In Search of a Factor Model for Option Returns

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Abstract

We propose a five-factor model that spans the cross-section of option returns. Our model consists of factors based on option illiquidity, option price, option-implied kurtosis, and the difference between realized volatility and option-implied volatility, along with the option market factor. We begin with a comprehensive list of option-based characteristics and construct option market factors. We show that the five-factor model subsumes the predictive power of established option return predictors. We also find that the proposed factor model performs well in explaining a large number of test assets. Lastly, we show that the model's performance in predicting option returns is largely driven by informational frictions and option demand pressure.

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We propose a five-factor model that spans the cross-section of option returns. Our model consists of factors based on option illiquidity, option price, option-implied kurtosis, and the difference between realized volatility and option-implied volatility, along with the option market factor. We begin with a comprehensive list of option-based characteristics and construct option market factors. We show that the five-factor model subsumes the predictive power of established option return predictors. We also find that the proposed factor model performs well in explaining a large number of test assets. Lastly, we show that the model's performance in predicting option returns is largely driven by informational frictions and option demand pressure.

Keywords: cross-section of option returns, factor model, option characteristics

JEL Classification: G11; G12; G13

1. Introduction

The identification of factors that capture the cross-sectional variation of asset returns is a central question in the asset pricing literature. Earlier studies have introduced various factor models that can explain the cross-section of stock returns, including the five-factor model of Fama and French (2015), the q-factor model of Hou, Xue, and Zhang (2015), the mispricing factors of Stambaugh and Yuan (2017), and the behavioral factors of Daniel, Hirshleifer, and Sun (2020). A number of recent articles have expanded the study of factor models to other asset classes, including currency (Lustig, Roussanov, and Verdelhan (2011)), commodity futures (Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014)), corporate bonds (Bai, Bali, and Wen (2019)), and cryptocurrency (Liu, Tsyvinski, and Wu (2021)).

However, the factor structure in the equity options market is less understood. The options market has grown dramatically and is playing an increasingly important role for both institutional and retail investors. According to Securities Industry and Financial Markets Association (SIFMA)[1], the number of options contracts traded on US exchange is around 7.47 billion (each contract entitles the option buyer/owner to 100 shares of the underlying stock upon expiration), and the total trading volume for equities was around 2,747 billion shares in 2020. The options trading volume is around 27% of the equity trading volume and has been increasing. Given the growing market capitalization and popularity of the options market, investigating the significance of option based characteristics and understanding the risk-return patterns in the options market are important research questions for empirical asset pricing.

Though traditional literature regards options as redundant assets (Black and Scholes (1973)), such a view has been rejected by recent work (e.g., Goyal and Saretto (2009), Cao and Han (2013), An et al. (2014), Zhan et al. (2020)). These studies have documented the informational role of options and the predictability of option returns. The options market has its unique features. The delta-hedged option position is immune to the movement of the underlying security and thus its exposure to stock market factors is expected to be small. Besides, the reasons for trading options can be quite different from trading stocks, such as informed trading, volatility-related trading, speculation, and hedging. Furthermore, option investors are often viewed as more sophisticated than stock market investors.[2]

[1] The statistics are from SIFMA Capital Markets Fact Book, https://www.sifma.org/resources/research/fact-book/
[2] See, for example, Easley, O'hara, and Srinivas (1998).

Given these unique features of the options market, we endeavor to identify robust option market factors while at the same time testing whether information from the options market itself is sufficient to construct powerful factors. We introduce a number of option-based characteristics motivated by earlier studies on both option and stock returns. The baseline option contract-level information, such as implied volatility, option Greeks are shown to be important determinants of option returns (Bali, Beckmeyer, Moerke, and Weigert (2021) and Büchner and Kelly (2021)). Illiquidity and momentum, which have been studied extensively on the stock market, also play a role in option returns (Christoffersen, Goyenko, Jacobs, and Karoui (2018) and Heston and Li (2020)). Bali and Murray (2013) examine the effects of risk-neutral moments in the option market and find evidence of positive skewness preference. The literature has also introduced option return predictors such as embedded leverage, volatility term structure, volatility-of-volatility (Karakaya (2013), Vasquez (2017), and Cao, Vasquez, Xiao, and Zhan (2019)). Moreover, many papers have used option-based variables to predict optionable stock returns (Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012) and An, Ang, Bali, and Cakici (2014)). Motivated by these papers, we construct a total of 20 option-based characteristics that can potentially predict future option returns.

We construct factors for each variable following the standard methodology introduced by Fama and French (1993, 2015). We generate factors using 2-by-3 double sorts based on option market size and each of the 20 option-based characteristics. The factor goes long the two portfolios with high values of an option-based characteristic and short the two portfolios with low values of the option-based characteristic. We then select a subset of factors that can span the full list of factors we propose through factor spanning tests. We find that factors based on option illiquidity, option price, option-implied kurtosis, and the difference between realized volatility and option-implied volatility, along with the market factor can provide significant, incremental information beyond other factors. The importance of these factors is not unexpected as Bali, Beckmeyer, Moerke, and Weigert (2021) find that information such as contract characteristics, risk-neutral moments, and illiquidity contribute most to option return predictability.

We further conduct a number of asset pricing tests to evaluate the performance of our proposed factor model. We find that the portfolios of options sorted on 20 option-based characteristics are all explained by our newly proposed factor model. The model has superior performance measured by average absolute alpha and Gibbons, Ross, and Shanken (1989) "GRS" test statistics when compared to a number of established equity, bond, and option factor models. We also use alternative test assets, which are long-short portfolios of options sorted by Green, Hand, and Zhang (2017) variables. Our factor model also has a remarkable explanatory power in explaining these alternative test assets.

Lastly, we investigate the economic channels underlying the model performance. We find that the return predictability of option-based variables that we use to build factors is more pronounced for options with higher information frictions and customer demand pressure. These results suggest that information friction and demand pressure largely explain the empirical performance of our factor model in predicting the cross-sectional variation in delta-hedged option returns..

Our paper contributes to several strands of literature. First, we expand the research that aims to construct empirically-motivated factor models to explain the cross-section of asset returns. Fama and French (1993) propose three factors including the equity market factor, size factor, and value factor and use them to capture stock returns. Ever since then, the literature has introduced various models for the stock market and other asset classes. Studies such as Fama and French (2015), Hou, Xue, and Zhang (2015), Stambaugh and Yuan (2017), and Daniel, Hirshleifer, and Sun (2020) propose various stock factor models with different motivations. Bai, Bali, and Wen (2019) construct bond market factors based on the prevalent risk characteristics: downside risk, credit risk, and liquidity risk. Bali and Murray (2021) generate a factor model based on the spread between physical and risk-neutral distributions of optionable stock returns. Liu, Tsyvinski, and Wu (2021) find that three factors – cryptocurrency market, size, and momentum – can well capture the cross-sectional cryptocurrency returns. Büchner and Kelly (2021) focus on options on the S&P 500 index and propose latent factors using the instrumented principal component analysis approach. Our paper focuses on the rapidly growing equity option market and constructs factors based on option characteristics solely. We show that the cross-section of option returns can be captured by a low-dimensional factor model.

Our paper also contributes to the nascent literature on predicting option returns. Goyal and Saretto (2009) find that options with high implied volatility relative to historical volatility earn lower returns. Bali and Murray (2013) find a strong negative relation between risk-neutral skewness and the skewness asset returns constructed from a pair of options and a position in the underlying stock. Karakaya (2013) finds that expected return on selling options with high embedded leverage is lower than selling options with low embedded leverage after controlling for moneyness-maturity[3]. Cao and Han (2013) show that idiosyncratic volatility of the underlying stock negatively predicts the cross-section of delta-hedged option returns. Vasquez (2017) finds a positive relationship between the slope of the implied volatility term structure, which is defined as the difference between the implied volatilities of long- and short-dated at-the-money options, and straddle returns in the cross-section. Christoffersen, Goyenko, Jacobs, and Karoui (2018) find evidence on illiquidity premia in equity option markets. Eisdofer, Goyal, and Zhdanov (2020) show that options written on stocks with low prices are over-priced. Cao, Vasquez, Xiao, and Zhan (2019) find that delta-hedged option returns consistently decrease in uncertainty of volatility. Fullwood, James, and Marsh (2021) find that long straddle positions on foreign exchange options with low (high) implied volatilities perform well (poorly). Büchner and Kelly (2021) find that option characteristics such as implied volatility, option Greeks are most relevant to capture option returns under the instrumented principal component analysis framework. Ramachandran and Tayal (2021) report a monotonic relation between various measures of short-sale constraints and delta-hedged returns of put options on overpriced stocks. Zhan, Han, Cao, and Tong (2021) uncover return predictability of delta-hedged option returns using a number of stock characteristics such as cash flow variance, analyst forecast dispersion, profitability, and so on. Bali, Beckmeyer, Moerke, and Weigert (2021) implement machine learning models to predict individual option returns using a large set of option-based and stock-based characteristics and document strong return predictability. We contribute to this line of literature by examining the predictive power of a large number of option and stock characteristics using traditional portfolio analysis. Our parsimonious factor model also shrinks the dimension of cross-sectional return predictors.

The rest of the paper proceeds as follows. Section 2 describes the data and key variables and examines the ability of option-based variables to predict the cross-section of option returns. In Section 3 we construct option market factors and select a robust factor model through factor spanning tests. Section 4 investigates the performance of the proposed factor model using various test assets and compares it with extant factor models. Section 5 explores the economic mechanisms driving the model performance and conducts various robustness checks. Section 6 concludes.

[3] Frazzini and Pedersen (2012) show that investors require lower returns on assets with higher embedded leverage and find that options with higher embedded leverage are more expensive. However, Karakaya (2013) shows that if controlling for moneyness and maturity, the variation in embedded leverage may mainly come from the ratio of stock price to option price and the relation between embedded leverage and option return is thus different.

2. Data and Variables

In this section, we introduce the data and main variables used in our study and examine the ability of option characteristics to predict future option returns.

2.1. Data and sample coverage

We collect data on both option and stock characteristics. The option data are mainly from OptionMetrics, which includes the daily closing bid and ask quotes, trading volume, open interest, implied volatility, and option Greeks of each option. Implied volatility and option Greeks are calculated by OptionMetrics using the binomial tree approach of Cox et al. (1979). We also collect detailed option trading data from Chicago Board Options Exchange (CBOE) open/close dataset. Stock price and volume data are from CRSP and accounting data are from Compustat. The institutional holding data are from Thomson Reuters (13F) database. The analyst coverage and forecast data are from I/B/E/S. Our sample period is from January 1996 to December 2019.

