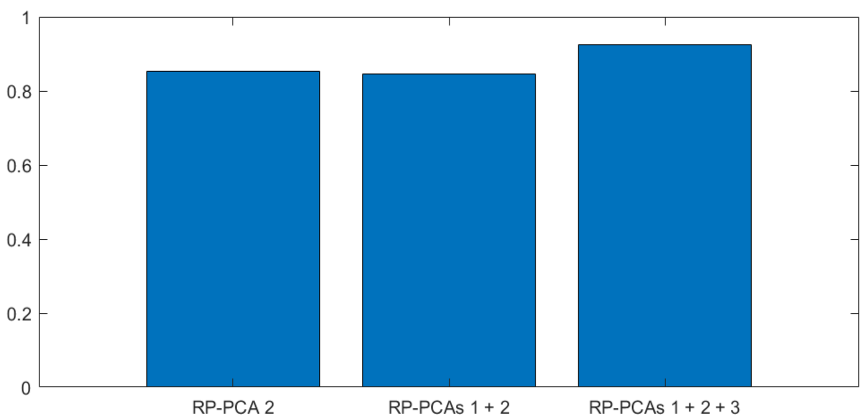
(d) The Three RP-PCA Factors



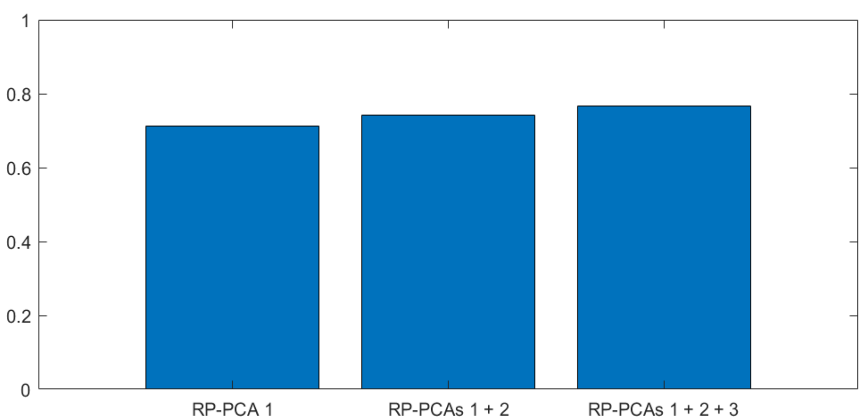
This figure shows the performance of the first three RP-PCA factors in terms of the relation between realized return and predicted return by the factors. The first three panels of the figure show the relation between average returns and predicted returns from models regressing the test assets onto the first three RPPCA individually. The last panel of the figure shows the relation between average returns and predicted returns using a model with the first three RP-PCA factors.

Figure 4: Relative Importance of the First Three RP-PCA Factors

(a) Correlation Between E(r) and Predicted(r)



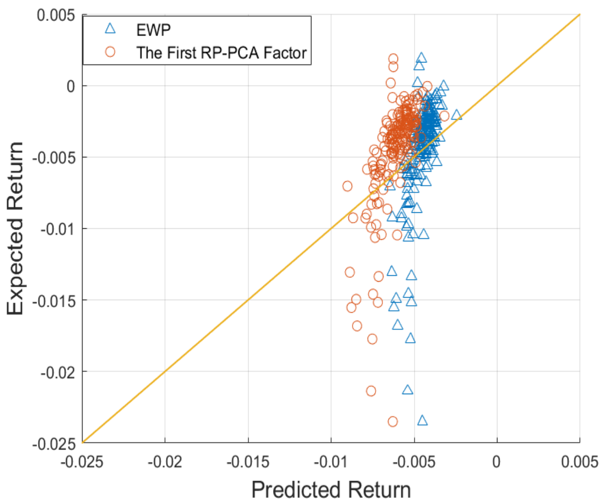
(b) Time-series Average Adj. R^2



Panel (a) shows how much the correlation between average return and predicted return improves when adding RP-PCA1 to a model containing RP-PCA2, and then adding RP-PCA3 to the other two factors. Panel (b) shows how much information about the time-series of delta-hedged call option returns is contained in each factor. We first regress each observation onto RP-PCA1 and report the Average Adjusted R2. Then we augment RP-PCA1 with RP-PCA2, and finally add RP-PCA3.

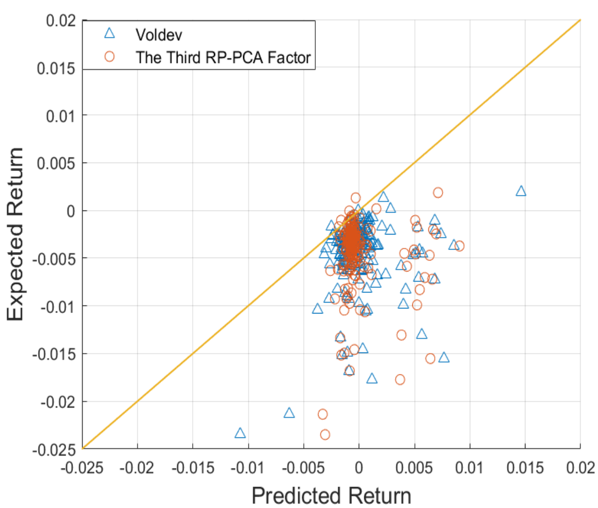
Figure 5: Comparison of the First Three RP-PCA Factors and the Three Selected Candidate Factors

