ÖZGÜR ŞAFAK AÇIKALIN OPTION-BASED VARIABLES AND FUTURE RETURNS Bilkent University 2023

WHAT DO THE OPTION-BASED VARIABLES TELL US ABOUT FUTURE RETURNS?

A Master's Thesis

by

ÖZGÜR ŞAFAK AÇIKALIN

The Department of Management
İhsan Doğramacı Bilkent
University
Ankara

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To My Family and Friends

WHAT DO THE OPTION-BASED VARIABLES TELL US ABOUT FUTURE RETURNS?

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

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In Partial Fulfillment of the Requirements for the Degree of
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THE DEPARTMENT OF
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İHSAN DOĞRAMACI BİLKENT UNIVERSITY
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By Özgür Şafak Açıkalın

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science in Business Administration.

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ABSTRACT

What Do the Option-based Variables Tell Us About Future Returns?

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August 2023

Option-based variables reflect investors' assessment of future risk and therefore contain information about expected stock returns. Early studies show that information flows from the options market to the equity market. Empirical evidence suggest that portfolios created using option-based variables have returns that cannot be fully explained by traditional asset pricing variables. Following Bali, Chabi-Yo and Murray (2022), this thesis examines the predictive power of option-based variables, such as the difference between call and put implied volatilities, the difference between realized volatility of the underlying stock and option implied volatility, and the change of the open interest in options. The options on stocks traded in the US stock exchanges in the period between 1996 and 2015 are analyzed. The study also investigates whether the predictive power of the option-based variables changes during periods of economic recession. The findings show that option-based variables increase the predictive power of the models when used with the traditional asset pricing variables. Option-based variables are found to be useful predictors of stock returns during recessions as well. The estimation model which includes option-based variables and stock characteristics outperforms CAPM and Fama-French three-factor model during both recession and expansion periods but the accuracy of the model is significantly lower during recessions. The model fails to estimate the future returns of high beta stocks as accurately as low beta stocks. Portfolios formed based on quintile values of the option-based variables create economically large but statistically insignificant abnormal returns.

Keywords: Implied Volatility, Open Interest, Options, Stock Returns, Realized Volatility

ÖZET

OPSİYON BAZLI DEĞİŞKENLER HİSSE GETİRİLERİ HAKINDA NE ANLATIYOR?

Açıkalın, Özgür Şafak

Yüksek Lisans. İşletme Bölümü

Tez Danışmanı: Doçent Dr. Zeynep Önder

Ağustos 2023

Opsiyon bazlı değişkenler yatırımcıların gelecekteki risk değerlendirmelerini yansıtır ve bu nedenle hisse senedi getirileri hakkında bilgi içerir. Önceki çalışmalar, bilginin opsiyon piyasasından hisse senedi piyasasına aktığını göstermektedir. Ampirik kanıtlar, opsiyon bazlı değişkenler kullanılarak oluşturulan portföylerin, geleneksel varlık fiyatlama değişkenleri tarafından tam olarak açıklanamayan getirilere sahip olduğunu göstermektedir. Bali, Chabi-Yo ve Murray (2022)'i takiben bu tez, call ve put opsiyon volatiliteleri arasındaki farklar, tarihsel volatilite ve opsiyon bazlı volatilite arasındaki fark ve opsiyonların açık kontrat sayısındaki değişimi gibi opsiyon bazlı değişkenlerin tahmin gücünü incelemektedir. Veriler Optionmetrics'ten elde edilmiştir. 1996-2015 yılları arasındaki dönemde ABD borsalarında işlem gören hisse senetleri üzerindeki opsiyonlar analiz edilmiştir. Çalışmada ayrıca ekonomik durgunluk dönemlerinde opsiyon bazlı değişkenlerin tahmin gücünün değişip değişmediği de araştırılmıştır. Elde edilen bulgular, opsiyona dayalı değişkenlerin geleneksel varlık fiyatlama değişkenleri ile birlikte kullanıldığında modellerin tahmin gücünü artırdığını göstermektedir. Opsiyona dayalı değişkenlerin durgunluk dönemlerinde de hisse senedi getirisi tahminlerinde faydalı olduğu bulunmuştur. Opsiyon bazlı değişkenler ve daha önce belirlenmiş değişkenleri içeren bir tahmin modeli hem durgunluk hem de genişleme dönemlerinde CAPM ve Fama-French üç faktör modelinden daha iyi performans gösterirken, durgunluk döneminde modelin doğruluğu genişleme dönemine kıyasla önemli ölçüde daha düşüktür. Model düşük betalı hisselerin getirilerini yüksek betalı hisselerin getirilerine kıyasla daha doğru tahmin etmiştir. Opsiyon bazlı değişkenler kullanılarak oluşturulan portföylerin getirilerinin istatistiki olarak önemsiz ancak ekonomik olarak yüksek getiriler yarattığı bulunmuştur.

Anahtar Kelimeler: Örtülü Oynaklık, Açık Kontrat, Opsiyonlar, Hisse Senedi Getirileri, Gerçekleşen Oynaklık

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CHAPTER I

INTRODUCTION

In efficient markets, option prices should not yield extra information about future stock returns since all information is reflected in asset prices. If the markets are efficient, investors should not earn abnormal future returns by using information from options market. However, most markets are not efficient due to several reasons, such as market frictions and information asymmetry. Empirical studies report that investors can predict future returns by using information obtained in option markets. It is more common and profitable for investors, especially for informed traders to take a position in the option market since the options provide higher leverage compared to stocks, while their downside risk is more predictable and low. A few studies (Bali and Murray (2021), Easley, O'Hara, and Srinivas (1998)) show that the informed traders first take action in the options market. Hence, the information obtained from the option market may predict future stock returns.