Moreover, we obtain the factor data from various sources. Fama and French factor data and risk-free rate are from Kenneth French's data library.[4] We collect q-factors of Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2021) from their global-q data library.[5] Data for Stambaugh and Yuan (2017) factors are from Robert Stambaugh's website.[6] Data for Daniel, Hirshleifer, and Sun (2020) factors are from Kent Daniel's website.[7] Data for Bai, Bali, and Wen (2019) bond market factors are from Turan Bali's website.[8] Data for Agarwal and Naik (2004) factors are from Vikas Agarwal. Data for Fung and Hsieh (2001) factors are from David Hsieh's data library.[9]

Our study focuses on options of common stocks (CRSP share codes 10 and 11). To screen extremely illiquid stocks, we remove stocks trading below $5 per share. Following Zhan, Han, Cao, and Tong (2021), we apply several filters. First, we exclude an option if the underlying stock paid a dividend during the remaining life of the option so the options we study are therefore

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5] http://global-q.org/factors.html.
[6] https://finance.wharton.upenn.edu/~stambaug/
[7] http://kentdaniel.net/data.php
[8] Data for Bai, Bali, and Wen (2019) bond market factors is from https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers
[9] Data for Fung and Hsieh (2001) factors is from http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-Fac.xls

effectively European-type. Second, to avoid biases related to the microstructure, we only keep options in which the trading volume and bid quote are strictly positive, the bid price is strictly smaller than the ask price, and the mid-point of the bid and ask quote is at least $1/8. Third, we exclude all option observations that violate obvious no-arbitrage conditions. Fourth, we exclude options with moneyness lower than 0.8 or higher than 1.2 to keep only at-the-money (ATM) options. Fifth, most of the options that we select each month have the same maturity. We drop options whose maturity is different from the majority of options. Lastly, we only retain stocks with both call and put options available after filtering.

2.2. Delta-hedged option return

Our main variable of interest is the return to delta-neutral call writing. The raw option return highly depends on the return of the underlying asset. To isolate the effect of the underlying stock price movement, we sell one contract of call option hedged by a long position in delta shares of the underlying stock, where delta is the hedge ratio under Black-Scholes model. Following previous studies such as Goyal and Sarreto (2009), Bali and Murray (2013), and Zhan, Han, Cao, and Tong (2021), we hold the position for one month without daily rebalancing.

Specifically, we calculate the return to delta-neutral call writing as follows:

$$HPR = \frac{\Delta_t \cdot S_{t+1} - C_{t+1}}{\Delta_t \cdot S_t - C_t} - 1,$$

where *C* and *S* denote the price of call option and stock, respectively and Δ denotes Black-Scholes delta. We focus on delta-neutral call writing so the initial investment is positive.

2.3. Option characteristics

We choose a list of option characteristics, which contain information on option prices, option volume, option Greeks, past option return distribution, and the shape of the option implied volatility surface. Motivated by previous studies on the cross-section of option returns and studies that use option-based measures to predict stock returns, we construct the following 20 variables. Some variables are on the level of the selected option contract and some variables are on the level of the underlying stock.

(1) Opt_ill: option illiquidity, which is measured as the option bid-ask spread divided by the average of bid and ask prices at last month end.

(2) Gamma: value of gamma for the selected option at last month end

(3) Vega: value of vega for the selected option at last month end

(4) Theta: value of theta for the selected option at last month end

(5) Volume: sum of option volume of the selected option during last month

(6) Price: option price, computed as the average of ask and bid price for the selected option, at last month end

(7) Emb_lev: embedded leverage, $\frac{\partial O/O}{\partial S/S}$, the elasticity of option price to stock price, at last month end. It is also computed as $\frac{S}{O}|\Delta|$, where S is the stock price, O is the option price, and Δ is option delta.

(8) VTS: volatility term structure, the difference between implied volatilities of long-term option and short-term options. We use volatility surface data and compute VTS as the difference between implied volatilities of at-the-money (|delta| = 0.5) options with 365 days to maturity and 30 days to maturity.

(9) VOV1: volatility of volatility, computed as the standard deviation of the stock's ATM implied volatilities (the average of the ATM call and ATM put implied volatilities) over all days in the previous month divided by the mean of these same implied volatilities. At least 12 daily ATM implied volatilities in a month are required to calculate this measure.

(10) VOV2: volatility of volatility, computed as the standard deviation of the percent change in stock's ATM implied volatilities (the average of the ATM call and ATM put implied volatilities) over all days in the previous month. At least 12 daily ATM implied volatilities in a month are required to calculate this measure.

(11) Impl_vol: option-implied (risk-neutral) volatility of the underlying stock at last month end

(12) Impl_skew: option-implied (risk-neutral) skewness of the underlying stock at last month end

(13) Impl_kurt: option-implied (risk-neutral) kurtosis of the underlying stock at last month end

(14) Lag_ret: last month return to delta-neutral call-writing of selected ATM short-term options. We enter the position at the beginning of last month and close the position at the end of last month.

(15) Vol_ret: volatility of option returns, calculated as the standard deviation of daily returns of selected ATM short-term options of this firm. For each day we compute the price of selling a delta-hedged call as $H_{t+1} = \Delta_t \cdot S_{t+1} - C_{t+1}$, where Δ_t is the delta at last month end, S_{t+1} is stock price at day *t*+1, and C_{t+1} is the option price at day *t*+1. We compute daily returns using values of H_{t+1} and compute Vol_ret as the standard deviation of daily returns, requiring at least 12 days.

(16) Cvol_ratio: total call option volume divided by total option volume (call plus put) for the given underlying stock during last month.

(17) CIV-PIV: the difference between ATM call option- and ATM put option-implied volatilities. We select options with 30 days to maturity and |delta| = 0.5 as ATM calls and ATM puts from volatility surface

(18) DCIV-DPIV: the difference between the changes in implied volatilities of ATM call and ATM put options. We select options with 30 days to maturity and |delta| = 0.5 as ATM calls and ATM puts from volatility surface.

(19) Vol_skew: the difference between OTM put option- and ATM put option-implied volatilities.. We use the options with 30 days to maturity.

(20) RV-IV: the difference between realized volatility (the standard deviation of daily stock returns during last month) and ATM option-implied volatility, defined as the average of ATM call and ATM put implied volatilities, at last month end.

Table 1 reports the summary statistics of delta-hedged option returns and option characteristics. Our sample includes 229,151 option-month observations and covers 6,243 unique firms. On average, there are 796 firms with available data each month. For each month, we calculate the cross-sectional mean, standard deviation, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile and then compute the time-series averages of these cross-sectional statistics. The average monthly return to delta-neutral call writing is 3.32% with a standard deviation of 4.92%.

3. Option market factors

In this section, we construct option market factors based on the option characteristics mentioned above and identify a robust factor model from the proposed factors.

3.1. The predictive power of option characteristics on option returns

We first examine the relation between return to delta-neutral call writing and option characteristics using portfolio-level analysis. Specifically, at the end of each month and for each option characteristic, we sort all options into quintiles based on the option characteristic and keep the position until the end of the next month. Quintile 1 contains options with the lowest values of the option characteristic and quintile 5 contains options with the highest values of the option characteristic. We use three weighting schemes: equal weight (EW), weight by stock market capitalization (SW), and weight by market value of option open interest (OW) to aggregate options in a portfolio.

Table 3 presents the time-series average of returns to delta-neutral call writing for the quintile portfolios sorted by each option characteristic, along with the difference in average returns between quintile portfolios. The long-short portfolio can be regarded as a trading strategy that writes the delta-hedged call in the top quintile and buys the delta-hedged call in the bottom quintile.

Out of the 20 variables we examine, we find that most of them can generate economically large and statistically significant return spreads during the sample period. 10 variables generate significant long-short spreads across all three weighting schemes. For example, the long-short portfolio based on Opt_ill generates a monthly return of 1.49% (*t*-stat.=17.72) when equal-weighted, 0.92% (*t*-stat.=13.28) when stock value-weighted, and 1.86 (*t*-stat.=13.27) when option value-weighted. This suggests that option illiquidity, measured by relative bid-ask spread is positively associated with option expensiveness. This finding is consistent with prior studies, e.g., Christoffersen, Goyenko, Jacobs, and Karoui (2018). The return spreads on implied skewness are 0.71%, 0.54%, and 0.99% under three weighting schemes and are all highly significant. The return spreads on implied kurtosis are 3.47%, 2.09%, and 3.30%, respectively. These results provide evidence that options on stocks with higher jump risk measured by implied skewness and kurtosis are more expensive. For some variables, we find significant return spreads under one or two weighting schemes out of the three weighting schemes. For VOL1 and VOL2, the option value-weighted return spreads are 0.46% (*t*-stat.=3.73) and 0.81% (*t*-stat.=6.25) and these results are consistent with findings of Cao, Vasquez, Xiao, and Zhan (2019), but the return spreads are insignificant if we weight by stock size. Six variables are significantly negatively related to next month's return: Vega, Volume, Price, Emb_lev, VTS, and RV-IV. For example, the return spreads formed by Price are -1.86% (*t*-stat.=-20.59), -0.99% (*t*-stat.=-10.80), and -1.89% (*t*-stat.=-11.72) when equal-weighted, stock value-weighted, and option value-weighted, respectively. This finding suggests that options with higher raw prices are cheaper in terms of delta-hedged return. The average return to writing options with higher VTS is lower than the average return to writing options with lower VTS. This result is consistent with Vasquez (2017), who finds that straddle portfolios with high slopes of the volatility term structure outperform straddle portfolios with low slopes. Variable RV-IV also leads to a significant return spread of 1.85%, 1.19%, and 1.68% under different weighting schemes. This could be explained by the "volatility mispricing" as argued by Goyal and Sarreto (2009) and could reflect the premium of variance risk.

3.2. Factor construction

We first create option market factors based on option characteristics mentioned above. We build a factor for each of the 20 option characteristics; Opt_ill, Gamma, Vega, Theta, Price, Emb_lev, VTS, VOV1, VOV2, Impl_vol, Impl_skew, Impl_kurt, Lag_ret, Vol_ret, Cvol_ratio, CIV-PIV, DCIV-DPIV, Vol_Skew, and RV-IV. The factor construction procedure is similar to Fama and French (1993) and relies on independent sorts. At the end of each month, we sort the options into two groups (small "S" and big "B") based on whether the option size is above or below the cross-sectional median. Independently, we sort the options into three groups (low "L", middle "M", or high "H") based on the given option characteristic. The breakpoints for option characteristics are 30th and 70th percentile values of the given variable among all options. Different from previous studies like Fama and French (1993, 2015) and Hou, Xue, and Zhang (2015) which use NYSE breakpoints, we use the full-sample breakpoints. They use NYSE breakpoints to mitigate the effects of microcaps, while our sample focuses on optionable stocks and our data filtering process leaves us with relatively large stocks[10], so microcaps are less of a concern for our study. The results are robust when we use NYSE breakpoints to construct our factors.[11]

The intersections of size and option characteristics produce six portfolios (SL, SM, SH, BL, BM, and BH). The option factor on the given characteristic is the average return of the two

[10] Bali and Murray (2021) show that historically the ratio of stocks that are optionable is from 25% to 75%, while they account for 85% to 98% of total market capitalization of stocks. Zhan, Han, Cao, and Tong (2021) show that the average firm size CRSP percentile is 80%.

[11] In Appendix Table 1, we report the performance of factors constructed using NYSE breakpoints. We construct the factors in the same way as before, except for that we replace the full-sample breakpoints with NYSE breakpoints when sorting options into portfolios.

portfolios with high values of the option-based variable minus the average return of the two portfolios with low values of the option-based variable, that is, $(r_{SH} + r_{BH})$/2-$(r_{SL} + r_{BL})$/2. For the option characteristics that have a negative relation with option returns, we take negative values of these variables so that we generate factors which have positive time-series average returns. The portfolios are option value-weighted using the market value of option open interest.