(a) EWP vs the First RP-PCA Factor

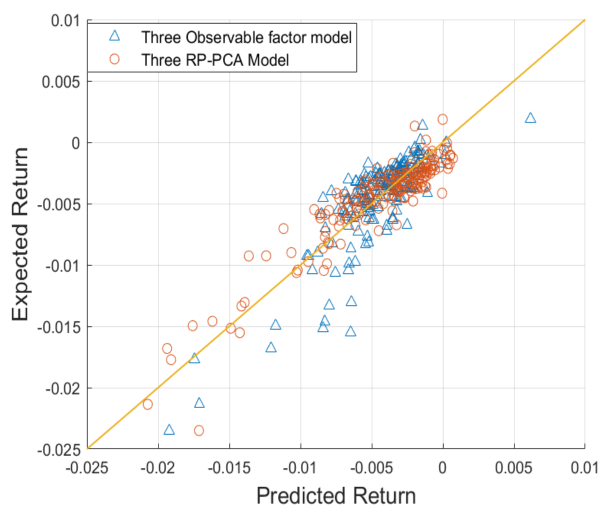


(b) VoV vs the Second RP-PCA Factor

(c) Voldev vs the Third RP-PCA Factor



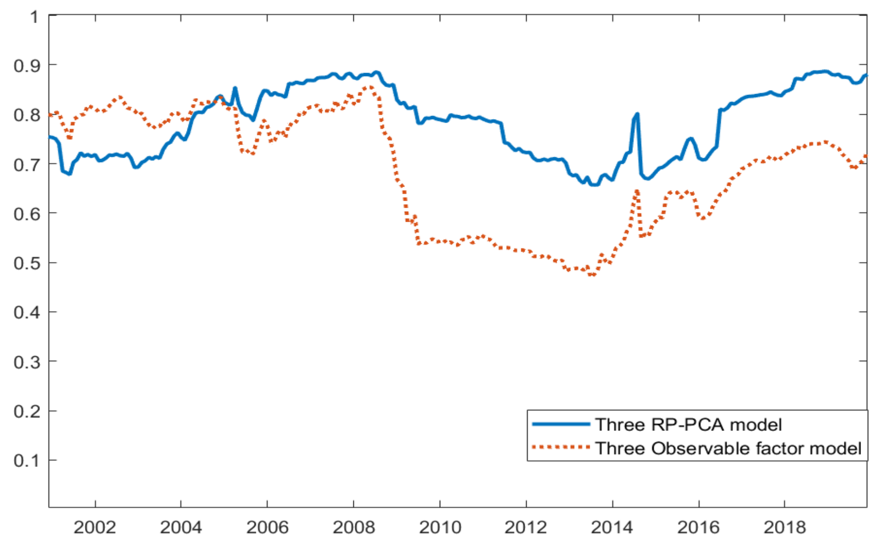
(d) Three Candidate Factors vs the Three RP-PCA Factors



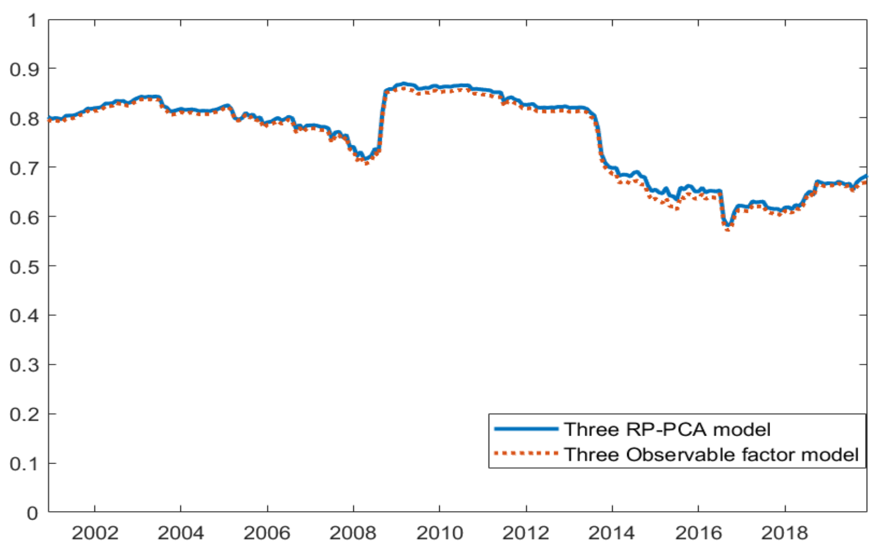
This figure shows the relationship between expected returns and predicted returns by each candidate factors compared to the RP-PCA factors in Panel (a), (b), and (c). Panel (d) compares the three observable factor model with the three RP-PCA model.

Figure 6: Correlation of Average Return and Predicted Return by the Four-factor Model Over Time

(a) Rolling Correlation Between E(r) and Predicted(r)



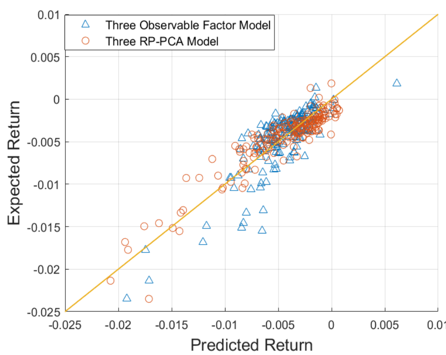
(b) Rolling Time-series Average Adj. R^2



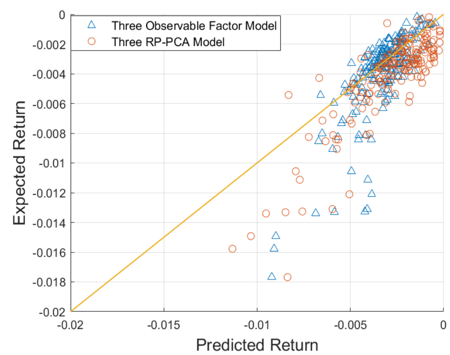
Panel (a) shows the correlation of average return and predicted returns by the three-factor model over time. We run monthly rolling regressions using 60-month of data with the 185 delta-hedged call portfolio returns as test assets. For each regression we calculate the correlation between the average returns of the delta-hedged portfolios and the predicted returns by our three-factor model. Panel (b) reports the average adjusted R^2 of the rolling window regressions over time.