Vast majority of the research (Sharpe (1964), Lintner (1965) and Black (1972), Fama and French (1993)), focus on cross-sectional returns of the stocks using both historical return data and the firm characteristics in their financial statements. CAPM, suggested by Sharpe (1964) and Fama and French's (1993) three-factor model, which includes market, size and value factors are the benchmark for most of the studies which try to explain the variation of the cross-sectional stock returns. Then, Carhart (1997) added the momentum factor suggested by Jegadeesh and Titman (1993) to Fama and French's three-factor model. Pastor and Stambaugh (2003) added an aggregate liquidity factor to Carhart's model. Fama and French (2015) proposed a five-factor model that includes a market factor, a size factor, a value factor, an investment factor, and a profitability factor. The objective of all of these papers is to explain anomalies based on variables constructed from accounting and historical stock market data that are present in the entire cross-section of US common stocks. One shortage of the previously proposed factor models is to capture abnormal returns related to the option-based variables for optionable stocks. Bali and Murray (2021) suggest an alternative factor model for optionable stocks and show that their model outperforms the previously established models.

As Bali and Murray (2021) state that previously-proposed factor models, including those that can explain the returns associated with a large number of anomaly variables, do not explain the returns of portfolios formed by sorting on option-based variables. They state that option-based factors matter because the actual market to trade according to investor's ideas and beliefs is the option market; thus, the option prices are affected by the informed trades and option-based variables might contain information regarding future equity returns. As Easley, O'Hara, and Srinivas (1998) show in their study, informed traders choose to trade in the options market rather than the equity market at first since the high leverage in the options market offers higher returns. They state that if the markets are efficient, the stock price should dictate the price movement of the underlying asset. They argue that if the option market is more compelling to informed traders, option transactions should yield information regarding the spot market prices. Based on their theoretical model, they show that under certain conditions such as decreasing depth of stock market, increasing depth of the options market and increasing leverage diverts informed traders to the options market who aims to maximize their profit. They suggest that positive option trades (buying calls and selling puts) and negative option trades (selling calls and buying puts) disclose information of informed investors to the other market participants. If their theory holds, the option market should yield information about future equity returns. Investors with negative thoughts on the stock would take positions via positive option trades and investors with positive views on the stock would take positions via negative option trades to maximize their profits. Thus, option markets will be a strong indicator of future equity returns. On the other hand, if options are used only as hedging vehicles, then all option trades would be liquidity-based. Following Bali and Murray (2021), this thesis investigates whether the options are only hedging instruments or they contain information about future equity returns, especially during recession periods.

My study aims to analyze the predictive power of option-based variables, suggested by earlier studies, to predict future stock returns and how their predictive power is affected during economic recession periods between 1996-2015. In this period, the US economy faced two recessions according to the National Bureau of Economic

Research (NBER). First, I investigate whether option-based variables are important predictors for future returns using fixed effect regression analysis. Second, I analyze how predictive power of the option-based variables changes during recession periods by using interactions of option-based variables and a recession dummy variable which indicates whether the US economy is in recession or expansion period.

The findings of the thesis show that option-based variables are useful predictors for future equity returns during expansion and recession periods. These option-based variables are call-put implied volatility differences, realized-implied volatility difference and the open interest change for individual underlying assets. Call-put implied volatility spreads are defined as at-the-money call-put implied volatility difference, out-of-the-money put and at-the-money call implied volatility spread and open interest weighted call-put implied volatility difference. Volatility spreads contain information on future equity returns. Fixed effect models in this study show that most of the option-variables have significant coefficient estimates. Findings show that these coefficient estimates increase in absolute terms during the recession periods. Thus, the findings support the theories on traders first taking a position in the options market rather than the spot market.

The remainder of the thesis is organized as follows. Section 2 summarizes the previous literature on the subject. Section 3 explains the hypothesis, methodology and contribution of the thesis. Section 4 describes the data. In Section 5, the empirical results are represented and Section 6 briefly concludes.

CHAPTER II

LITERATURE REVIEW and THEORETICAL BACKGROUND

In this section, I first provide the theoretical background to explain why option-based variables can predict future stock returns. Second, I briefly explain the variables that are used to predict future stock returns and the option-based factor model suggested by Bali and Murray (2021) and Bali, Chabi-Yo, Murray (2022). I also briefly mention the literature on predicting how stock returns change during recession periods.

In the literature, several papers show that option-based variables are important predictors of future stock returns. In general, call-put implied volatility spread is used. In order to understand why volatility spread predicts future stock returns, it is important to understand the fundamentals of the put-call parity. Put-call parity for European options relies on current call and put option prices, the price of the underlying asset and a risk-free rate. It is a no-arbitrage relation that states that for every European put-call option combination with the same underlying asset, expiration date and strike price, Equation 1 must hold. A deviation from a put-call parity indicates an expensive put (call) option relative to the call (put) option.

$$C + Xe^{rt} = P + S \tag{1}$$

C: *Price of the call option*

Xe^{rt}: *Present value of the strike price*

P: *Price of the put option*

S: *Price of the underlying stock*

Several papers argue that deviations from put-call parity can arise in the presence of short-sale constraints on the underlying stocks (e.g., Lamont and Thaler (2003), Ofek and Richardson (2003), and Ofek, Richardson and Whitelaw (2004). If the price of a put option is sufficiently high relative to the price of the corresponding call and the underlying asset, buying the put is a suitable alternative for short-selling the stock. Ofek et al. (2004) show that stocks with relatively expensive puts subsequently earn negative abnormal returns. Battalio and Schultz (2006) question these findings, arguing that short sale constraints have little impact and that careful use of intraday options data, rather than closing quotes, resolves most of the apparent violations of put-call parity. As Cochrane (2005) points out, however, they do not address the finding of negative average returns on the underlying stocks subsequent to observing such deviations from put-call parity.

As Cremers and Weinbaum (2010) mention, these conflicting results may result from market frictions such as high transaction costs. The deviation from put-call parity might be an outcome of short-selling constraints. On the other hand, if informed traders choose to trade in the options market first and thus the price reflection observed in the options market might not be instantly observed in the equity market. Cremers and Weinbaum (2010) findings show that short sale restrictions do not explain the deviation from the put-call parity and their results are in line with the idea that informed traders trade in the options market.