Panel A of Table 3 presents the summary statistics for the newly proposed option factors. Out of the 19 variables we examine[12], 18 factors have economically large and statistically significant average returns. They have average returns ranging from 0.23% (*t*-stat.=2.30) to 3.72% (*t*-stat.=28.41). For example, factor Opt_ill has an average return of 1.37% with a *t*-statistic of 15.41. The only exception is Vol_skew, which has an average value of 0.16% with a *t*-statistic of 1.33. In a similar vein to Fama and French (1993, 2015), Hou, Xue, and Zhang (2015), and Bai, Bali, and Wen (2019), we include the market factor to capture the common variation in returns over time. The option market factor is defined as the option value-weighted return of all options in our sample minus the risk-free rate. The option market factor has an average value of 2.44% per month with a *t*-statistic of 20.04. Next, we examine whether the factors are explained by the option market factor. We regress the time-series of monthly returns of option factors on the market factor and investigate whether the CAPM alphas are significantly different from zero. In Table 3, besides the time-series average, we report the alphas of the time-series regressions of each newly constructed factor on the option market factor. The CAPM alphas for 14 factors remain statistically significant after adjusting for the option market factor. We then examine the correlations between these 14 factors. In Panel B of Table 3, we report the time-series correlations. We find that the correlations between many factors are large in magnitude. For example, the factors Gamma, Theta, and Price have pairwise correlations that are all above 0.9. The factors Impl_vol and Vol_std are highly correlated with the market factor, with respective correlations of 0.64 and 0.56. The correlation between the CIV-PIV and DCIV-DPIV factors is 0.58. Thus, it is reasonable to expect that some of these highly correlated factors may fail the factor spanning tests.

3.3. Factor spanning tests and common factor model

[12] Due to the high correlation between option size and option volume, we do not construct the corresponding factor for option volume.

Having constructed a number of option market factors and investigated their individual performances, we proceed to choose a parsimonious factor model that has significant enough explanatory power. The high correlations between some option factor pairs suggest that some factors may be captured by a combination of other factors. Therefore, the large set of factors we constructed may be spanned by a smaller set of factors. We begin with the 14 factors that are not absorbed by the option market factor (i.e., those that passed the CAPM test) and then conduct the factor spanning tests. Specifically, we regress each factor on all other factors including the option market factor and examine whether the alphas are distinguishable from zero. If a factor produces statistically significant alpha after being regressed on other factors, the factor is meant to provide significant, incremental information.

Table 4 reports the results of factor spanning tests. For each factor, we report the intercept from the time-series regression of the given factor on a factor model consisting of all other factors. We find that the alphas of the factors Opt_ill, Price, Impl_kurt, and RV-IV relative to other factors are positive and statistically significant. In the regression of factor Opt_ill, the intercept is 0.92% per month with a *t*-statistic of 5.07. In the regressions to explain the factors Price, Impl_kurt, and RV-IV, the intercepts are 0.26%, 0.52%, and 0.80% per month with *t*-statistics of 2.98, 2.72, and 3.15, respectively. However, the alphas of the other 10 factors are all small and statistically insignificant. These spanning tests indicate that the factors Opt_ill, Price, Impl_kurt, and RV-IV provide independent, incremental information and other factors may be redundant. Therefore, we propose a factor model that consists of these four factors and the option market factor. We call this factor model OPT5. The importance of these factors is not unexpected. For example, Bali, Beckmeyer, Moerke, and Weigert (2021) use machine learning approaches and find that contract characteristics, risk-neutral moments, and illiquidity are of the highest importance in terms of their contribution to option return predictability.

We next examine whether extant factor models can explain the returns of our newly proposed option factors. We consider a comprehensive list of factor models from various asset classes. Specifically, we include the equity market factors such as Fama French (1993) three-factor model (FF3), Fama-French (2015) five-factor model (FF5), Fama-French (2018) six-factor model (FF6), Q4 factor model of Hou, Xue, and Zhang (2015), Q5 factor model of Hou, Mo, Xue, and Zhang (2021), Stambaugh and Yuan (2017) mispricing factor model (SY), Daniel, Hirshleifer, and Sun (2020) behavioral factor model (DHS). We also include Bai, Bali, and Wen (2019) corporate bond factor model (BBW), Agarwal and Naik (2004) factor model (AN), Fung and Hsieh (2001) factor model (FH), and three volatility factors including zero-beta straddle return of the S&P 500 index option (Coval and Shumway, 2001), value-weighted zero-beta straddle return of S&P 500 individual stock options, and the change in the CBOE Market Volatility Index (VOL3 hereafter). Motivated by Zhan, Han, Cao, and Tong (2021), we also construct option factors based on idiosyncratic volatility (IVOL) and Amihud (2002) illiquidity of the underlying stock. We call this two-factor model IA model. Similar to OPT5 factors, IVOL factor is constructed based on a double 2-by-3 sort on firm size and firm-specific volatility (IVOL) and the Amihud illiquidity factor is formed using a double 2-by-3 sort on firm size and stock illiquidity. Due to the high correlations between firm size, IVOL, and Amihud ILLIQ measure, we use dependent sorts and the option returns are weighted by firm size following Zhan, Han, Cao, and Tong (2021).[13] In Table 5, we report the alphas of factors in our proposed OPT5 model relative to extant factor models. We find that all factors remain economically large and statistically significant after controlling for their exposures to extant factors. Thus, the option factors we introduce provide information beyond established factor models proposed in the literature.

4. Factor model performance

In this section, we investigate whether our proposed factor model can capture systematic variation in option returns based on a broad set of option characteristics and firm-specific variables. We also compare the relative performance of these new factors with extant factor models in the literature.

4.1. Explaining portfolios sorted on option characteristics

Through factor spanning tests, we identify five factors that are unexplained by a combination of other factors, but this result does not suffice to suggest that they can capture the return variation generated by other variables. We thus test whether the OPT5 model can largely explain the long-short portfolios formed by sorting on option characteristics. We use the 20 option characteristics previously used to generate Table 2. Table 6 presents the abnormal return (alpha) from the new five-factor model for each long-short portfolio. As expected, the long-short portfolios formed by sorting on Opt_ill, Price, Impl_kurt, and RV-IV load heavily on the corresponding factors and are all explained by our OPT5 model. Opt_ill, Price, Impl_kurt, and RV-IV portfolios have the five-

[13] The results are similar if we construct IVOL and Amihud factors using option size as weights.

factor (OPT5) alphas of 0.23%, 0.25%, 0.50%, and 0.22% per month with corresponding *t*-statistics of 1.04, 1.15, 1.57, and 0.73. What is more interesting is to examine the ability of OPT5 model to explain the remaining 16 long-short portfolios. We find that for all of these 16 long-short portfolios, the alphas relative to the OPT5 model are insignificantly different from zero, with *t*-statistics ranging from 0.19 to 1.81. For example, embedded leverage long-short portfolio has a raw return spread of 4.09% (*t*-stat.=23.75). When we regress the 5-1 return spread on the OPT5 factors, the embedded leverage arbitrage portfolio has high exposure to the Impl_kurt factor, with a beta coefficient of 0.97 and also has statistically significant exposures to the factors RV-IV and MKT. After accounting for the five factors, its OPT5 alpha is significantly reduced to 0.14% per month and becomes statistically insignificant with a *t*-statistic 0.39. Putting 20 test assets together, we find that the average absolute value of the raw long-short portfolio return is 1.76% and the average absolute alpha relative to our OPT5 model is only 0.39% per month. So the alpha based on option characteristics is reduced by around 80% by our OPT5 model. We also perform the Gibbons, Ross, and Shanken (1989) "GRS" test of whether the 20 alphas are all equal to zero. We find a GRS statistic of 1.84 and the associated *p*-value is 0.02.

4.2. Comparing with other factor models

In this section, we compare our OPT factor model with a number of established factor models. We include the equity market factors from Fama and French (1993, 2015, 2018), Q4 factors from Hou, Xue, and Zhang (2015), Q5 factors from Hou, Mo, Xue, and Zhang (2021), the mispricing factors from Stambaugh and Yuan (2017), and the behavioral factors from Daniel, Hirshleifer, and Sun (2020). We also consider factors from corporate bond market (Bai, Bali, and Wen (2019)), factors for hedge funds that are constructed using option data (Agarwal and Naik (2004) and Fund and Hsieh (2001)), and three market volatility factors. Moreover, following Zhan, Han, Cao, and Tong (2021), we also include option factors that are constructed based on idiosyncratic volatility (IVOL) and Amihud illiquidity (ILLIQ) of underlying stocks. Lastly, we include the option CAPM model, which consists of the equity option market factor only. In Table 7, we report the average absolute alpha across the 20 long-short portfolios and the GRS statistic testing whether the alphas are jointly zero.

The delta-hedged position is immune to the movement of the underlying stock price. Earlier studies have provided evidence that the traditional risk factors from the stock market are unable to price delta-hedged option returns.[14] Our results from established equity market factors are consistent with these findings and show that the average absolute alpha barely changes. The GRS tests all strongly reject the null hypothesis, with GRS statistics all above 40. The factor models proposed by BBW, AN, and FH generate, respectively, the average absolute alphas of 1.54%, 1.76%, and 1.76% per month with the associated GRS statistics of 26.99, 49.60 and 50.22. Furthermore, the three volatility factors generate an average absolute alpha of 1.82% and GRS-statistic of 56.18. The one-factor model with the option market factor, or option CAPM, leaves 14 significant alphas and the CAPM-adjusted alpha is 1.42% per month. The declines in the economic magnitudes of the return spreads are small relative to the average raw return spreads. The IA model, which consists of two factors constructed based on the monthly returns of delta-hedged options sorted on IVOL and Amihud illiquidity (ILLIQ), performs the best among extant factor models. However, it stills leaves 12 long-short portfolio return spreads (out of 20) unexplained. It shrinks the average absolute alpha from 1.76% to 1.01% per month and the GRS statistic equals 13.36.

Overall, these results show that existing factors are insufficient to capture the return spreads generated by option characteristics and confirm the superior performance of our proposed OPT5 model. Specifically, OPT5 reduces the raw return spread averaged across the 20 long-short portfolios from 1.76% to 0.39% per month. As reported in Table 6, OPT5 explains the return spreads on all of the 20 long-short portfolios.

4.3. Alternative test assets

Our prior analyses are based on returns of delta-hedge equity options sorted by 20 option characteristics as test assets. Lewellen, Nagel, and Shanken (2010) point out that pricing characteristic-sorted portfolios that may not have enough variation in factor loadings is a low hurdle. They suggest including alternative portfolios in the tests. The literature has also embraced the practice of using a large number of test assets to evaluate model performance. For example, Hou, Xue, and Zhang (2015) examine nearly 80 anomalies and show that the q-factor model can digest many of the anomalies. Fama and French (2016) consider anomalies like accruals, net share issues, momentum, and volatility and show that the list of anomalies shrinks in the five-factor model. Bali and Murray (2021) investigate the model performance of option-based factors to explain more than one hundred stock return predictors.

[14] See, e.g., Cao and Han (2013), Zhan, Han, Cao, and Tong (2021), Büchner and Kelly (2021).