Figure 7: Comparison of the Three Observable Factor Model and Three RP-PCA Model with Additional Test Assets

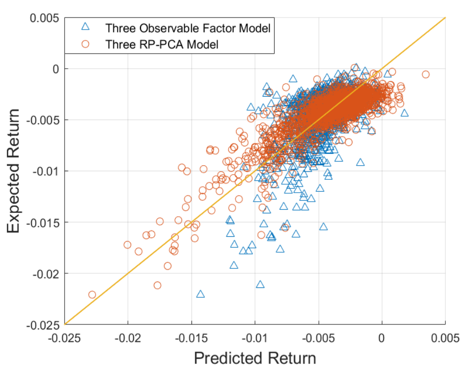
(a) Delta-hedged Call Portfolios



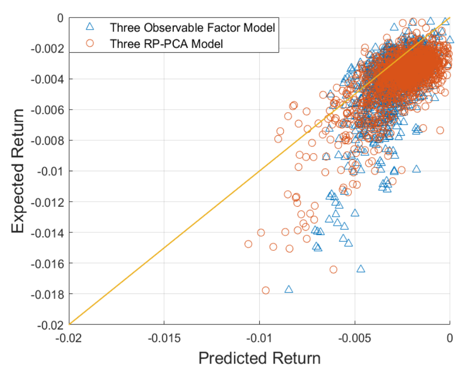
(b) Delta-hedged Put Portfolios



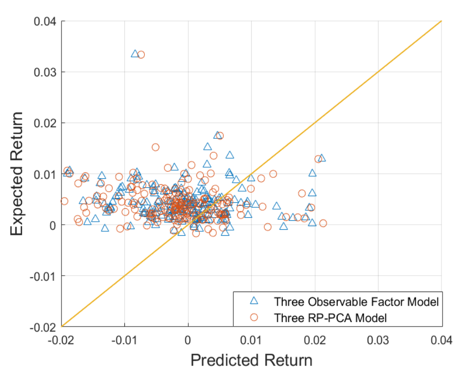
(c) Delta-hedged Call Portfolios - Placebo



(d) Delta-hedged Put Portfolios - Placebo



(e) Stock Portfolios



This figure shows the relation between average return and predicted return by the three observable factor model and three RP-PCA model with additional test aseets. Panel (a) reports results for 185 delta-hedged call option portfolios. Panel (b) reports results for 185 portfolios of delta-hedged put option, constructed using the same characteristics as the call portfolios. We also built 1520 (1517) portfolios of delta-hedged call (put) option returns based on 152 characteristics not used for the previous portfolios. Panel (c) and (d) report results for these two sets of portfolios. Panel (e) reports results for long-short stock portfolio returns of 190 stock return predictors used in Chen and Zimmermann (2022). The sample period is from January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 1: Delta-hedged Option Return Sorted by 19 Characteristics