2.1 Option-based Variables to Predict Future Equity Returns

Higher call (put) implied volatilities compared to put (call) implied volatility might yield information on future returns since if an investor pays a higher price for the call option of a stock, she is more confident that the stock will go up. Expensive put options indicate reverse. Bali and Hovakimian (2009) try to analyze whether the spread between the realized volatility and implied volatility explains the cross-sectional variance of stock returns. Their results support the idea that information flows from the options market to the equity market. They do not find any significant information on stock returns by using only implied volatilities, but they find statistically sound models when they add realized volatility to their model and use all three measures together (call, put implied volatilities and realized volatility). A high call-put implied volatility spread (call minus put implied volatility) implies that the call option prices exceed the levels indicated by the put option prices and the put-call parity.

Cremers and Weinbaum find that volatility spread between call and put implied volatilities yield information about future stock returns. They show that stocks with expensive call options (stocks with high volatility spread and high change in the volatility spread) significantly outperform stocks with expensive puts (stocks with low volatility spreads and low change in the volatility spread). In line with Easley, O'Hara and Srinivas (1998) model, they show that if the liquidity of options is high and the underlying stocks' liquidity is low, the predictability increases. High call implied volatilities relative to put implied volatilities suggest that calls are expensive relative to puts, and high put implied volatilities relative to call implied volatilities indicate the opposite.

An, Ang, Bali, and Cakici (2014) test for the change of implied volatilities of both put and call options and find that stocks with an increase in call implied volatility yield high future stock returns and the opposite scenario holds for stocks with increasing volatility in put options. The reasoning of their research is very similar to Cremers and Weinbaum (2010)'s study which indicates that higher call (put) implied volatility reflects investors' positive (negative) expectations on stock returns.

If an investor pays a premium for a very low exercise-priced put option, it indicates that she wants to minimize her downside risk and has a negative outlook for the underlying asset. The volatility smirk represents the relationship between the strike price and implied volatilities for stocks using at-the-money, in-the-money and out-of-the-money options. While at-the-money options have the smallest implied volatilities, out-of-the-money and in-the-money options have higher implied volatilities. Xing, Zhang, and Zhao (2010) show that stocks with steeper smirks underperform compared to the stocks with flatter smirks. Again, they suggest that informed traders choose to trade in the options market rather than the equity market. In order to define the steepness of the smirk, they use the difference between the implied volatilities of out-of-the-money (OTM) put options and the implied volatilities of at-the-money (ATM) call options. OTM puts become expensive compared to ATM calls, and volatility smirks become especially prominent before big negative jumps in price levels, for example, during the year preceding the 1987 stock market crash. In an option pricing model, Pan (2002) incorporates both a jump risk premium and a volatility risk premium and shows that investors' aversion toward negative jumps drives the volatility smirks. For OTM put options, the jump risk premium component represents 80% of the total risk premium, while the premium is only 30% for OTM calls. In other words, investors tend to choose OTM puts to express their worries concerning possible future negative jumps. Consequently, OTM puts become more expensive before large negative jumps.

Other option-based variables that have been examined in the literature include option-implied jump risk and option-implied tail risk. Option-implied jump risk is a measure of the probability of a large price jump, while option-implied tail risk is a measure of the probability of extreme negative returns. Barndorff-Nielsen and Shephard (2004) found that option-implied jump risk was a significant predictor of future stock returns, while Christoffersen and Jacobs (2004) found that option-implied tail risk was a significant predictor of future returns.

Bali, Hu, Murray (2019) show that option-implied skewness and kurtosis are related with stock returns. They separate the skewness and kurtosis to systematic and unsystematic parts and show that, the idiosyncratic part of the skewness and kurtosis are related to stock returns. They use analyst target prices to calculate expected returns in their study.

In addition to the volatility spreads, several studies investigate whether open interest is a useful indicator of future stock returns. Krieger, Fodor, Doran (2011) analyze the impact of the weekly change in open interest of options on future returns. They use all the options with 30 to 365 days to its expiration to calculate a stock's put/call interest at that week. They do not use the nominal change in the open interest. Instead, they use percentage change in the open interest compared to the previous week, which eliminates the scaling problem. Each week they sort stocks into quintiles based on open interest change measure. In addition to the change in call and put open interest, they also use the ratio of call-to-put open interest change as well. Then, by using other control variables to form high-low portfolios, they analyze the excess returns of these portfolios. They find that the portfolios with high call open interest change and low put open interest change outperform the portfolios with low call open interest change since the increasing demand for a call option and decreasing demand for a put option reflects investors' positive view on stocks. They show that portfolios with high ratio of call-to-put open interest changes significantly outperform as well.

Krieger, Fodor, Doran (2011) estimate Fama and Macbeth (1973) regression on weekly returns using control variables such as book-to-market ratio, market value, momentum and implied volatility in addition to the open interest measures. Their results show that put open interest change's coefficient on weekly stock returns is positive and statistically significant. However, they do not find strong evidence in Fama and Macbeth (1973) regression for the change in the open interest of call options.

2.2 Option-based Factor Models

As several studies show that portfolios formed by using option-based variables, earn abnormal returns which cannot be explained by the traditional asset pricing models. Bali and Murray (2021) develops an asset pricing factor model by using seven previously proposed option-based factors that explain the stock returns with a dataset spanning from 1996 to 2017. These factors are:

1. Difference between the implied volatility and realized volatility

2. Difference between the implied volatilities of near-the-money call and put options

3. Volatility spread

4. Skew

5. Ratio of the trading volume of the stock to option trading volume

6. Difference between the change of the at-the-money call-implied volatility and change in at-the-money put-implied volatility

7. Volatility of the implied volatilities

The first variable is the difference between implied volatility based on option prices and realized volatility obtained from historical stock prices. The second factor is the difference between the implied volatilities of near-the-money call and put options. These two factors are proposed by Bali and Hovakimian (2009) and have a positive relation with stock returns. The third factor is VS (volatility spread) which is calculated as the difference between the call and put implied volatilities' weighted average of expiration and strike price matched call and put options' implied volatilities where the weight is the average of the open interest of the call and put options of the same exercise price and expiration date for that stock. Cremers and

Weinbaum (2010) find that stocks with high volatility spreads have higher future returns. The fourth factor, Skew, is calculated as the difference between the implied volatilities of the at-the-money call option and the out-of-the-money put option. Xing, Zhang, and Zhao (2010) show that the higher the Skew, the lower the future realized stock returns are. The fifth factor is the ratio of the stock's trading volume to option trading volume. Johnson and So (2012) find a positive relation between this ratio and future stock returns. The sixth factor is the difference between the change in the at-the-money call-implied volatility and the change in at-the-money put-implied volatility. An, Ang, Bali, and Cakici (2014) show that this factor is positively related to future stock returns. The seventh factor is the volatility of the implied volatilities, which Baltussen, Van Bekkum, and Van Der Grient (2018) show, has a negative relation with future returns. A detailed description of how these variables are given in the Variables section.