Zhan, Han, Cao, and Tong (2021) document that a number of firm characteristics that are well known to predict stock returns can also predict the cross-section of option returns. Bali, Beckmeyer, Moerke, and Weigert (2021) implement machine learning techniques to predict individual option returns and find that stock-based measures offer substantial incremental predictive power when considered alongside option-based characteristics. Thus, we create test assets based on firm characteristics. Green, Hand, and Zhang (2017, GHZ hereafter) introduce 102 firm characteristics and examine the cross-sectional relation between these characteristics and stock returns.[15] Following the procedure in Section 2.4, at the end of each month, we sort the options in our sample into quintile portfolios based on each of the GHZ variables. We take the long-short portfolios of options sorted by GHZ variables as test assets. We exclude dummy variables and make slight modifications to the discrete variables of GHZ. In the Internet Appendix Section 2, we report the details of long-short portfolios formed on GHZ variables and how we deal with the discrete variables.

We combine the 20 long-short portfolios based on option characteristics and 93 long-short portfolios based on stock characteristics together to obtain a larger set of test assets. We then regress each of the long-short portfolios on our OPT5 model. In Table 8, we present the model performance. We find that only 15 (out of 113) variables generate significant alphas with respect to the OPT5 model. The average absolute alpha is reduced from 1.07% to 0.55% per month. Besides, the GRS statistic testing whether all alphas are jointly equal to zero yields a modest GRS statistic of 1.78. These results suggest that the OPT5 model also does a good job in explaining alternative test assets.

4.4. Sharpe ratios

In the mean-variance framework, a factor model can explain return variations of test assets if and only if the efficient frontier of the test assets lies in the span of the factors. Barillas and Shanken (2017) suggest that the Sharpe ratio of the tangency portfolio is what matters for model comparison. Thus, in this section, we report the Sharpe ratios of our proposed factor model.

Table 9 reports the mean, standard deviation, and Sharpe ratios of individual factors and the tangency portfolio. The annualized Sharpe ratios for Opt_ill, Price, Impl_kurt, RV-IV, and

[15] We thank Jeremiah Green for providing the code needed to calculate the GHZ variables. The code is posted on his website: https://sites.google.com/site/jeremiahrgreenacctg/home

MKT are 3.50, 3.91, 4.92, 2.84, and 4.85, respectively. These Sharpe ratios are substantially higher than those of the traditional stock market factors.[16]

We construct the tangency portfolio in two ways. First, we calculate tangency portfolio weights using expected returns and variance-covariance matrix estimated from the full sample. Then we combine the factor returns and tangency portfolio weights to get the tangency portfolio. We call this the full-sample approach. Second, we construct the tangency portfolio using an expanding-window approach. For each month *t*, we calculate the portfolio weights using expected returns and variance-covariance matrix estimated using data from January 1996 through month *t*-1. Then we use these calculated weights to construct the tangency portfolio for month *t*. To ensure that we have at least 60 months to estimate the portfolio weights, our sample starts from January 2001. In Table 9 in the column labeled "Tangency-Full" we report the statistics of tangency portfolio constructed using the full-sample method. In the column labeled "Tangency-Expanding" we report the statistics of tangency portfolio constructed using the expanding-window approach. The tangency portfolio constructed from our OPT5 model reaches an impressive annualized Sharpe ratio of 8.83 using a full-sample methodology. When we use the expanding-window methodology, the Sharpe ratio is almost the same, which suggests that the OPT5 model does generate a substantially high Sharpe ratio that is implementable.

5. The underlying mechanisms and robustness

In this section, we investigate the economic mechanisms that drive the performance of our proposed option market factors and conduct a battery of robustness checks.

5.1. Informational frictions

We explore why option return predictability driven by the option-based characteristics persists. Hong and Stein (1999) propose a theoretical model and show that the return predictability is due to gradual diffusion of information across investors. Hirshleifer, Lim, and Teoh (2011) suggest

[16] The corresponding *annualized* Sharpe ratios for Opt_ill, Price, Impl_kurt, RV-IV, and option market factors are 3.50, 3.91, 4.92, 2.84, and 4.85, respectively, and they are significantly higher than the annualized Sharpe ratios for the equity market (MKT), size (SMB), value (HML), investment (CMA), profitability (RMW), and momentum (MOM) factors of Fama-French (1993, 2015, 2018) for the common sample period 1996-2019, which are 0.52, 0.17, 0.15, 0.33, 0.4, and 0.26, respectively.

that limited attention leads to neglect of (or delayed reaction to) information. We thus hypothesize that informational frictions contribute to the predictive power of option-based variables.

Zhang (2006) introduces several measures of information uncertainty and investigates the role of these measures in price continuation anomalies and cross-sectional variation in stock returns. Zhang (2006) uses measures like firm age, analyst coverage, and dispersion of analyst forecast (standard deviation of analysts' earnings estimates divided by the average earnings estimate) to proxy for the level of information uncertainty and finds evidence that market reaction to new information is incomplete for firms with higher levels of information uncertainty. The level of institutional ownership also affects informational frictions. Institutional investors are more sophisticated and better informed. They are able to use rigorous theoretical models and collect more information on option pricing. Thus, higher institutional ownership may lead to more efficient option pricing. Eisdorfer, Goyal, and Zhdanov (2020) show that institutional ownership helps to ameliorate option mispricing related to stock price.

Rather than relying on a single measure for information frictions, we follow previous studies such as Atilgan, Bali, Demirtas, and Gunaydin (2020)[17] and Liu, Tsyvinski, and Wu (2021) and create a composite information friction score based on these four measures: firm age, institutional ownership, analyst coverage, and analyst forecast dispersion. Since we do not have a direct measure of institutional ownership at the option level, we use the level of institutional ownership at the underlying stock level. With this composite measure, we can capture the different dimensions of information frictions in these measures. At the end of each month, each firm is given the corresponding score of its decile rank for information friction measures. We take negative values of firm age, institutional ownership, and analyst coverage so a higher value indicates a higher level of information friction. The information friction score (IF hereafter) is the sum of the four scores so that it ranges from 4 to 40 and a higher value is associated with a higher level of information friction.

To examine the information in different option characteristics simultaneously, we combine the key variables in our OPT5 model. In a similar spirit to Stambaugh and Yuan (2017), we construct a composite score for the option-based variables that we use to build OPT5 factors:

[17] Atilgan, Bali, Demirtas, and Gunaydin (2020) generate a composite score based on six measures: Amihud illiquidity, level of institutional ownership, firm age, analyst coverage, dispersion of analyst earnings forecast, and idiosyncratic volatility and show that the return predictability of left-tail momentum is higher for stocks with higher composite measure.

Opt_ill, Price, Impl_kurt, and RV-IV. At the end of each month, each firm is assigned to the decile portfolio for all option-based variables and we take the decile ranks. We take negative values of Price and RV-IV so a higher value predicts higher future return to delta-neutral call writing. The option-based composite score (OScore hereafter) is the sum of the four scores and it ranges from 4 to 40.

Having constructed a composite information friction score and a composite option-based factor score, we proceed to conduct independent sorts to study how informational frictions affect the return predictability by option-based variables. We assign the options to one of the three IF groups and one of the three OScore groups based on values of IF and OScore independently. This sorting exercise produces 9 portfolios. In Table 10, we report the option value-weighted return of each portfolio and the return spread of tercile portfolios. We find that for options belonging to the group with low level of information frictions, the long-short portfolio return spread based on OScore is 1.52% per month (*t*-stat.=11.14). When it comes to the high information friction group, the return spread increases to 3.44% per month with a *t*-statistic of 13.52. Finally, the last row and the column of Table 10 presents the difference-in-differences (diff-in-diff) test results; i.e., the difference between the average return spread of 3.44% per month (*t*-stat.=13.52) for high-IF portfolio and the average return spread of 1.52% per month (*t*-stat.=11.14) for low-IF portfolio. Consistent with our expectations, the diff-in-diff return spread is economically and statistically significant at 1.92% per month (*t*-stat.=6.68), showing that the return predictability in the cross-section of delta-hedged option returns is significantly influenced by informational frictions. Overall, these results are in line with the notion that the return predictability is stronger in the sample of options written on stocks with high information uncertainty, largely held by retail investors, and that receive low investor attention..

5.2. Option demand pressure

In the options market, demand by end-users is another channel that may underpin the performance of option factors. We now investigate the role that demand pressure plays in option return predictability by option characteristics that we use to build factors.

The literature provides evidence that option demand pressure affects option pricing. Bollen and Whaley (2004) show that changes in implied volatility are related to buying pressure from public order flow. Garleanu, Pedersen, and Poteshman (2009) model demand-pressure effects on option prices and find a positive cross-sectional relationship between option expensiveness and end-user demand for equity options. Cao and Han (2013) present evidence that option market makers charge premiums for options with high end-user demand. Muravyev (2016) demonstrates the effect of inventory risk faced by market-makers on option prices and finds that past order imbalances have large predictive power for option returns. Ramachandran and Tayal (2021) show that put options on overpriced stocks that face more binding short-sale constraints will witness a higher option demand and thus are more expensive. Bali, Beckmeyer, Moerke, and Weigert (2021) also investigate how option demand by professional investors and public customers affects option return predictability. The machine learning methods in their study point to high predictability in cases where public customers are buying options and professionals facilitate their buying by shorting. Therefore, we hypothesize that the impact of option characteristics on option returns may be more pronounced for options that face higher demand pressure from customer investors.

We construct customer demand measures using the following procedure. We use open/close dataset from CBOE. This dataset contains information on end-users' trades and classifies the traders into different trader types and order types. Following previous studies such as Bali, Beckmeyer, Moerke, and Weigert (2021), we define the trade as a customer trade if CBOE classifies it into "public customer" type. The customer demand (CD hereafter) is computed as follows: CD=$\frac{OpenBuy-OpenSell}{OpenBuy+OpenSell}$, where OpenBuy is the total volume of open buy orders and OpenSell is the total volume of open sell orders. Due to the availability of CBOE open/close data, the sample for these analyses starts from January 2009.

We focus on open positions because open positions are shown to be more informative than close positions (Pan and Poteshman (2006)). Garleanu, Pedersen, and Poteshman (2009) show that demand pressure of a particular option not only raises the price of this option but also raises the prices of other options in the underlying. We, therefore, follow previous studies and aggregate options across moneyness and maturities to calculate the demand pressure at the level of the underlying stock.

Following Section 5.1, we construct a composite option-based score using four variables in OPT5 model: Opt_ill, Price, Impl_kurt, and RV-IV. Then we independently sort the options into three groups based on customer demand and OScore and calculate option value-weighted returns in each portfolio. Table 11 presents the results of bivariate portfolio sorts. We find that the return predictability generated by OScore is 2.35% for options that face low customer demand. It increases to 2.89% for options that face high customer demand. . Finally, the last row and the column of Table 11 presents the diff-in-diff test results. Specifically, the difference in return spreads on OScore-sorted portfolios of options that face low vs. high customer demand is economically larger, 0.54% per month, and statistically significant (*t*-stat.=2.16). These results provide evidence that the performance of option-based variables is driven by the demand pressure from unsophisticated investors.

5.3. Robustness check

In this subsection, we conduct a battery of robustness checks. We show that the methodological choices we make are not crucial to our model's performance and the explanatory power of our model persists over time.

As discussed earlier, we use the breakpoints of all options in our sample because we have a number of filters and the firms in our sample are relatively large. So the microcap effect is less of a concern for our study. For robustness check, we reconstruct the factors using the NYSE breakpoints and the other procedures are the same as before. Appendix Table 1 reports the model performance. The results show that option market factors constructed using NYSE breakpoints have comparable performances to those constructed using full-sample breakpoints.