	1	2	3	4	5	6	7	8	9	10	L-S
Size	-1.57	-0.87	-0.60	-0.44	-0.31	-0.27	-0.24	-0.16	-0.08	-0.06	1.51***
	(-11.2)	(-6.1)	(-5.0)	(-4.2)	(-3.0)	(-2.8)	(-2.5)	(-1.7)	(-0.8)	(-0.7)	(14.0)
Ivol	-0.17	-0.10	-0.18	-0.16	-0.25	-0.24	-0.44	-0.58	-0.93	-1.55	-1.38***
	(-2.5)	(-1.2)	(-2.0)	(-1.6)	(-2.5)	(-2.1)	(-3.4)	(-4.8)	(-7.1)	(-10.1)	(-11.4)
Voldev	-2.48	-1.04	-0.56	-0.39	-0.24	-0.21	-0.05	0.05	0.17	0.20	2.68***
	(-19.3)	(-9.7)	(-5.3)	(-3.4)	(-2.4)	(-2.2)	(-0.5)	(0.5)	(1.6)	(1.6)	(19.0)
Vts	-2.28	-0.81	-0.41	-0.29	-0.17	-0.16	-0.13	-0.04	-0.07	-0.20	2.08***
	(-16.1)	(-6.4)	(-4.0)	(-2.7)	(-1.6)	(-1.7)	(-1.3)	(-0.5)	(-0.6)	(-1.9)	(17.3)
BM	-1.05	-0.62	-0.51	-0.39	-0.41	-0.31	-0.29	-0.16	-0.28	-0.38	0.67***
	(-9.1)	(-6.0)	(-4.8)	(-3.9)	(-4.1)	(-2.8)	(-2.9)	(-1.3)	(-2.8)	(-2.9)	(6.8)
Credit	0.00	-0.09	-0.17	-0.29	-0.56						-0.57***
	(0.0)	(-1.0)	(-1.9)	(-2.7)	(-4.2)						(-5.9)
VOV	0.02	-0.02	-0.10	-0.14	-0.23	-0.31	-0.34	-0.55	-0.99	-1.89	-1.91***
	(0.2)	(-0.3)	(-1.0)	(-1.4)	(-2.3)	(-2.9)	(-3.0)	(-4.8)	(-7.6)	(-12.7)	(-13.7)
Illiquidity	-0.04	-0.11	-0.20	-0.28	-0.26	-0.39	-0.44	-0.48	-0.89	-1.43	-1.39***
	(-0.5)	(-1.1)	(-2.1)	(-2.9)	(-2.5)	(-3.8)	(-4.1)	(-3.5)	(-7.8)	(-9.9)	(-12.2)
Reversal	-0.92	-0.58	-0.31	-0.35	-0.37	-0.31	-0.33	-0.41	-0.40	-0.61	0.31***
	(-5.9)	(-4.8)	(-2.8)	(-3.6)	(-4.1)	(-3.3)	(-3.7)	(-4.0)	(-3.8)	(-5.2)	(2.7)
Mom	-0.69	-0.54	-0.44	-0.41	-0.43	-0.37	-0.25	-0.36	-0.36	-0.69	0.00
	(-4.0)	(-4.6)	(-4.4)	(-4.1)	(-4.7)	(-4.1)	(-2.5)	(-3.8)	(-3.4)	(-5.9)	(-0.0)
VarCF	-0.19	-0.21	-0.25	-0.19	-0.21	-0.43	-0.43	-0.68	-0.73	-1.15	-0.96***
	(-2.1)	(-2.2)	(-2.9)	(-1.7)	(-2.1)	(-4.2)	(-4.0)	(-6.6)	(-5.3)	(-8.8)	(-9.0)
Ch	-0.15	-0.17	-0.20	-0.25	-0.27	-0.29	-0.38	-0.43	-0.62	-1.54	-1.39***
	(-1.3)	(-1.7)	(-1.9)	(-2.4)	(-2.3)	(-2.8)	(-3.6)	(-3.6)	(-5.7)	(-10.9)	(-11.3)
Disp	-0.18	-0.29	-0.18	-0.12	-0.25	-0.28	-0.42	-0.44	-0.62	-0.72	-0.53***
	(-2.0)	(-3.0)	(-1.9)	(-1.1)	(-2.5)	(-2.6)	(-3.8)	(-3.0)	(-4.8)	(-5.6)	(-5.6)
ShareIss1y	-0.25	-0.21	-0.29	-0.32	-0.34	-0.38	-0.44	-0.65	-0.73	-0.91	-0.66***
	(-2.3)	(-2.2)	(-3.2)	(-3.2)	(-3.2)	(-3.4)	(-3.6)	(-6.0)	(-6.1)	(-7.4)	(-6.9)
ShareIss5y	-0.60	-0.21	-0.29	-0.34	-0.47	-0.37	-0.34	-0.53	-0.57	-0.41	0.19**
	(-6.2)	(-2.0)	(-2.9)	(-3.1)	(-4.8)	(-3.5)	(-2.4)	(-5.5)	(-5.1)	(-3.6)	(2.2)
PM	-1.67	-0.63	-0.26	-0.26	-0.19	-0.22	-0.23	-0.25	-0.14	-0.32	1.35***
	(-10.1)	(-5.3)	(-2.0)	(-2.6)	(-1.9)	(-2.2)	(-2.3)	(-2.7)	(-1.6)	(-3.4)	(9.8)
Price	-1.74	-1.03	-0.60	-0.44	-0.22	-0.15	-0.11	-0.14	-0.07	-0.07	1.66***
	(-10.9)	(-7.5)	(-4.9)	(-4.3)	(-2.3)	(-1.6)	(-1.2)	(-1.6)	(-0.8)	(-0.8)	(13.3)
Profit	-0.92	-0.58	-0.26	-0.21	-0.21	-0.21	-0.17	-0.20	-0.20	-0.44	0.47***
	(-6.7)	(-4.7)	(-2.2)	(-1.6)	(-2.0)	(-2.3)	(-1.9)	(-2.0)	(-2.2)	(-4.5)	(4.5)
XFIN	-0.33	-0.23	-0.22	-0.28	-0.34	-0.30	-0.44	-0.45	-0.63	-1.41	-1.08***
	(-3.7)	(-2.3)	(-2.3)	(-2.6)	(-3.1)	(-2.7)	(-4.2)	(-4.4)	(-5.2)	(-9.1)	(-8.4)

At the end of each month, we construct decile or quintile portfolios by sorting on 19 characteristics. Size is the natural logarithm of the market value of the firm's equity. Ivol, the stock return idiosyncratic volatility, is defined as the standard deviation of the residuals from regressing the stock's returns in excess of the one-month Treasury bill rate on the Fama-French 3-factor model.

Voldev is the log difference between the realized volatility and the Black-Scholes implied volatility for at-the-money options with 30 days of maturity. Vts is the slope of volatility term structure (Vts), defined as the difference between long-term and short-term implied volatility. BM is the ratio of book equity to market equity. Credit is credit ratings, provided by Standard & Poor's and mapped to 22 numerical values, where 1 corresponds to the highest rating (AAA) and 22 corresponds to the lowest rating (D). VOV is volatility of volatility, defined as standard deviation of implied volatility daily change in the past month. Illiquidity is defined as the average of the daily ratio of the absolute stock return to dollar volume over the previous month in Amihud (2002). Reversal is stock return reversal, defined as the lagged one-month return. Mom is stock return momentum, defined as the cumulative return on the stock over the 11 months ending at the beginning of the previous month. VarCF is cash flow variance, defined as the 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. Ch is cash-to-assets ratio, defined as the value of corporate cash holdings over the value of the firm's total assets. Disp is analyst earnings forecast dispersion, defined as standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast. ShareIss1Y is one-year new issues, defined as the change in shares outstanding in the past one year. ShareIss5Y is five-year new issues, defined as the change in number of shares outstanding in the past five years. PM is profit margin, defined as earnings before interest and tax scaled by revenues. Price is stock price, defined as the log of stock price at the end of last month. Profit is profitability, defined as earnings divided by book equity in which earnings are defined as income before extraordinary items. Xfin is total external financing, defined as net share issuance plus net debt issuance minus cash dividends, scaled by total assets. We report 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 2019 for stocks in the OptionMetrics database.