Bali and Murray (2021) create five value weighted portfolios based on option-based values. They calculate the performance of a strategy by going long in the fifth portfolio (stocks with the highest option-based variable) and going short in first portfolio (stock with the lowest option-based variable). They find that long-short portfolios created based on the ratio of volumes and volatility of the implied volatilities do not generate excess returns for their sample. For the remaining five variables, they find that the long-short portfolios generate significantly positive returns and significantly positive alphas compared to the previously established factor models of CAPM, Fama-French three-factor model, Carhart’s four-factor model, Fama-French factor model plus liquidity factor, Fama French’s five-factor model and lastly, Hou, Xue and Zhang's four-factor model that includes the market factor, a size factor, an investment factor, and a profitability factor.

Bali, Chabi-Yo and Murray (2022) focus on the significant five factors from the previous research. At the end of each month, they divide stocks into two groups based on their market values. Then, they create 3 different portfolios based on option-based variables, while the breakpoints are the 30^{th} and 70^{th} percentile of that variable among optionable stocks. In order to calculate the factors' excess return in month t+1, they take the average excess return of the high and low Market valued portfolios for the stocks with high values of the given option-based variable minus that of the above-median and below-median market valued portfolios for the stocks with low values of that option-based variable. Their results are in line with the Bali and Murray (2021) study. All of the factors generate significant excess returns over their timespan. They also test for an out-of-sample dataset, which again yields similar results.

Since all the variables besides the difference between the realized volatility and implied volatility are somewhat the difference between the call and put implied volatilities, they think that some of these might be redundant. So, they try to determine whether the excess returns generated by a factor might be explained by using the remaining option-based factors and the Market factor. After their analysis, they found that the alphas of two factors, difference of call and put implied volatilities and Skew, do not generate significantly positive alphas relative to the factor models created by the remaining factors, which indicates that these are the redundant factors. So, their option-based factor models consist of the Market factor, the difference between the implied and realized volatility, the volatility spread and the change in the difference of the implied volatilities.

2.3 Predicting Equity Returns During the Recession Periods

The uncertainty significantly increases during the recession periods and force traders to change their investment habits and strategies. Behavioral theories suggest that prices are not dictated by the fundamentals of the underlying asset; instead, they are determined by the sentiment of the investors, which is mostly overly exaggerated; thus, mispricing occurs from the fundamental values of the assets. Lemmon and Portniaguina (2006) show that investor sentiment can predict future returns of small-valued stocks, while Daniel, Hirshleifer, and Subrahmanyam (1998) show that good(bad) news related to the economy and stocks lead to overpricing (underpricing) of the assets. Chung, Hung, Yeh (2012) study the cross-sectional predictability of equity returns across different economic states. Their findings show that sentiment is a significant predictor for future stock returns during expansion periods. On the other hand, they show that during recession periods, sentiment metrics do not yield significant information on future equity returns. Thus, I investigate whether the option implied information which reflects investors' outlook for the future might yield information on future returns during the recession periods since the informed traders, which are mostly institutional investors and take positions with large amounts.

CHAPTER III

HYPOTHESES AND METHODOLOGY

In this section, I try to explain the hypotheses of this thesis. Also, a detailed explanation of the methodology is presented.

First, I analyze whether option-based variables are significant estimators of the future returns of optionable stocks.

Implied volatility spreads, as shown in the literature are significant factors to estimate future returns. Higher call implied volatility compared to the put implied volatility yields positive views of the investors on the asset, while higher put implied volatility compared to call implied volatility reflects the negative outlook of the investors. I use option-based variables as independent variables in addition to the previously established factors as control variables, namely size (value), book-to-market and market return variables, to see their ability to predict future stock returns. Bookmarket, value and marketreturn variables are used as control variables in the models. Value is calculated as the share price times the shares outstanding at the end of the given month for each stock. Marketreturn is obtained from the Fama-French's factor library as the sum of the risk-free rate and the market risk premium and bookmarket is calculated as the firm's book value per share multiplied by the number of shares outstanding at end of the previous fiscal year and divided to the market value of the stock at the end of month t. All of the data to calculate the control variables are obtained from WRDS database.

I analyze the regression coefficients and their significance change during the recession. In order to estimate betas for each option-based variable, I estimate the coefficients of the following regression model.

$$Return_{i,t+1} = \alpha_i + \beta 1\ OPT_{i,t} + \beta 2\ marketreturn_t + \beta 3\ value_{i,t} + \beta 4\ B/M_{i,t} + \varepsilon_{i,t} \tag{2}$$

In Equation 2, $Return_{i,t+1}$ represents stock i's return in month t+1. $OPT_{i,t}$ represents stock i's option-based variable at month t. OPT represents the option-based variable in the model. $marketreturn_t$, $value_{i,t}$, $B/M_{i,t}$ are the control variables. I estimate betas for every variable and report them.

Second, I try to analyze whether the predictive powers of the option-based variables change during the recession periods because in these periods the volatility and downside risk become important factors for investment decisions. I test whether the coefficients obtained from fixed effect models of option-based variables and their interaction variables with the recession variable (recession variable takes the value 1 during the recession periods, 0 otherwise) and expect their coefficients to be significant. In addition to the fixed effect models, the model is also estimated individually to obtain beta values for each stock.

In Equation 3, I add $OPT_{i,t} * recession_t$ and $recession_t$ to the models. $OPT_{i,t} * crisis_t$ is either 0 or equal to $OPT_{i,t}$ depending on whether $recession_t$value, which is a binary variable indicating whether the economy is in recession or not

$$Return_{i,t+1} = \alpha_i + \beta 1\ OPT_{i,t} + \beta 2\ marketreturn_t + \beta 3\ value_{i,t} + \beta 4\ B/M_{i,t} + +\beta 5\left(OPT_{i,t} * recession_t\right) + \beta 6\ recession_t + \varepsilon_{i,t} \tag{3}$$

I run a final regression which contains all the option-based and control variables and their interactions with the recession variable.