In the stock market, the return predictability of many variables has weakened or become insignificant in recent years (Chordia, Subrahmanyam, and Tong (2014) and McLean and Pontiff (2016)). Our primary empirical analyses so far are based on the sample period from January 1996 to December 2019. During this 20-year period, the option market has changed a lot and thus it is interesting to examine whether the common factors for the option market perform well over time. To check whether the performance of proposed option market factors is sensitive to the sample period, we divide the full sample into two subsamples and re-examine the performance of these factors for each subsample. We divide the sample into two periods: January 1996 to December 2007 and January 2008 to December 2019. The results are reported in Appendix Table 2. We find that for both the early period and recent period, our proposed option factors have economically large and statistically significant average returns and can well capture the return spreads generated by a number of variables.

6. Conclusion

An extensive literature has examined the factor structure in the cross-section of stock returns. The literature has also proposed factor models for other asset classes such as corporate bonds, currencies, commodities, and cryptocurrencies. However, the research on the common factors that capture the cross-section of option returns is relatively scarce. Given the market size and the importance of options as an asset class, we are in search of a factor model in the cross-section of option returns using information only from the option market itself.

We first introduce a number of option characteristics and investigate the ability of these variables to predict future option returns. We then construct option market factors based on each of the option characteristics. Next, through factor spanning tests, we identity a subset of factors which provide significant, incremental information beyond other factors. The factor model we identify consists of four factors constructed based on option illiquidity, option price, option-implied kurtosis, and the spread between the physical and risk-neutral (option-implied) measures of volatility, as well as the option market factor.

The pricing tests demonstrate the superior performance of our proposed option market factor model. This five-factor model is able to explain the long-short return spreads generated by all 20 option characteristics considered in the paper. The magnitudes of the alphas of these long-short portfolios shrink by a large proportion with respect to our proposed factor model. Our model also outperforms established factor models measured by statistics such as the average absolute alpha and GRS statistics. Moreover, we form a large number of test assets based on the firm characteristics of Green, Hand, and Zhang (2017). We sort the options on each of the GHZ variables and form long-short portfolios. We find that our model has a remarkable success rate in explaining the test assets based on GHZ variables.

We further explore the underlying mechanism that drives the model performance. We show that the return predictability of option-based variables which we use to construct our proposed factors is significantly stronger for firms with higher information frictions. We also find that the predictive power is associated with the net demand from customer investors.

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Table 1. Summary Statistics

This table reports the time-series average of cross-sectional statistics. OptionReturn is the buy and hold return to delta-neutral call selling until moth end. Opt_ill is option illiquidity. Gamma, Vega, Theta are option Greeks Gamma, Vega, and Theta, respectively. Volume is the total volume during last month. Price is option price. Emb_Lev is embedded leverage. VTS is volatility term structure. VOV1 and VOV2 are two specifications for volatility-of-volatility measure. Impl_vol is implied volatility. Impl_skew is implied skewness. Impl_kurt is implied kurtosis. Lag_ret is option return in last month. Vol_ret is the volatility of daily option return during last month. Cvol_ratio is call option volume divided by total option volume. CIV-PIV is the difference of implied volatility between ATM call and put option. DCIV-DPIV is the difference of change in implied volatility between ATM call and put option. Vol_skew is the difference of implied volatility between OTM put and ATM call. RV-IV is the difference between realized volatility and implied volatility. The details of variable definitions are in the Appendix. The sample period is from January 1996 to December 2019.

	Mean	StdDev	P10	P25	Median	P75	P90
OptionReturn	3.32	4.92	-1.55	1.17	3.30	5.63	8.36
Opt_ill	0.17	0.16	0.04	0.08	0.12	0.20	0.33
Gamma	0.10	0.06	0.04	0.06	0.08	0.13	0.18
Vega	6.13	7.00	1.59	2.64	4.58	7.56	11.54
Theta	-9.30	8.91	-16.49	-11.01	-7.24	-4.74	-3.30
Volume	932.78	3794.25	1.17	16.99	102.46	493.33	1860.07
Price	2.51	2.42	0.80	1.23	1.94	3.07	4.59
Emb_Lev	9.63	4.03	5.44	6.78	8.83	11.67	14.82
VTS	-0.02	0.06	-0.08	-0.04	-0.01	0.01	0.03
VOV1	0.08	0.05	0.04	0.05	0.07	0.10	0.13
VOV2	0.06	0.05	0.03	0.04	0.05	0.07	0.10
Impl_vol	0.47	0.19	0.26	0.32	0.43	0.57	0.71
Impl_skew	-1.89	3.11	-4.26	-2.86	-1.63	-0.76	-0.15
Impl_kurt	0.12	0.30	0.00	0.01	0.02	0.07	0.36
Lag_ret	0.57	12.47	-4.40	-0.03	2.13	4.18	6.80
Vol_ret	0.07	0.73	0.00	0.01	0.01	0.02	0.04
Cvol_ratio	0.64	0.18	0.41	0.53	0.65	0.76	0.86
CIV-PIV	-0.01	0.06	-0.05	-0.02	0.00	0.01	0.03
DCIV- DPIV	0.00	0.08	-0.06	-0.02	0.00	0.02	0.06
Vol_Skew	0.07	0.08	0.00	0.03	0.05	0.09	0.14
RV-IV	-0.02	0.19	-0.18	-0.10	-0.03	0.05	0.15

Table 2. Average Returns of Portfolios of Delta-Neutral Call Writing Sorted by Option-based Characteristics

This table reports the average monthly returns of delta-neutral equity call writing sorted on various characteristics of the option described in Table 1. At the end of each month, we rank all stocks with options traded into quintiles by the option characteristics. For each stock, we sell one contract of call option against a long position of Δ shares of the underlying stock, where Δ is the Black-Scholes call option delta. The position is held for one month without rebalancing the delta-hedges. We use three weighting schemes when computing the average return of a portfolio of delta-neutral call writing on stocks: weight by the market capitalization of the underlying stock (SW), equal weight (EW), and weight by the market value of option open interest (OW) at the beginning of the period. The table reports the return for each quintile option portfolio as well as the 5-1 spread return (i.e., difference between the returns of the top and bottom quintile portfolios). All returns in this table are expressed in percent. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

		1	2	3	4	5	H-L
Opt_ill	EW	2.68	2.92	3.20	3.61	4.17	1.49***
		(19.73)	(22.01)	(24.96)	(27.51)	(32.72)	(17.72)
	SW	1.85	2.08	2.27	2.53	2.77	0.92***
		(17.09)	(18.38)	(20.82)	(21.08)	(24.64)	(13.28)
	OW	2.35	2.72	3.18	3.51	4.22	1.86***
		(18.42)	(18.76)	(21.45)	(23.19)	(28.17)	(13.27)
Gamma	EW	2.69	2.84	3.12	3.67	4.26	1.57***
		(19.49)	(24.93)	(24.39)	(26.82)	(30.85)	(17.10)
	SW	1.84	1.97	2.01	2.23	2.73	0.89***
		(14.37)	(19.43)	(19.38)	(19.27)	(22.50)	(9.92)
	OW	2.32	2.46	2.75	3.18	3.87	1.55***
		(16.26)	(18.46)	(19.70)	(18.64)	(26.12)	(10.11)
Vega	EW	5.66	3.77	2.88	2.39	1.89	-3.77***
		(31.35)	(26.35)	(24.98)	(21.96)	(17.51)	(-31.65)
	SW	4.83	3.15	2.41	2.05	1.61	-3.22***
		(26.16)	(22.94)	(19.97)	(20.24)	(15.79)	(-24.15)
	OW	6.06	3.88	2.87	2.36	1.77	-4.30***
		(26.93)	(22.25)	(21.20)	(18.97)	(15.80)	(-21.96)
Theta	EW	2.65	2.86	3.18	3.68	4.21	1.56***
		(19.37)	(24.90)	(24.75)	(27.20)	(29.70)	(16.09)
	SW	1.83	1.98	2.03	2.33	2.71	0.88***
		(14.88)	(20.05)	(18.75)	(19.75)	(23.46)	(10.58)
	OW	2.29	2.54	2.72	3.29	3.90	1.62***
		(16.42)	(18.73)	(19.14)	(18.57)	(25.82)	(10.50)
Volume	EW	3.40	3.37	3.37	3.37	3.12	-0.28***
		(28.03)	(25.82)	(25.29)	(24.18)	(24.36)	(-3.95)
	SW	2.38	2.28	2.18	2.04	1.94	-0.44***
		(23.16)	(21.05)	(19.59)	(18.40)	(17.30)	(-6.23)

	OW	2.85	2.89	2.81	2.86	2.58	-0.27*
		(16.30)	(19.47)	(23.91)	(21.05)	(20.04)	(-1.76)
Price	EW	4.34	3.67	3.26	2.84	2.48	-1.86***
		(29.30)	(26.62)	(25.95)	(23.57)	(20.52)	(-20.59)
	SW	2.69	2.33	2.09	1.96	1.70	-0.99***
		(21.26)	(19.39)	(19.95)	(19.48)	(14.15)	(-10.80)
	OW	4.03	3.21	2.86	2.60	2.14	-1.89***
		(23.66)	(20.48)	(18.47)	(19.92)	(15.64)	(-11.72)
Emb_Lev	EW	5.92	3.71	2.90	2.35	1.72	-4.20***
		(32.51)	(23.82)	(23.06)	(21.60)	(19.33)	(-31.45)
	SW	4.91	3.22	2.55	2.01	1.59	-3.31***
		(28.76)	(19.75)	(19.47)	(19.26)	(16.68)	(-23.62)
	OW	5.63	3.11	2.38	2.02	1.54	-4.09***
		(26.05)	(17.66)	(15.82)	(18.21)	(15.89)	(-24.12)
VTS	EW	5.08	3.30	2.86	2.52	2.86	-2.22***
		(30.23)	(23.63)	(22.47)	(22.04)	(26.47)	(-20.96)
	SW	3.62	2.50	2.02	1.78	1.63	-1.99***
		(21.74)	(19.88)	(16.48)	(17.77)	(16.71)	(-17.17)
	OW	4.60	2.74	2.27	1.86	1.94	-2.65***
		(22.62)	(19.79)	(15.79)	(15.46)	(16.44)	(-15.66)
VOV1	EW	3.34	3.16	3.20	3.22	3.69	0.35***
		(25.87)	(25.11)	(23.75)	(24.19)	(28.00)	(4.44)
	SW	2.24	2.04	2.01	1.98	2.14	-0.10
		(20.48)	(18.42)	(17.49)	(17.24)	(18.04)	(-1.19)
	OW	2.65	2.47	2.55	2.48	3.11	0.46***
		(21.91)	(18.51)	(16.30)	(19.70)	(18.62)	(3.73)
VOV2	EW	3.20	3.10	3.18	3.29	3.84	0.65***
		(25.30)	(24.10)	(24.50)	(25.05)	(27.83)	(8.34)
	SW	2.17	2.02	1.93	1.99	2.29	0.13*
		(20.34)	(19.35)	(17.57)	(17.56)	(18.18)	(1.72)
	OW	2.53	2.52	2.43	2.65	3.35	0.81***
		(18.22)	(20.80)	(17.46)	(19.63)	(19.81)	(6.25)
Impl_vol	EW	1.56	2.22	2.83	3.69	6.29	4.73***
		(18.82)	(21.74)	(22.24)	(24.33)	(32.88)	(33.60)
	SW	1.55	2.05	2.65	3.34	5.27	3.71***
		(16.99)	(19.81)	(19.88)	(19.02)	(28.43)	(24.52)
	OW	1.48	2.01	2.42	3.19	5.87	4.38***
		(17.12)	(17.64)	(16.97)	(18.37)	(26.47)	(24.49)
Impl_skew	EW	2.97	3.17	3.08	3.28	3.67	0.71***
		(25.07)	(25.52)	(23.84)	(23.41)	(25.63)	(6.86)
	SW	1.86	1.94	2.01	2.19	2.39	0.54***
		(16.79)	(16.64)	(15.79)	(17.57)	(18.25)	(6.65)