Table 2: Summary Statistics of the Long-short Factors

	Mean	Std. Dev.	10th. Pctl.	25th. Pctl.	50th. Pctl.	75th. Pctl.	90th. Pctl.	Skew	Kurt
Size	1.42	1.71	-0.80	0.52	1.42	2.48	3.50	-0.12	1.2
Ivol	-1.28	1.96	-3.44	-2.51	-1.56	-0.30	1.25	1.04	2.1
Voldev	2.58	2.34	0.38	1.37	2.31	3.62	5.02	2.87	24.8
Vts	1.99	2.00	-0.03	0.81	1.85	3.02	4.22	0.24	1.7
BM	0.68	1.70	-0.98	-0.18	0.60	1.44	2.42	1.03	10.1
Credit	-0.54	1.66	-2.05	-1.32	-0.67	0.02	0.95	3.43	27.5
VOV	-1.81	2.31	-3.77	-3.01	-1.93	-0.76	0.37	2.03	19.2
Illiquidity	-1.29	1.81	-3.35	-2.19	-1.35	-0.44	0.75	0.56	3.4
Reversal	0.31	2.03	-1.80	-0.71	0.32	1.47	2.58	-1.29	7.4
Mom	0.01	2.47	-2.45	-0.98	0.27	1.22	2.44	-3.85	35.4
VarCF	-0.87	1.70	-2.56	-1.80	-0.92	0.02	1.08	0.04	4.6
Ch	-1.34	2.07	-3.52	-2.47	-1.38	-0.30	1.01	-0.30	4.1
Disp	-0.53	1.63	-2.22	-1.33	-0.59	0.26	1.40	0.26	2.2
ShareIss1y	-0.60	1.59	-2.20	-1.37	-0.53	0.11	0.98	-1.93	22.2
ShareIss5y	0.18	1.42	-1.27	-0.63	0.09	0.84	1.77	0.54	3.7
PM	1.25	2.29	-0.90	0.35	1.40	2.29	3.38	-4.12	43.4
Price	1.57	2.02	-1.11	0.62	1.65	2.76	3.64	-0.17	1.5
Profit	0.47	1.82	-1.27	-0.33	0.53	1.49	2.41	-1.37	6.1
XFIN	-1.01	2.16	-3.02	-2.14	-1.24	-0.20	1.05	2.06	13.5
Strad	-0.11	0.33	-0.42	-0.35	-0.20	0.03	0.27	1.92	5.5
EWP	-0.39	1.60	-1.94	-1.30	-0.58	0.18	1.35	1.88	8.1

This table reports summary statistics of the returns on long-short portfolios (in percentage). The factors are long-short return spread sorted by 19 characteristics. The definition of the characteristics is provided in Section 3.3. Sample period is from January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 3: Correlation Matrix of the Candidate Factors in the Equity Option Market

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1-Size	100																				
2-Ivol	-43	100																			
3-Voldev	15	-1	100																		
4-Vts	14	-28	46	100																	
5-BM	-3	-4	-15	11	100																
6-Credit	-34	48	16	-11	-21	100															
7-VOV	-28	52	0	-32	-28	53	100														
8-Illiquidity	-78	33	-19	-5	1	26	21	100													
9-Reversal	17	-26	1	5	-22	-13	-1	2	100												
10-Mom	29	-33	-23	-2	-7	-47	-42	-6	18	100											
11-VarCF	-44	40	-4	-21	2	37	49	34	-4	-31	100										
12-Ch	-14	29	-23	-20	-28	-5	6	25	10	31	-6	100									
13-Disp	-29	40	11	-9	-7	32	33	27	-13	-26	34	8	100								
14-ShareIss1y	-4	33	4	-20	-40	22	36	0	19	1	14	26	18	100							
15-ShareIss5y	12	23	25	8	-3	10	3	-19	-22	-8	-18	5	19	19	100						
16-PM	21	-35	-25	5	41	-50	-56	-24	-13	31	-35	-21	-23	-36	2	100					
17-Price	65	-59	6	14	-5	-37	-50	-49	30	54	-48	-15	-35	-9	-12	34	100				
18-Profit	18	-30	14	32	14	-19	-20	-15	12	-3	-17	-33	-26	-17	-6	24	21	100			
19-XFIN	-27	48	20	-20	-44	48	55	29	2	-26	21	32	36	53	18	-70	-35	-37	100		
20-Strad	-2	20	5	1	3	16	10	4	-4	-11	14	-1	9	7	-2	-4	-10	8	6	100	
21-EWP	-29	58	4	-8	13	39	17	25	-34	-27	16	13	31	5	30	-18	-40	-28	30	35	100

This table reports correlation matrix (in %) of the 21 candidate factors in the equity option market. The factors are long-short return spread sorted by 19 characteristics, the straddle return of the S&P 500 index, and the equally-weighted portfolio that averages the 185 characteristic-based delta-hedged portfolios. The definition of the characteristics is provided in Section 3.3. Sample period is from January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 4: Estimation for the Number of Factors in the Delta-hedged Option Portfolios

	Number of Factors
Eigenvalue Ratio (ER) estimator in Ahn and Horenstein (2013)	1
Growth Ratio (GR) estimator in Ahn and Horenstein (2013)	1
Edge Distribution (ED) estimator in Onatski (2010)	1
Modified Bayesian information criterion (BIC3) estimator in Bai and Ng (2002)	3
Information Criterion (IC1) estimator in Bai and Ng (2002)	6
Modified Information Criterion estimator (ABC) in Alessi et al. (2010)	1

This table presents results obtained from estimating the number of factors using the Eigenvalue Ratio (ER) and Growth Ratio (GR) estimators of Ahn and Horenstein (2013), the Edge Distribution (ED) estimator of Onatski (2010), the BIC3 and IC1 estimators of Bai and Ng (2002), and the Modified Information Criterion estimator (ABC) of Alessi et al. (2010). The test assets are 185 characteristic-sorted delta-hedged option portfolios reported in Table 1. The sample period is January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 5: Risk-Premium-PCA with Different Number of Factors