For every option-based variable, I also run the regressions in Equation 2 and 3 for every individual stock in my sample without the intercept variable and report the average betas and number of positive, negative, significant and insignificant beta estimates of the option-based variables.

Due to the different characteristics of the two recession periods in the data, I define the recession variable to take the value 1 only during the 2008 recession to see whether this distinction affects the predictive power of the models and the coefficients of the option-based variables.

I argue that the coefficient estimates in of option-based variables in Equation 2 will be significant during 1996-2015 period since the option market contains information on future returns since the informed traders first take position in the option market rather than the equity market. During the recession periods, I expect option market might be helpful to predict future returns since the informed traders might invest in e options market in the bear market as well. In the models with the regression dummy in Equation 3, I expect the sum of their coefficient and their coefficient with the interaction variable to increase in absolute term.

The accuracy of the Final Model, which includes all of the option-based variables, their interactions with the recession variable and control variables, to predict the monthly future sock returns, Final Model's prediction ability is compared with the CAPM and Fama-French's three-factor model (FF Model) by using the mean squared error of the estimations. First, I calculate the mean squared error for individual securities in each month and then take the mean of the average individual errors for comparison. I take the difference between the squared errors of estimated returns of Final Model, CAPM and FF Model and test whether the average difference is lower than zero. Then, I test whether the final model estimates are significantly more accurate than both CAPM and FF Model during the full sample period and recession periods. I also test whether the final model's predictive power differs during the expansion and recession periods. Finally, I tried to analyze whether the option-based variables can predict future returns of the high beta stocks as accurately as low beta stocks with the same methodology.

In addition to fixed effect models to estimate betas, I formed monthly quintile portfolios based on the option-based variable values and report their average returns, alphas on CAPM and FF Model to analyze whether a portfolio construction strategy of buying and selling stocks based on their option-based characteristics would yield abnormal returns.

CHAPTER IV

DATA AND DESCRIPTIVE STATISTICS

In this section, data used in the analyses and the descriptive statistics of the option-based variables are represented.

A brief description and the expected coefficients of the option-based variables can be found in Table 1. A more detailed explanation of how they are computed is explained in the following paragraphs.

4.1 Data Description

I obtained the option data from OptionMetrics. It contains information on both option prices and option-based variables. The traded options data include the daily end-of-day best bid, best ask, implied volatility, and Greeks for options traded on the

Chicago Board Options Exchange. Volatility measures are annualized and multiplied with 100.

Table 1: Brief explanation of the variables and their expected coefficient signs in the regression results

Variable	Description	Expected Coefficient
DIV	Monthly change of Call-Put implied volatility difference	Positive
CV-PV	Difference between near-the money Call and Put implied volatilities	Positive
CV (PV)	Near-the-money (strike price close to spot price) call (put) implied volatility	Positive (Negative)
Skew	difference between the implied volatilities of out-of-the-money put option and at-the-money call option	Negative
VS	Open interested weighted average of Call-Put implied volatilities	Positive
IV-RV	Difference between option implied volatility and realized volatility	Positive
DCOI (DPOI)	Percentage change of the call (put) open interest compared to the previous month	Positive (Negative)

As Bali, Chabi-Yo and Murray’s (2022) methodology, I only kept observations with a positive best bid price, the best offer price that is greater than the best bid price, a positive implied volatility, which indicates that the option price does not violate simple no-arbitrage conditions, positive open interest, and whose bid-ask spread scaled by the mid-price is less than 0.5. In addition, I only kept the stocks whose price exceeds 1 dollar at the end of the given month. Then, as far as I could manage, I tried to replicate the authors' methodology to constitute the variables of the previously proposed factor models. The data included in the study covers the 1996-2015 period, which has 235 months.

Individual CAPM and FF Model betas and stock price data are obtained from the WRDS database's Fama French library for each of the three factors. In order to calculate the beta of a stock for each factor in month t, the past 60 months' monthly returns are being used. If there are not enough historical data, minimum of 24 months has been used to calculate beta. I only kept the stocks with at least 24 monthly returns to have meaningful regression estimates. NBER business cycle data is used to determine whether the economy is in recession or not. Then by merging the WRDS data with the OptionMetrics data, we are only left out with the price, recession, beta and option-based variables of the optionable stocks. According to NBER, the first recession period was between March 2001 and November 2001. The second recession period was between December 2007 and June 2009.

The optionable stocks have higher market values than other stocks. As Bali and Murray (2021) mention, even though historically only 25% to 75% of all stocks are optionable, these stocks account for between 85% and 98% of total stock market capitalization. As it can be seen in Figure 1, the number of optionable stocks steadily increased from 1996 to 2015 since the hedging and leverage advantages of the derivative markets appeal to more investors.

Figures 2 and 3 show that both call and put implied volatilities significantly increased during the 2008 recession (Recession 2) but not as much in the 2001 recession. As mentioned earlier, call-put implied volatility difference is a significant estimator for future equity returns, as shown by the previous works. In Figure 4, we see that CV-PV (difference between the call and put implied volatility) significantly decreased in the 2008 recession, indicating cheaper calls and expensive puts, which shows that put implied volatilities are higher than the call implied volatilities than usual and the market is in a bearish environment, indicating that investors who trade in the options market have negative future views on the underlying assets. Thus, I expect that whether the economy is in recession might affect the predictive power of the option-based variables.