	OW	2.39	2.48	2.58	3.04	3.38	0.99***
		(19.78)	(17.54)	(15.44)	(16.77)	(18.90)	(6.78)
Impl_kurt	EW	1.79	2.41	2.98	3.74	5.26	3.47***
		(19.98)	(21.97)	(20.71)	(25.04)	(33.24)	(33.93)
	SW	1.61	2.03	2.32	2.97	3.70	2.09***
		(17.63)	(20.28)	(17.28)	(18.07)	(22.19)	(16.69)
	OW	1.55	2.05	2.40	2.88	4.85	3.30***
		(18.73)	(20.49)	(17.69)	(15.50)	(24.32)	(20.33)
Lag_ret	EW	3.83	2.71	2.64	2.97	4.00	0.17*
		(26.44)	(22.41)	(22.39)	(22.31)	(25.77)	(1.79)
	SW	2.30	1.93	1.84	1.99	2.77	0.48***
		(14.11)	(16.55)	(16.82)	(13.56)	(16.36)	(3.42)
	OW	3.27	2.26	2.22	2.32	3.63	0.36**
		(15.96)	(18.98)	(18.06)	(14.41)	(17.23)	(2.00)
Vol_ret	EW	1.94	2.60	3.10	3.83	4.67	2.73***
		(20.68)	(22.46)	(23.20)	(21.85)	(29.53)	(25.99)
	SW	1.66	2.07	2.24	2.50	3.07	1.41***
		(14.77)	(15.92)	(18.41)	(14.23)	(14.77)	(10.16)
	OW	1.74	2.38	2.66	3.28	4.33	2.60***
		(15.42)	(18.08)	(19.96)	(16.78)	(16.46)	(12.54)
Cvol_ratio	EW	3.09	2.98	3.19	3.55	3.81	0.72***
		(25.57)	(23.96)	(25.41)	(25.05)	(28.38)	(15.48)
	SW	2.07	1.87	2.02	2.23	2.32	0.25***
		(16.57)	(15.73)	(18.43)	(19.71)	(21.53)	(3.50)
	OW	2.60	2.17	2.59	3.05	3.49	0.89***
		(17.04)	(15.28)	(20.16)	(20.68)	(18.25)	(6.11)
CIV-PIV	EW	3.48	2.82	2.67	2.97	4.68	1.21***
		(27.93)	(22.68)	(21.76)	(23.65)	(28.64)	(12.26)
	SW	2.29	1.94	1.85	2.06	2.99	0.70***
		(18.85)	(17.12)	(15.74)	(19.92)	(21.87)	(7.64)
	OW	3.48	2.38	2.23	2.50	3.92	0.45***
		(18.81)	(17.57)	(14.67)	(19.04)	(22.11)	(2.66)
DCIV-DPIV	EW	3.52	2.81	2.68	3.04	4.54	1.01***
		(27.51)	(23.36)	(22.00)	(24.58)	(29.42)	(14.20)
	SW	2.27	1.93	1.81	2.11	2.91	0.64***
		(19.57)	(18.39)	(16.08)	(19.54)	(20.78)	(8.19)
	OW	3.48	2.41	2.19	2.54	3.93	0.45***
		(20.13)	(18.27)	(15.95)	(19.00)	(23.47)	(2.68)
Vol_Skew	EW	4.12	2.82	2.93	3.15	3.59	-0.53***
		(23.69)	(22.02)	(25.25)	(25.89)	(26.93)	(-4.01)
	SW	2.32	1.88	1.99	2.21	2.60	0.28*
		(16.79)	(18.80)	(18.02)	(19.79)	(16.69)	(1.90)

	OW	3.23	2.24	2.29	2.77	3.83	0.60^{**}
		(16.49)	(18.43)	(18.75)	(20.17)	(17.78)	(2.45)
RV-IV	EW	5.09	3.08	2.61	2.57	3.24	-1.85^{***}
		(33.79)	(26.03)	(21.77)	(20.88)	(22.25)	(-18.72)
	SW	3.47	2.16	1.89	1.83	2.28	-1.19^{***}
		(25.47)	(19.31)	(17.63)	(17.38)	(15.23)	(-10.14)
	OW	4.44	2.47	2.27	2.12	2.76	-1.68^{***}
		(27.31)	(18.24)	(16.59)	(16.07)	(13.56)	(-9.53)

Table 3. Summary Statistics of Option-based Factors

This table presents the summary statistics and time-series correlations of the option-based factors. At the end of each month t we sort stocks into two groups based on option size and three groups based on the given option characteristic. The option size breakpoint is taken to be the median option size among all options in our sample. The breakpoints for the option characteristics are the 30th and 70th percentile values of the given variable among all options in our sample. Portfolios are formed by assigning all options in the sample to one of the six groups based on these breakpoints. The factor value at month t+1 is the average return of two portfolios with high values of the option-based variable minus the average return of two portfolios with low values of the option-based variable. RawRet presents the raw value of the constructed factor. Alpha presents the intercept coefficient of regression of each factor on market factor MKT. Market factor is the option-size weighted return minus risk-free rate. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. In Panel A, we report the summary statistics. In Panel B, we report the time-series correlations.

Panel A: Summary statistics of option market factors

	Opt_ill	Vega	Gamma	Theta	Price	Emb_Lev	VTS	VOV1	VOV2	Impl_vol
RawRet	1.37***	3.28***	1.39***	1.42***	1.58***	3.38***	1.89***	0.30***	0.46***	3.72***
	(15.41)	(24.42)	(12.89)	(12.47)	(15.28)	(27.18)	(18.50)	(3.86)	(6.02)	(28.41)
Alpha	2.04***	2.65***	1.92***	1.93***	1.94***	1.74***	0.67***	-0.12	0.13	1.90***
	(9.25)	(8.83)	(6.81)	(6.69)	(7.27)	(5.90)	(4.33)	(-0.71)	(0.79)	(6.90)

	Impl_skew	Impl_kurt	Lag_ret	Vol_ret	Cvol_ratio	CIV-PIV	DCIV- DPIV	Vol_skew	RV-IV
RawRet	0.50***	2.41***	0.23**	2.24***	0.83***	0.65***	0.63***	0.16	1.31***
	(6.46)	(23.80)	(2.30)	(19.53)	(11.39)	(6.42)	(8.02)	(1.33)	(14.26)
Alpha	-0.09	1.18***	-0.01	0.76***	0.50***	0.81***	0.71***	-0.32	1.86***
	(-0.35)	(4.09)	(-0.06)	(4.03)	(2.97)	(4.64)	(5.11)	(-1.50)	(7.94)

Panel B: Time-series correlations of option market factors

	Opt_ ill	Vega	Gam ma	Theta	Price	Emb_ lev	VTS	Imp_ vol	Imp_ kurt	Vol_ ret	Cvol_ ratio	CIV-PIV	DCIV -DPIV	RV-IV	MKT
Opt_ill	1.00														
Vega	0.31	1.00													
Gamma	0.51	0.63	1.00												
Theta	0.52	0.68	0.96	1.00											
Price	0.47	0.62	0.92	0.90	1.00										
Emb_lev	-0.14	0.54	-0.09	-0.04	-0.10	1.00									
VTS	-0.14	0.42	-0.09	-0.07	-0.08	0.70	1.00								
Impl_vol	-0.14	0.54	-0.10	-0.06	-0.09	0.98	0.71	1.00							
Impl_kurt	-0.16	0.34	-0.21	-0.16	-0.20	0.78	0.63	0.78	1.00						
Volret	-0.13	0.44	-0.02	0.03	0.02	0.62	0.51	0.62	0.55	1.00					
Cvol_ratio	0.03	0.26	0.20	0.13	0.22	0.20	0.16	0.21	0.12	0.18	1.00				
CIV-PIV	0.10	0.10	0.09	0.08	0.09	0.07	0.08	0.05	-0.10	0.06	0.02	1.00			
DCIV-DPIV	0.05	0.10	0.01	0.01	-0.02	0.08	0.08	0.09	-0.05	0.00	0.02	0.58	1.00		
RV-IV	0.31	0.21	0.21	0.23	0.17	0.01	-0.03	0.00	-0.08	-0.21	-0.12	0.14	0.16	1.00	
MKT	-0.35	0.25	-0.26	-0.24	-0.18	0.59	0.55	0.64	0.51	0.56	0.19	-0.08	-0.05	-0.24	1.00

Table 4. Factor Spanning Tests

This table presents the alphas of each factor after being regressed on other factors, including the market factor. Market factor is the option-size weighted return minus risk-free rate. For example, the Alpha of Opt_ill presents the alpha of regression of factor Opt_ill on other 13 factors and the market factor. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	Opt_ill	Vega	Gamma	Theta	Price	Emb_Lev	VTS
Alpha	0.92***	0.04	0.04	-0.09	0.26***	0.04	0.30
	(5.07)	(0.23)	(0.56)	(-0.99)	(2.98)	(0.62)	(1.40)
	Impl_vol	Impl_kurt	Vol_ret	Cvol_ratio	CIV-PIV	DCIV-DPIV	RV-IV
Alpha	0.10	0.52***	-0.07	-0.04	0.12	0.23	0.80***
	(1.51)	(2.72)	(-0.30)	(-0.19)	(0.65)	(1.44)	(3.15)