	K=1	K=2	K=3	K=4	K=5	K=6
Sharpe Ratio	0.42	1.41	1.54	1.55	1.55	1.59
Correlation Pred(r)-Exp(r)	0.66	0.85	0.93	0.93	0.93	0.93
Average Adjusted R2	0.71	0.74	0.77	0.78	0.79	0.80
Av. Anualized Abs. Alpha	0.342	0.021	0.015	0.014	0.014	0.014

This table report five metrics for six models sequentially adding the first RP-PCA factor to the sixth RP-PCA factor: Sharpe Ratio, the correlation between expected return and predicted return, average adjusted R2 (time-series), and the Average Annualized Absolute Alpha. The sample period is January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 6: R^2 of regressing RP-PCA Factors on Candidate Factors

RP-PCA1		RP-PCA2		RP-PCA3	
R^2	Factor	R^2	Factor	R^2	Factor
0.99	EWP	0.47	VOV	0.51	Voldev
0.42	Ivol	0.36	Price	0.32	Mom
0.24	Xfin	0.25	Size	0.27	PM
0.23	Credit	0.24	PM	0.21	Credit
0.17	Price	0.21	Ivol	0.20	Ch
0.14	Disp	0.21	Xfin	0.13	Vts
0.14	Straddle Ind	0.18	Illiquidity	0.11	Xfin
0.13	ShareIss1Y	0.18	VarCF	0.11	VOV
0.12	VOV	0.15	Vts	0.03	Profit
0.12	Profit	0.12	Credit	0.03	BM
0.12	PM	0.11	Ch	0.02	VarCF
0.11	Size	0.09	Mom	0.01	Disp
0.10	VarCF	0.08	Profit	0.01	Illiquidity
0.09	Illiquidity	0.07	Disp	0.01	Size
0.06	ShareIss5Y	0.07	BM	0.01	Reversal
0.05	Mom	0.05	Voldev	0.00	ShareIss5Y
0.05	Reversal	0.04	ShareIss1Y	0.00	Price
0.05	Vts	0.02	Reversal	0.00	Ivol
0.04	Ch	0.01	ShareIss5Y	0.00	Straddle Ind
0.01	BM	0.01	Straddle Ind	0.00	EWP
0.00	Voldev	0.01	EWP	0.00	ShareIss1Y

We regress each of the three RP-PCA factors on the 21 factor candidates discussed in Section 3.3. This table reports the R^2's of the regressions. The sample period is January 1996 to December 2019.

Table 7: Model Comparison: Three RP-PCA factor model vs Three Observable factor model

	Three RP-PCA factor model	Three Observable factor model
Sharpe Ratio	1.54	1.39
Correlation Pred(r)-Exp(r)	0.93	0.84
Average Adjusted R2	0.77	0.75
Av. Anualized Abs. Alpha	0.015	0.018

This table reports five performance metrics for the three RP-PCA factor model and the three observable factor model: Sharpe Ratio, the correlation between expected return and predicted return, and average adjusted R2 (time-series), average annualized absolute alpha. The sample period is January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 8: Model Comparison with Additional Sets of Test Assets

	185 delta-hedged call option returns	185 delta-hedged put option returns	1520 delta-hedged call option returns	1517 delta-hedged put option returns	190 long-short stock returns
Panel A: Three RP-PCA factor model					
Correlation Pred(r)-Exp(r)	0.93	0.85	0.84	0.72	-0.13
Average Adjusted R2	0.77	0.69	0.72	0.66	0.04
Av. Anualized Abs. Alpha	0.015	0.018	0.015	0.019	0.105
Panel B: Three Observable factor model					
Correlation Pred(r)-Exp(r)	0.84	0.78	0.62	0.50	-0.09
Average Adjusted R2	0.75	0.68	0.71	0.65	0.03
Av. Anualized Abs. Alpha	0.018	0.016	0.016	0.014	0.098

This table shows the performance metrics of the three RP-PCA model (in panel A) and the three observable factor model (in panel B) across test assets. We consider 185 portfolios of delta-hedge call option returns, 185 portfolios of delta-hedge put option returns constructed using the same characteristics as the call portfolios, and 1520 (1517) portfolios of delta-hedge call (put) option returns based on 152 characteristics not used for the previous portfolios. Finally, we also consider long-short stock portfolio returns of 190 stock returns predictors used in Chen and Zimmermann (2022). The sample period is January 1996 to December 2019 for stocks in the OptionMetrics database.

Table 9: Canonical Correlations of the three RP-PCA Factors Estimated from Different Samples

	3 RP-PCA Call Option Factors	3 RP-PCA Call Option Factors Placebo	3 RP-PCA Put Option Factors	3 RP-PCA Put Option Factors Placebo	3 Observable Factor Model
3 RP-PCA Call Option Factors	(1.00 , 1.00 , 1.00)				
3 RP-PCA Call Option Factors Placebo	(0.99 , 0.96 , 0.73)	(1.00 , 1.00 , 1.00)			
3 RP-PCA Put Option Factors	(0.93 , 0.54 , 0.02)	(0.93 , 0.58 , 0.11)	(1.00 , 1.00 , 1.00)		
3 RP-PCA Put Option Factors Placebo	(0.93 , 0.42 , 0.03)	(0.93 , 0.60 , 0.12)	(0.99 , 0.93 , 0.79)	(1.00 , 1.00 , 1.00)	
3 Observable Factor model	(1.00 , 0.83 , 0.73)	(1.00 , 0.78 , 0.32)	(0.92 , 0.42 , 0.28)	(0.92 , 0.26 , 0.20)	(1.00 , 1.00 , 1.00)
3 RP-PCA Stock Returns Factors	(0.29 , 0.17 , 0.02)	(0.26 , 0.21 , 0.04)	(0.37 , 0.28 , 0.00)	(0.36 , 0.23 , 0.04)	(0.28 , 0.27 , 0.01)
5 RP-PCA Stock Returns Factors	(0.38 , 0.29 , 0.08)	(0.37, 0.26 , 0.21)	(0.39 , 0.37 , 0.13)	(0.38 , 0.35 , 0.07)	(0.37 , 0.29 , 0.08)