Figure 1: Number of stocks in the sample, 1996-2015

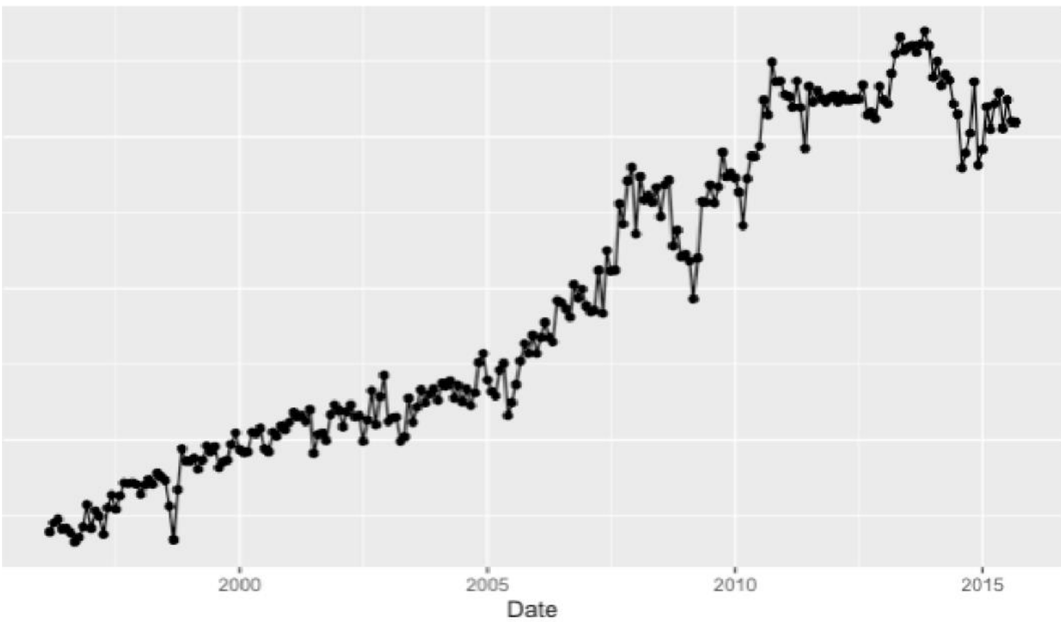

Figure 2: Average call implied volatility of the sample over time

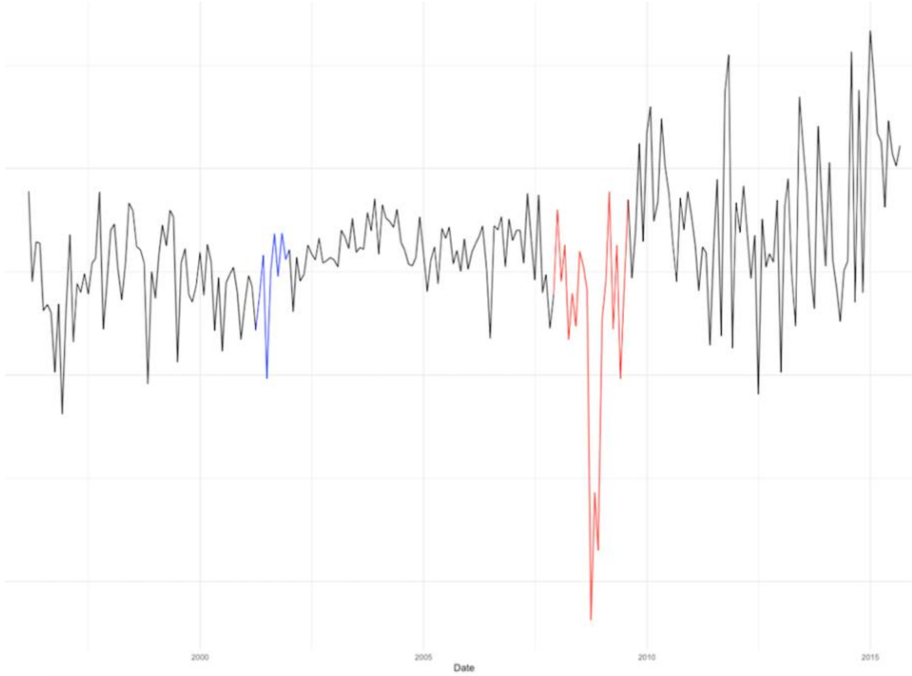

Figure 3: Average put implied volatility of the sample over time

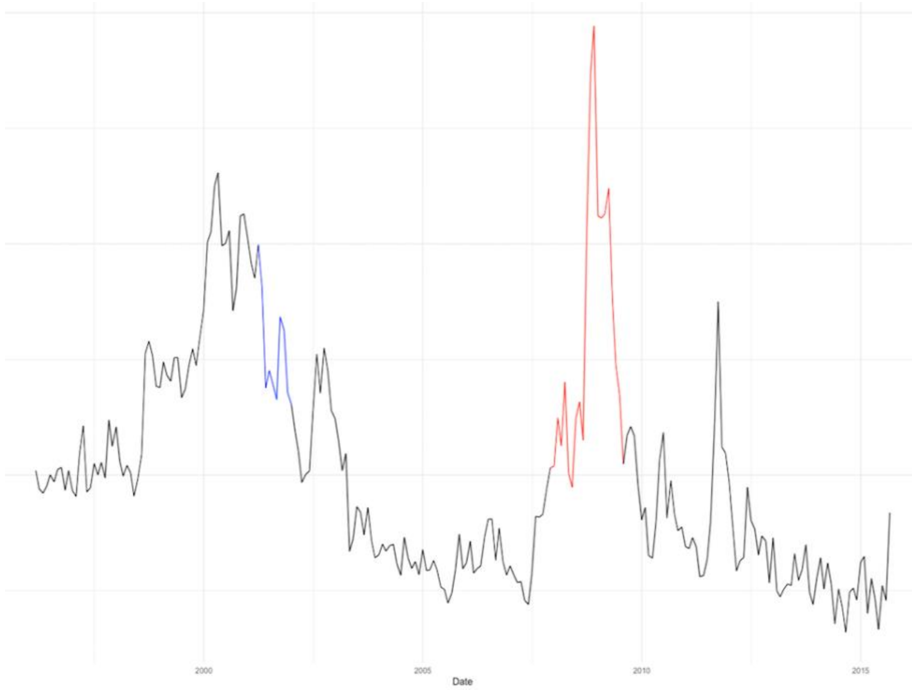

Figure 4: Average call-put implied difference of the sample over time

4.2 Variable Construction

For each stock i and each month t, I define CV (call implied volatility) and PV (put implied volatility) to be the average implied volatility of calls and puts, respectively, on the last trading day of month t. CV and PV are calculated using options on stock i with between 30 and 91 days to expiration and with absolute value of the natural log of the ratio of the strike price of the option to the stock's price, less than or equal to 0.1. CV – PV is measured as the difference between CV and PV.