Table 5. Performance of Selected Factors

In this table, we summarize the raw values of the option-based factors and the alphas of regressions of constructed factors on other existing factor models. Raw means the raw value of the factors. Each column represents the alpha of the constructed option market factor with respect to existing factor model. IA is IVOL+Amihud factors which are IVOL and Amihud factors from 2-by-3 sorting on firm size. FF3, FF5, and FF6 are Fama-French 3, 5, and 6 factors. Q4 is Hou, Xue, and Zhang (2015) Q factors. Q5 is Hou, Mo, Xue, and Zhang (2021) Q-5 factors. SY is Stambaugh and Yuan (2017) factor model. DHS is Daniel, Hirschleifer, and Sun (2020) factor model. BBW is Bai, Bali, and Wen (2019) factor model. VOL3 include three volatility factors: the Coval and Shumway (2001) zero-beta straddle return of the S&P 500 Index option, the value-weighted zero-beta straddle returns of S&P 500 individual stock options, and change in the Chicago Board Options Exchange Market Volatility Index. AN is Agarwal and Naik (2004) factor model. FH is Fung and Hsieh (2001) factor model. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	Opt_ill	Price	Impl_kurt	RV-IV	MKT
Raw	1.37***	1.58***	2.41***	1.31***	2.44***
	(15.41)	(15.28)	(23.80)	(14.26)	(20.04)
IA	1.14***	1.14***	1.48***	1.35***	1.77***
	(9.15)	(6.67)	(9.97)	(6.81)	(10.86)
FF3	1.38***	1.57***	2.38***	1.33***	2.38***
	(15.89)	(15.35)	(22.27)	(14.31)	(17.61)
FF5	1.41***	1.55***	2.39***	1.32***	2.36***
	(14.93)	(13.13)	(21.94)	(14.23)	(17.53)
FF6	1.38***	1.54***	2.41***	1.28***	2.38***
	(14.98)	(13.78)	(22.37)	(14.92)	(18.01)
Q4	1.39***	1.55***	2.45***	1.28***	2.42***
	(14.45)	(14.03)	(21.35)	(12.38)	(15.72)
Q5	1.34***	1.51***	2.36***	1.19***	2.41***
	(13.87)	(12.41)	(19.66)	(10.80)	(16.69)
SY	1.28***	1.52***	2.50***	1.12***	2.56***
	(12.28)	(12.73)	(18.77)	(10.07)	(17.41)
DHS	1.37***	1.54***	2.43***	1.12***	2.56***
	(15.35)	(16.43)	(19.82)	(10.07)	(17.41)
BBW	1.37***	1.59***	2.41***	1.32***	2.42***
	(15.48)	(15.34)	(22.20)	(14.24)	(18.41)
VOL3	1.45***	1.70***	2.40***	1.44***	2.22***
	(14.94)	(14.67)	(20.43)	(13.35)	(21.25)
AN	1.45***	1.64***	2.38***	1.45***	2.24***
	(14.32)	(14.30)	(17.69)	(12.84)	(14.97)
FH	1.41***	1.62***	2.33***	1.39***	2.21***
	(14.97)	(15.16)	(20.55)	(14.83)	(15.95)

Table 6. Performance of Selected Factor Model to Explain Option-based Long-short Spreads

This table presents the performance of selected factor model to explain the 20 long-short spreads on option characteristics. "H-L" reports the raw return spread based on the sorting variable. "Alpha OPT5" reports the alpha of regressing long-short spread on selected factor model OPT5. $\overline{|RawRet|}$ and $\overline{|\alpha|}$ report the average absolute return and absolute alpha. GRS stat reports the GRS test statistic for the test of the null hypothesis that the factor model explains all return spreads. GRS P-value reports the GRS p-value for the test of the null hypothesis that the factor model explains all return spreads. OPT5 includes 5 factors: Opt_ill, Price, Impl_kurt, RV-IV, and MKT. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

Sort Variable	H-L	Alpha OPT5	Sort Variable	H-L	Alpha OPT5
Opt_ill	1.86***	0.23	Impl_vol	4.38***	0.14
	(13.51)	(1.04)		(24.26)	(0.36)
Gamma	1.55***	0.28	Impl_skew	0.99***	-0.62
	(10.50)	(1.23)		(6.58)	(-1.55)
Vega	-4.30***	-0.32	Impl_kurt	3.30***	-0.50
	(-22.49)	(-0.69)		(20.65)	(-1.57)
Theta	1.62***	0.37	Lag_ret	0.36**	-0.81
	(10.95)	(1.53)		(1.99)	(-1.28)
Volume	-0.27*	-0.70	Vol_ret	2.60***	-0.32
	(-1.82)	(-1.51)		(12.98)	(-0.53)
Price	-1.89***	-0.25	Cvol_ratio	0.89***	-0.48
	(-11.92)	(-1.15)		(6.05)	(-0.80)
Emb_Lev	-4.09***	0.14	CIV-PIV	0.45***	0.50
	(-23.75)	(0.39)		(2.65)	(1.23)
VTS	-2.65***	0.09	DCIV-DPIV	0.45***	0.51
	(-15.94)	(0.19)		(2.69)	(1.13)
VOV1	0.46***	0.30	Vol_Skew	0.60**	-0.39
	(3.77)	(0.74)		(2.56)	(-0.76)
VOV2	0.81***	0.57*	RV-IV	-1.68***	-0.22
	(6.17)	(1.81)		(-9.78)	(-0.73)
$\overline{|RawRet|}$:1.76					
$\overline{|\alpha|}$: 0.39					
GRS stat: 1.84					
GRS P-value: 0.02					

Table 7. Horse Race of Factor Models

In this table, we summarize the performance of each factor model to explain the 20 long-short spreads on option characteristics in table 6. $\overline{|\alpha|}$ reports the average absolute value of raw return or alpha. In the column labeled "GRS", we report the GRS test-statistic and the p-value associated with GRS test in parentheses. We include 5 factors-Opt_ill, Price, Impl_kurt, RV-IV, and MKT in OPT5. MKT includes the option market factor. IA is IVOL+Amihud factors which are IVOL and Amihud factors from 2-by-3 sorting on firm size. FF3, FF5, and FF6 are Fama-French 3, 5, and 6 factors. . Q4 is Hou, Xue, and Zhang (2015) Q factors. Q5 is Hou, Mo, Xue, and Zhang (2021) Q-5 factors. SY is Stambaugh and Yuan (2017) factor model. DHS is Daniel, Hirschleifer, and Sun factor model. BBW is Bai, Bali, and Wen factor model. VOL3 include three volatility factors: the Coval and Shumway (2001) zero-beta straddle return of the S&P 500 Index option, the value-weighted zero-beta straddle returns of S&P 500 individual stock options, and change in the Chicago Board Options Exchange Market Volatility Index. AN is Argawal and Naik factor model. FH is Fung and Hsieh factor model.

Model	$\overline{|\alpha|}$	GRS	Model	$\overline{|\alpha|}$	GRS
Raw	1.76		Q5	1.70	45.67
					(0.00)
OPT5	0.39	1.84	SY	1.75	43.86
		(0.02)			(0.00)
MKT	1.42	19.61	DHS	1.77	47.04
		(0.00)			(0.00)
IA	1.01	13.36	BBW	1.54	26.99
		(0.00)			(0.00)
FF3	1.76	55.65	VOL3	1.82	56.18
		(0.00)			(0.00)
FF5	1.74	50.24	AN	1.76	49.60
		(0.00)			(0.00)
FF6	1.74	49.44	FH	1.76	50.22
		(0.00)			(0.00)
Q4	1.77	52.89			
		(0.00)			

Table 8. Performance of Selected Factor Model to Explain 20 Option-based and 93 GHZ Variables

This table presents the performance of OPT5 model to explain quintile portfolios formed by a list of variables. In addition to the 20 option-based variables, the tests in this table include portfolios formed by sorting on the 93 variables examined in Green, Hand, and Zhang (2017). We use each variable to construct long-short portfolios of options using the same methodology as described in Table 2. We exclude dummy variables in GHZ variables and make slight modifications for discrete variables. $\overline{|RawRet|}$ / $\overline{|\alpha|}$ reports the average absolute value of raw return or alpha. # Significant Alphas is the number of significant alphas of the long-short spreads being regressed on selected factor model at 5% level. OPT5 includes 5 factors: Opt_ill, Price, Impl_kurt, RV-IV, and MKT. GRS stat reports the GRS test statistic for the test of the null hypothesis that the factor model explains all return spreads. GRS p-value reports the GRS p-value for the test of the null hypothesis that the factor model explains all return spreads.

	Raw	OPT5
$\overline{|RawRet|}$ / $\overline{|\alpha|}$	1.07	0.55
# Significant Alphas		15
GRS stat		1.78
GRS p-value		(0.00)

Table 9. Sharpe Ratios

This table presents Sharpe ratios for individual factors and for the tangency portfolio constructed from the factors in selected factor model OPT5. The rows "Mean", "SD" and "Sharpe Ratio" present annualized mean factor return, standard deviation, and Sharpe ratios for individual factors and tangency portfolios. "Tangency-Full" presents the tangency portfolio constructed from the full sample. "Tangency-Expanding" presents the results using an expanding window methodology. Specifically, from January 2001, we calculate tangency portfolio weights from the expected factor returns and factor covariances estimated using data from January 1996 to the latest month. The mean, SD, and Sharpe ratios are calculated using returns from January 2001 through December 2019. OPT5 includes 5 factors: Opt_ill, Price, Impl_kurt, RV-IV, and MKT.

	Opt_ill	Price	Impl_kurt	RV-IV	MKT	Tangency-Full	Tangency-Expanding
Mean	16.44	18.96	28.80	15.72	29.28	22.32	21.00
SD	4.68	4.85	5.85	5.58	6.06	2.53	2.36
Sharpe Ratio	3.50	3.91	4.92	2.84	4.85	8.83	8.83

Table 10. Information Frictions and Factor Performance

This table reports the double-sorting results of option returns on information friction score and composite option-based score. At the end of each month, we sort the options based on the information friction composite score (IF) and option-based composite score (OScore) into three groups independently. Information friction score is based on four proxies related to information frictions: firm age, institutional ownership, analyst coverage, and analyst forecast dispersion. OScore is the composite score using variables Opt_ill, Price, Impl_kurt, and RV-IV. We take negative values of option price and RV-IV so a higher value is associated with higher return to delta-neutral call selling. It presents the average return in each portfolio and the return spread between options with high value and low value for each option-based variable. It also presents the difference in high-minus-low spread. All returns in this table are expressed in percent. The sample period is from January 1996 to January 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	OScore Low	OScore Mid	OScore High	H-L
IF Low	1.87	2.62	3.39	1.52***
	(17.39)	(21.77)	(19.06)	(11.14)
IF Mid	1.81	3.08	4.08	2.27***
	(10.30)	(18.65)	(19.67)	(10.25)
IF High	2.15	3.87	5.59	3.44***
	(8.29)	(13.74)	(24.43)	(13.52)
H-L	0.28	1.25***	2.20***	1.92***
	(1.18)	(5.09)	(9.70)	(6.68)

Table 11. Customer Demand and Factor Performance

This table reports the double-sorting results of option returns on customer demand and composite option-based score. At the end of each month, we sort the options based on customer demand and option-based composite score (OScore) into three groups independently. Customer demand is (OpenBuy-OpenSell)/(OpenBuy+OpenSell), where OpenBuy and OpenSell are open buy and open sell volumes of public customers of all call options of the underlying stock. We use open/close data from CBOE. OScore is the composite score using variables Opt_ill, Price, Impl_kurt, and RV-IV. We take negative values of option price and RV-IV so a higher value is associated with higher return to delta-neutral call selling. It presents the average return in each portfolio and the return spread between options with high value and low value for each option-based variable. It also presents the difference in high-minus-low spread. All returns in this table are expressed in percent. The sample period is from January 2009 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	OScore Low	OScore Mid	OScore High	H-L
CD Low	1.42	2.33	3.78	2.35***
	(12.38)	(14.95)	(18.72)	(14.70)
CD Mid	1.65	2.83	5.31	3.63***
	(10.24)	(13.45)	(17.24)	(11.22)
CD High	1.72	3.07	4.61	2.89***
	(11.72)	(15.66)	(23.05)	(14.05)
H-L	0.30**	0.74***	0.84***	0.54**
	(2.08)	(5.38)	(4.43)	(2.16)

Supplementary Appendix:

In Search of a Factor Model for Option Returns

1. Variable Definitions

Option-based Characteristics	
Op_size	Option market size, option open interest times option price at last month end.
Opt_ill	Option illiquidity, measured as the option bid-ask spread divided by the average of bid and ask prices.
Gamma	Value of Gamma at last month end
Vega	Value of Vega at last month end
Theta	Value of Theta at last month end
Volume	Sum of option volume of the selected option during last month
Price	Option price, computed as the average of ask and bid price, at last month end
Emb_Lev	Embedded leverage: $\frac{\partial O/O}{\partial S/S}$, the elasticity of option price to stock price, at last month end
VTS	Volatility term structure, the difference between implied volatility of long-term option and short-term option. We use volatility surface data and compute VTS as difference between implied volatility of at-the-money (|delta| = 0.5) options with 365 days to maturity and 30 days to maturity.
VOV1	Volatility of volatility, computed as the standard deviation of the stock's ATM implied volatilities (the average of the ATM call and ATM put implied volatilities) over all days in the previous month divided by the mean of these same implied volatilities. At least 12 daily ATM implied volatilities in a month are required to calculate this measure. Data is from volatility surface.