We calculate the sample canonical correlations between the first three RP-PCA factors estimated from each sample and the 3 Observable Factor model constructed from delta-hedged call option portfolios. We also include in the comparison the first five RP-PCA factors estimated from stock returns since Lettau and Pelger (2020b) find that five RP-PCA are necessary to fit the time-series and cross-section of stock returns. The sample period is January 1996 to December 2019 for stocks in the OptionMetrics database.

A Appendix

Table A1: Predictor Definition in the Placebo Test

	Description	Reference
1	Change in capital investment (industry adjusted)	Abarbanell and Bushee (1998)
2	Effective tax rate	Abarbanell and Bushee (1998)
3	Gross margin growth to sales growth	Abarbanell and Bushee (1998)
4	Sales growth over inventory growth	Abarbanell and Bushee (1998)
5	Sales growth over overhead growth	Abarbanell and Bushee (1998)
6	Change in sales over change in receivables	Abarbanell and Bushee (1998)
7	Laborforce efficiency	Abarbanell and Bushee (1998)
8	Change in gross margin over sales	Abarbanell and Bushee (1998)
9	Broker-dealer leverage beta	Adrian, Etula, and Muir (2014)
10	Idiosyncratic risk	Ali, Hwang, and Trombley (2003)
11	Earnings consistency	Alwathainani (2009)
12	Change in capital expenditurec (two years)	Anderson and Garcia-Feijoo (2006)
13	Change in capital expenditure (three years)	Anderson and Garcia-Feijoo (2006)
14	Systematic volatility	Ang, Hodrick, Xing, and Zhang (2006b)
15	Downside beta	Ang, Chen, and Xing (2006a)
16	Change in order backlog	Baik and Ahn (2007)
17	Change in return on assets	Balakrishnan, Bartov, and Faurel (2010)
18	Change in return on equity	Balakrishnan, Bartov, and Faurel (2010)
19	Return on assets (quarterly)	Balakrishnan, Bartov, and Faurel (2010)
20	Maximum return over month	Bali et al. (2011)
21	Return skewness	Bali, Engle, and Murray (2016)
22	Idiosyncratic skewness using three-factor model	Bali, Engle, and Murray (2016)
23	Cash-based operating profitability	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)
24	Operating profitability R&D adjusted	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)
25	Sales-to-price	Barbee Jr, Mukherji, and Raines (1996)
26	Firm age	Barry and Brown (1984)
27	Earnings-to-Price ratio	Basu (1977)
28	Employment growth	Belo, Lin, and Bazdresch (2014a)
29	Inventory growth	Belo and Lin (2012)
30	Brand capital to assets	Belo, Lin, and Vitorino (2014b)
31	Market leverage	Bhandari (1988)
32	Momentum based on FF3 residuals	Blitz, Huij, and Martens (2011)
33	Net payout yield quarterly	Boudoukh, Michaely, Richardson, and Roberts (2007)
34	Payout yield	Boudoukh, Michaely, Richardson, and Roberts (2007)
35	Net debt financing	Bradshaw, Richardson, and Sloan (2006)
36	Past trading volume	Brennan, Chordia, and Subrahmanyam (1998)
37	Return on invested capital	Brown and Rowe (2007)
38	Failure probability	Campbell, Hilscher, and Szilagyi (2008)
39	Earnings announcement return	Chan, Jegadeesh, and Lakonishok (1996)
40	Advertising expense	Chan, Lakonishok, and Sougiannis (2001)
41	R&D over market cap	Chan, Lakonishok, and Sougiannis (2001)
42	R&D to sales	Chan, Lakonishok, and Sougiannis (2001)