For each stock i and month t, ΔCIV is defined as the difference between the implied CV at month t and month t-1. ΔPIV is defined as the difference between the PV at month t and month t-1. An et al. (2014) find a negative cross-sectional relation between the changes between call and put implied volatilities and future stock returns. I use ΔCIV -ΔPIV instead so that this measure has a positive relation with future stock returns. ΔCIV -ΔPIV is represented as DIV in the models.

IV (Implied volatility) is calculated as the average of CV and PV. RV (realized volatility) is calculated as the square root of 252 times the standard deviation of the daily returns of the given stock during month t. Bali and Hovakimian (2009) found a negative relationship between RV-IV and future stock returns. I use IV-RV, instead of RV-IV so that the variable has a positive relation with future stock returns.

To calculate VS (Volatility spread), for each stock i and each month t, I take all combinations of the expiration date and strike price for which data for both a call and a put are available. For each such combination, I calculate the difference between the implied volatility of the call and the implied volatility of the put. VS is defined as the weighted average of the difference between the call and put implied volatilities, with the weight of each expiration date and strike price combination is the average of call open interest and put open interest of that combination.

Skew is calculated following Xing, Zhang, and Zhao (2010) using traded options data from the last trading day of each month for options with between 10 and 60 days to expiration (inclusive). For each stock i in month t, Skew is defined as the implied volatility of an out-of-the-money (OTM) put option minus the implied volatility of an at-the-money (ATM) call option. The ATM call implied volatility is calculated from call options with moneyness closest to 1.0, requiring that the option's moneyness be between 0.95 and 1.05. The OTM put implied volatility is taken from the put option with moneyness closest to but less than 0.95, requiring that the moneyness be at least 0.8. Moneyness is defined as the ratio of the strike price of the option to the spot price of the stock. Xing et al. (2010) find a negative relationship between this measure and future stock returns.

The last option-based variables I use in this study are related with change in open interest proposed by Krieger, Fodor, Doran (2011). The only difference is that I use the monthly change in call/put open interest in percentage to form DCOI and DPOI variables for my analysis. In order to form these variables, I require both month t and month t-1 should have call/put open interests above 0. If at least one of these option-based measures cannot calculated for stock i at month t, the observation is excluded from the sample.

Tables 2, 3 and 4 present summary statistics of option-based variables I used in my analysis. In Table 2, one can see the summary statistics for the full 1996-2015 period, while Table 3 shows the summary statistics during the first recession period. Table 4 represents summary statistics during the second recession period during the timespan of this study. Similar to Figure 3, the mean of the volatility spread metrics are mostly higher in absolute terms during the second recession period compared to the first recession period. Table 5 represents the correlation between option-based and control variables. The sample consists of observations which all of the variables below can be calculated. Mean values of DIV, VS and CV-PV decrease during recession periods which indicates that put implied volatilities are relatively higher than the call implied volatilities in the recession periods Also, both CV and PV are higher in the recession periods as a results of market uncertainty. Are observed in Figures 2 and 3.

Among the option-based variables CV and PV have the highest correlation. They are highly correlated with IV-RV. CV-PV, Skew and VS which are in the form of the differences between call-put implied volatilities have high correlation between them.

Table 2: Descriptive statistics of the option-based variables for the full period, 1996-2015

	DIV	Skew	VS	CV-PV	IV-RV	recession	CV	PV	DCOI	DPOI
Min	-96.166	-100.834	-52.034	-161.845	-966.1	0	8.455	8.814	-0.999	-1
1st quartile	-1.206	2.82	-0.885	-1.474	-221.12	0	26.0045	26.5331	-0.213	-0.2
Median	0.006	5.909	-0.192	-0.439	-185.87	0	34.262	34.789	0.046	0.048
Mean	0	6.513	-0.31	-0.719	-194.13	0.132	37.518	38.237	0.0291	0.375
3rd Quartile	1.231	9.671	0.509	0.472	-157.38	0	44.86	45.613	0.33	0.345
Max	79.016	117.505	40.212	62.714	32.01	1	220.847	241.497	3083	1199
Std. Dev	3.643	6.179	1.936	3.07	52.15	0.338	16.339	16.782	10.738	6.57
N	89,667	89,667	89,667	89,667	89,667	89,667	89,667	89,667	89,667	89,667

Table 3: Descriptive statistics of the option-based variables during the first recession period

	DIV	Skew	VS	CV-PV	IV-RV	CV	PV	DCOI	DPOI
Min	-46.133	-89.376	-50.099	-54.6263	-443.23	16.84	13.67	-0.99	-0.97
1st quartile	-1.644	3.385	-1.17	-1.889	-255.92	34.26	35.47	-0.16	-0.13
Median	-0.052	6.258	-0.39	-0.703	-214.33	44.76	45.62	0.12	0.11
Mean	0.072	6.97	-0.62	-1.073	-222.56	50.14	51.21	0.388	0.43
3rd Quartile	1.612	6.784	0.21	-0.185	-181.65	61.65	63.17	0.42	0.43
Max	72.568	69.582	28.541	62.714	-68.23	156.36	159.89	90.9	49.62
Std. Dev	5.89	6.96	2.66	4.34	57.13	20.59	20.7	2.6	2.1
N	1972	1972	1972	1972	1972	1972	1972	1972	1972

Table 4: Descriptive statistics of the option-based variables during the second recession period

	DIV	Skew	VS	CV-PV	IV-RV	CV	PV	DCOI	DPOI
Min	-96.1667	-29.326	-52.039	-100.339	-638.62	12.25	11.11	-0.9949	-0.97843
1st quartile	-1.539	4.596	-1.55	-2.122	-270.63	36.52	37.53	-0.233	-0.179
Median	0.048	7.734	-0.601	-0.925	-227.43	46.51	47.73	0.037	-0.058
Mean	0.0586	8.525	-0.99	-1.489	-237.02	50.18	51.67	0.022	0.2396
3rd Quartile	1.622	11.713	0.1811	0.16	-193.98	60.17	62.01	0.339	0.329
Max	79.016	117.505	18.222	57.394	-89.24	220.85	214.96	39.276	72.99
Std. Dev	4.84	6.74	2.67	4.26	60.06	19.47	20.32	1.144	1.45
N	9890	9890	9890	9890	9890	9890	9890	9890	9890