VOV2	Volatility of volatility, computed as the standard deviation of the percent change in stock's ATM implied volatilities (the average of the ATM call and ATM put implied volatilities) over all days in the previous month. At least 12 daily ATM implied volatilities in a month are required to calculate this measure. Data is from volatility surface.
Impl_vol	Implied volatility of the option at last month end
Impl_skew	Option risk neutral skewness at last month end.
Impl_kurt	Option risk neutral kurtosis at last month end.
Lag_ret	Last month return to delta-neutral call-writing of selected ATM short-term option. We enter the position at the beginning of last month and closes the position at the end of last month
Vol_ret	Volatility of option return, calculated as the standard deviation of daily return of selected ATM short-term option of this firm. For each day we compute the price of selling a delta-hedged call as $H_{t+1} = \Delta_t \cdot S_{t+1} - C_{t+1}$. Δ_t is the delta at last month end, S_{t+1} is stock price at day t+1 and C_{t+1} is the option price at day t+1. We compute daily returns using values of H_{t+1} and compute Vol_ret as the standard deviation of daily returns, requiring at least 12 days.
Cvol_ratio	Total call option volume divided by total option volume (call plus put) for the given underlying stock during last month.
CIV-PIV	The difference of implied volatility between ATM call option and ATM put option. We select options with 30 days to maturity and |delta| = 0.5 as ATM calls and ATM puts from volatility surface
DCIV- DPIV	The difference of change in implied volatility between ATM call option and ATM put option. We select options with 30 days to maturity and |delta| = 0.5 as ATM calls and ATM puts from volatility surface.
Vol_Skew	The difference of implied volatility between OTM put option and ATM put option. We use the options with 30 days to maturity.
RV-IV	The difference between realized volatility (the standard deviation of daily stock return during last month) and implied volatility.

2. Portfolio Construction for Discrete GHZ Variables

This section introduces how we deal with discrete variables from Green, Hand, and Zhang (2015) when forming quintile portfolios. These variables are discrete variables and if we form quintile portfolios based on the 20^{th}, 40^{th}, 60^{th}, and 80^{th} percentiles of these variables, there may not be enough observations in all quintile portfolios. Thus, we need to make modifications to the way we create long-short portfolios.

The first variable is CHFEPS, which is the change in forecasted EPS. We divide the options in our sample into three groups: CHFEPS >0, CHFEPS=0, and CHFEPS<0. We take the return spread between options for which CHFEPS >0 and options for which CHFEPS<0 as the long-short portfolio.

The second variable is CHNANALYST, which is the change in number of analysts. We divide the options in our sample into three groups: CHNANALYST <=-2, -2< CHNANALYST <2, and CHNANALYST >=2. We take the return spread between options for which CHNANALYST >=2 and options for which CHNANALYST <=-2 as the long-short portfolio.

The third variable is NINCR, which is the number of earnings increases. We divide the options in our sample into three groups: NINCR =0, NINCR=1, and NINCR >=2. We take the return spread between options for which NINCR >=2 and options for which NINCR=0 as the long-short portfolio.

The fourth variable is PS, which is the financial statement score. We divide the options in our sample into three groups: PS<=3, 3<PS<7, and PS >=7. We take the return spread between options for which PS >=7 and options for which PS<=3 as the long-short portfolio.

Table A1. Performance of Selected Factor Model to Explain Option-based Long-short Spreads Constructed Using NYSE-breakpoints

This table presents the performance of selected factor model to explain the 20 long-short spreads on option-market variables. These factors are constructed using NYSE breakpoints. "H-L" reports the raw return spread based on the sorting variable. "Alpha OPT5" reports the alpha of regressing long-short spread on selected factor model OPT5. $\overline{|RawRet|}$ and $\overline{|\alpha|}$ report the average absolute return and absolute alpha. GRS stat reports the GRS test statistic for the test of the null hypothesis that the factor model explains all return spreads. GRS P-value reports the GRS p-value for the test of the null hypothesis that the factor model explains all return spreads. OPT5 includes 5 factors: Opt_ill, Price, Impl_kurt, RV-IV, and MKT. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

Sort Variable	H-L	Alpha OPT5	Sort Variable	H-L	Alpha OPT5
Opt_ill	1.66***	0.53**	Impl_vol	4.37***	0.60
	(9.10)	(2.15)		(17.72)	(1.15)
Gamma	1.75***	0.55**	Impl_skew	1.25***	-0.46
	(6.98)	(1.99)		(5.43)	(-1.03)
Vega	-4.30***	-0.88*	Impl_kurt	3.04***	-0.28
	(-17.16)	(-1.87)		(14.15)	(-0.87)
Theta	1.83***	0.55**	Lag_ret	0.03	-0.77
	(7.39)	(2.39)		(0.12)	(-1.31)
Volume	-0.00	-0.71	Vol_ret	2.25***	-0.02
	(-0.01)	(-1.57)		(9.47)	(-0.04)
Price	-2.16***	-0.21	Cvol_ratio	1.16***	-0.31
	(-8.67)	(-0.98)		(5.41)	(-0.60)
Emb_Lev	-3.96***	-0.21	CIV-PIV	0.68***	0.60
	(-16.35)	(-0.52)		(2.80)	(1.54)
VTS	-2.44***	-0.05	DCIV- DPIV	0.75***	0.54
	(-11.24)	(-0.11)		(3.49)	(1.23)
VOV1	0.61***	0.37	Vol_Skew	-0.35	-0.11
	(3.54)	(0.93)		(-1.05)	(-0.22)
VOV2	0.71***	0.54*	RV-IV	-1.81***	-0.27
	(3.84)	(1.73)		(-8.15)	(-0.77)

$\overline{|RawRet|}$: 1.76

$\overline{|\alpha|}$: 0.43

GRS stat: 2.23

GRS P-value: 0.00

Table A2. Performance of Selected Factor Model to Explain Option-based Long-short Spreads During Sub-periods

This table presents the performance of selected factor model to explain the 20 long-short spreads on option-market variables during sub-periods. "H-L" reports the raw return spread based on the sorting variable. "Alpha OPT5" reports the alpha of regressing long-short spread on selected factor model OPT5. $\overline{|RawRet|}$ and $\overline{|\alpha|}$ report the average absolute return and absolute alpha. GRS stat reports the GRS test statistic for the test of the null hypothesis that the factor model explains all return spreads. GRS P-value reports the GRS p-value for the test of the null hypothesis that the factor model explains all return spreads. OPT5 includes 5 factors: Opt_ill, Price, Impl_kurt, RV-IV, and MKT. In Panel A, the sample period is from January 1996 to December 2007. In Panel B, the sample period is from January 2008 to December 2019.

Panel A: January 1996 to December 2007

Sort Variable	H-L	Alpha OPT5	Sort Variable	H-L	Alpha OPT5
Opt_ill	1.66***	0.15	Impl_vol	4.37***	1.03*
	(9.10)	(0.45)		(17.72)	(1.68)
Gamma	1.75***	-0.00	Impl_skew	1.25***	-0.03
	(6.98)	(0.00)		(5.43)	(-0.05)
Vega	-4.30***	-0.81	Impl_kurt	3.04***	-0.15
	(-17.16)	(-1.48)		(14.15)	(-0.40)
Theta	1.83***	0.17	Lag_ret	0.03	-1.91**
	(7.39)	(0.38)		(0.12)	(-2.39)
Volume	-0.00	-1.25*	Vol_ret	2.25***	0.41
	(-0.01)	(-1.65)		(9.47)	(0.64)
Price	-2.16***	-0.33	Cvol_ratio	1.16***	-0.83
	(-8.67)	(-0.87)		(5.41)	(-1.16)
Emb_Lev	-3.96***	-0.47	CIV-PIV	0.68***	0.99*
	(-16.35)	(-0.88)		(2.80)	(1.65)
VTS	-2.44***	-0.76	DCIV- DPIV	0.75***	1.18**
	(-11.24)	(-1.40)		(3.49)	(2.40)
VOV1	0.61***	0.42	Vol_Skew	-0.35	-0.86
	(3.54)	(0.92)		(-1.05)	(-1.33)
VOV2	0.71***	0.63	RV-IV	-1.81***	-0.54
	(3.84)	(1.35)		(-8.15)	(-1.13)

$\overline{|RawRet|}$: 1.76

$\overline{|\alpha|}$: 0.65

GRS stat: 1.72

GRS P-value: 0.04

Panel B: January 2008 to December 2019

Sort Variable	H-L	Alpha OPT5	Sort Variable	H-L	Alpha OPT5
Opt_ill	2.06***	0.32	Impl_vol	4.40***	-0.61
	(10.22)	(0.97)		(16.56)	(-1.62)
Gamma	1.36***	0.64**	Impl_skew	0.73***	-1.28**
	(8.93)	(2.36)		(4.07)	(-2.17)
Vega	-4.30***	0.22	Impl_kurt	3.55***	-0.71
	(-14.68)	(0.35)		(15.48)	(-1.62)
Theta	1.40***	0.56**	Lag_ret	0.69***	0.16
	(9.15)	(2.06)		(3.21)	(0.19)
Volume	-0.54***	-0.11	Vol_ret	2.94***	-1.19
	(-3.68)	(-0.24)		(9.42)	(-1.53)
Price	-1.62***	-0.19	Cvol_ratio	0.62***	0.20
	(-8.69)	(-0.88)		(3.23)	(0.22)
Emb_Lev	-4.23***	0.58	CIV-PIV	0.22	0.09
	(-17.29)	(1.57)		(0.93)	(0.14)
VTS	-2.87***	0.81	DCIV- DPIV	0.16	0.45
	(-11.53)	(1.44)		(0.64)	(0.59)
VOV1	0.31*	-0.20	Vol_Skew	1.55***	-0.09
	(1.85)	(-0.29)		(6.31)	(-0.16)
VOV2	0.92***	0.27	RV-IV	-1.55***	0.04
	(4.82)	(0.70)		(-5.86)	(0.11)

$\overline{|RawRet|}$: 1.80

$\overline{|\alpha|}$: 0.44

GRS stat: 0.92

GRS P-value: 0.56