43	Cash productivity	Chandrashekar and Rao (2009)
44	Share turnover volatility	Chordia, Subrahmanyam, and Anshuman (2001)
45	Volume variance	Chordia, Subrahmanyam, and Anshuman (2001)
46	R&D ability	Cohen, Diether, and Malloy (2013)
47	Asset growth	Cooper, Gulen, and Schill (2008)
48	Long-vs-short EPS forecasts	Da and Warachka (2011)
49	Composite equity issuance	Daniel and Titman (2006)
50	Intangible return using BM	Daniel and Titman (2006)
51	Intangible return using CFtoP	Daniel and Titman (2006)
52	Intangible return using EP	Daniel and Titman (2006)
53	Intangible return using Sale2P	Daniel and Titman (2006)
54	Long-run reversal	De Bondt and Thaler (1985)
55	Medium-run reversal	De Bondt and Thaler (1985)
56	Equity Duration	Dechow, Sloan, and Soliman (2004)
57	Operating cash flows to price	Desai, Rajgopal, and Venkatachalam (2004)
58	Dimson beta	Dimson (1979)
59	Organizational capital	Eisfeldt and Papanikolaou (2013)
60	Earnings forecast to price	Elgers, Lo, and Pfeiffer Jr (2001)
61	Growth in long term operating assets	Fairfield, Whisenant, and Yohn (2003)
62	Total assets to market	Fama and French (1992)
63	Book to market using December ME	Fama and French (1992)
64	Book leverage (annual)	Fama and French (1992)
65	CAPM beta	Fama and MacBeth (1973)
66	CAPM beta squared	Fama and MacBeth (1973)
67	Earnings conservatism	Francis, LaFond, Olsson, and Schipper (2004)
68	Earnings persistence	Francis, LaFond, Olsson, and Schipper (2004)
69	Accrual quality	Francis, LaFond, Olsson, and Schipper (2005)
70	Analyst value	Francis, LaFond, Olsson, and Schipper (2005)
71	Analyst optimism	Francis, LaFond, Olsson, and Schipper (2005)
72	Pension funding status	Franzoni and Marin (2006)
73	Frazzini-Pedersen beta	Frazzini and Pedersen (2014)
74	52 week high	George and Hwang (2004)
75	Percent operating accruals	Hafzalla et al. (2011)
76	Percent total accruals	Hafzalla et al. (2011)
77	Tangibility	Hahn and Lee (2009)
78	Coskewness	Harvey and Siddique (2000)
79	Capital turnover	Haugen and Baker (1996)
80	Net income / book equity	Haugen and Baker (1996)
81	Volume to market equity	Haugen and Baker (1996)
82	Volume trend	Haugen and Baker (1996)
83	Momentum without the seasonal part	Heston and Sadka (2008)
84	Off season long-term reversal	Heston and Sadka (2008)
85	Off season reversal years 6 to 10	Heston and Sadka (2008)
86	Off season reversal years 11 to 15	Heston and Sadka (2008)
87	Off season reversal years 16 to 20	Heston and Sadka (2008)
88	Return seasonality years 2 to 5	Heston and Sadka (2008)
89	Return seasonality years 6 to 10	Heston and Sadka (2008)
90	Return seasonality years 11 to 15	Heston and Sadka (2008)
91	Return seasonality years 16 to 20	Heston and Sadka (2008)

92	Return seasonality last year	Heston and Sadka (2008)
93	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang (2004)
94	Change in net operating assets	Hirshleifer, Hou, Teoh, and Zhang (2004)
95	Depreciation to PPE	Holthausen and Larcker (1992)
96	Industry concentration (sales)	Hou and Robinson (2006)
97	Industry concentration (assets)	Hou and Robinson (2006)
98	Industry concentration (equity)	Hou and Robinson (2006)
99	Revenue surprise	Jegadeesh and Livnat (2006)
100	Momentum (12 month)	Jegadeesh and Titman (1993)
101	Momentum (6 month)	Jegadeesh and Titman (1993)
102	Change in recommendation	Jegadeesh, Kim, Krische, and Lee (2004)
103	Tail risk beta	Kelly and Jiang (2014)
104	Cash flow to market	Lakonishok, Shleifer, and Vishny (1994)
105	Revenue growth rank	Lakonishok, Shleifer, and Vishny (1994)
106	Real dirty surplus	Landsman, Miller, Peasnell, and Yeh (2011)
107	Taxable income to income (quarterly)	Lev and Nissim (2004)
108	Days with zero trades	Liu (2006)
109	Days with zero trades	Liu (2006)
110	Days with zero trades	Liu (2006)
111	Growth in book equity	Lockwood and Prombutr (2010)
112	Growth in advertising expenses	Lou (2014)
113	Enterprise multiple	Loughran and Wellman (2011)
114	Composite debt issuance	Lyandres, Sun, and Zhang (2008)
115	change in ppe and inv/assets	Lyandres, Sun, and Zhang (2008)
116	Efficient frontier index	Nguyen and Swanson (2009)
117	Operating leverage	Novy-Marx (2011)
118	Intermediate momentum	Novy-Marx (2012)
119	Gross profits / total assets	Novy-Marx (2013)
120	Asset liquidity over book assets	Ortiz-Molina and Phillips (2014)
121	Asset liquidity over market	Ortiz-Molina and Phillips (2014)
122	CF to debt	Ou and Penman (1989)
123	Current ratio	Ou and Penman (1989)
124	Change in current ratio	Ou and Penman (1989)
125	Change in quick ratio	Ou and Penman (1989)
126	Change in sales to inventory	Ou and Penman (1989)
127	Quick ratio	Ou and Penman (1989)
128	Sales to cash ratio	Ou and Penman (1989)
129	Sales to inventory	Ou and Penman (1989)
130	Sales to receivables	Ou and Penman (1989)
131	Leverage component of BM	Penman, Richardson, and Tuna (2007)
132	Enterprise component of BM	Penman, Richardson, and Tuna (2007)
133	Net debt to price	Penman, Richardson, and Tuna (2007)
134	Order backlog	Rajgopal, Shevlin, and Venkatachalam (2003)
135	Change in current operating assets	Richardson, Sloan, Soliman, and Tuna (2005)
136	Change in current operating liabilities	Richardson, Sloan, Soliman, and Tuna (2005)
137	Change in equity to assets	Richardson, Sloan, Soliman, and Tuna (2005)
138	Change in financial liabilities	Richardson, Sloan, Soliman, and Tuna (2005)
139	Change in net financial assets	Richardson, Sloan, Soliman, and Tuna (2005)
140	Total accruals	Richardson, Sloan, Soliman, and Tuna (2005)

141	IPO and age	Ritter (1991)
142	Book to market using most recent ME	Barr Rosenberg and Lanstein (1985)
143	Accruals	Sloan (1996)
144	Asset turnover	Soliman (2008)
145	Change in asset turnover	Soliman (2008)
146	Change in noncurrent operating assets	Soliman (2008)
147	Change in net noncurrent op assets	Soliman (2008)
148	Change in net working capital	Soliman (2008)
149	Change in profit margin	Soliman (2008)
150	Return on net operating assets	Soliman (2008)
151	Inventory growth	Thomas and Zhang (2002)
152	Change in taxes	Thomas and Zhang (2011)