Table 5: Correlation table of the option-based and control variables

	DIV	Skew	VS	CV-PV	IV-RV	recession	CV	PV	DCOI	DPOI	value	bookmarket	marketreturn
DIV	1.00	-0.19	0.35	0.47	0.02	0.01	0.05	-0.04	0.01	0.00	0.00	0.00	-0.01
Skew	-0.19	1.00	-0.44	-0.41	-0.10	0.11	0.13	0.20	-0.01	-0.01	0.09	-0.01	-0.05
VS	0.35	-0.44	1.00	0.81	0.15	-0.13	-0.13	-0.27	0.01	0.00	0.05	-0.02	0.08
CV-PV	0.47	-0.41	0.81	1.00	0.09	-0.09	-0.05	-0.23	0.00	0.00	0.06	-0.01	0.03
IV-RV	0.02	-0.10	0.15	0.09	1.00	-0.30	-0.71	-0.71	-0.01	-0.02	0.17	-0.02	0.17
recession	0.01	0.11	-0.13	-0.09	-0.30	1.00	0.30	0.31	0.00	-0.01	-0.02	0.01	-0.22
CV	0.05	0.13	-0.13	-0.05	-0.71	0.30	1.00	0.98	0.01	0.01	-0.24	0.01	-0.18
PV	-0.04	0.20	-0.27	-0.23	-0.71	0.31	0.98	1.00	0.01	0.01	-0.25	0.01	-0.18
DCOI	0.01	-0.01	0.01	0.00	-0.01	0.00	0.01	0.01	1.00	0.09	0.00	0.00	0.00
DPOI	0.00	-0.01	0.00	0.00	-0.02	-0.01	0.01	0.01	0.09	1.00	-0.01	0.00	-0.02
value	0.00	0.09	0.05	0.06	0.17	-0.02	-0.24	-0.25	0.00	-0.01	1.00	-0.04	0.00
bookmarket	0.00	-0.01	-0.02	-0.01	-0.02	0.01	0.01	0.01	0.00	0.00	-0.04	1.00	-0.01
marketreturn	-0.01	-0.05	0.08	0.03	0.17	-0.22	-0.18	-0.18	0.00	-0.02	0.00	-0.01	1.00

CHAPTER V

EMPIRICAL RESULTS

In this section, first I represent the regression model estimations for the full period 1996-2015. Then, results of the regressions with recession interaction variable is reported. Then, individual regressions and the average coefficients are presented. In the final parts of this section, prediction ability of the model is reviewed, including portfolios formed based on option-based variables.

5.1 Fixed Effects Models

I tried to analyze each option-based variable's ability to explain the future equity returns by fixed effects regressions including the control variables. All the option-based variables are included in the models separately, except CV and PV; DCOI and DPOI. They are included in the same models because previous studies indicate that they have to be controlled in the analysis. Results are reported in Table 6.

In addition to running separate regressions, I combined all of the independent variables with the control variables in Model 8.a.

The results of the regressions are in-line with both Bali, Murray, Chabi-Yo (2022) and Easley, O'Hara and Srinivas (1998). Findings show nearly all of the option-based variables have the expected signed coefficients and high significance. Thus, these results suggest that the option-market yields information on future returns.

DIV, CV-PV, VS and IV-RV have positive and significant coefficients as expected. Skew, which is a put-call implied volatility difference has a negative and significant coefficient in Model 2.a. CV has a positive and PV has a negative and significant coefficients when used together in the regression Model 6.a. Contradicting with Krieger, Fodor, Doran (2011) findings, Model 7.a shows that neither DCOI nor DPOI are significant estimators for future equity returns. The conflicting result is probably due to the difference of the time frequency of their study and mine. They use weekly changes in the open interests, while I use monthly changes.

Except IV-RV, DCOI and DPOI, all of the remaining option-based factors are somewhat a form of the difference between call and put implied volatilities. As expected, even though all of their coefficients are significant when I ran separate regressions, in Model 8.a CV and PV's coefficients are not significant. This is due to the existence of IV-RV which has a high correlation with both of them. I do not use CV-PV in model 8.a since VS and Skew have a very strong linear relationship with CV-PV and CV-PV is a linear combination of CV and PV.

Table 6: Results of fixed effects regressions.

Model	1.a	2.a	3.a	4.a	5.a	6.a	7.a	8.a
DIV	0.094***							0.040***
	9.114							*3.421*
Skew		-0.055***						-0.037***
		-8.724						*-5.258*
CV						0.161***		0.038
						12.086		*1.684*
PV						-0.138***		0.033
						-10.611		*1.461*
CV-PV			0.136***					
			10.497					
VS				0.249***				0.187***
				11.954				*5.38*
IV-RV					0.008***			0.019***
					9.946			*18.143*
DCOI							0.002	0.002
							0.665	*0.563*
DPOI							0.005	0.006
							0.885	*1.208*
marketreturn	0.148***	0.143***	0.144***	0.139***	0.131***	0.162***	0.148***	0.153***
	16.818	*16.207*	*16.361*	*15.701*	*14.606*	*17.802*	*16.753*	*16.821*
value	-0.025***	-0.025***	-0.026***	-0.026***	-0.028***	-0.024***	-0.025***	-0.024***
	-13.185	*-12.923*	*-13.51*	*-13.705*	*-14.241*	*-12.142*	*-13.182*	*-12.147*
bookmarket	-0.137***	0.140***	0.137***	0.137***	0.141***	0.132***	0.137***	0.132***
	5.905	*6.058*	*5.931*	*5.928*	*6.092*	*5.712*	*5.937*	*5.704*

∗∗∗, ∗∗, and ∗ indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively of the coefficients. The italic numbers below the coefficients estimates represent the t-statistic for each estimation.

5.2 Regression Results with Recession Variable

To analyze the how the predictive powers of the variables change during the recession periods, I use the binary recession variable and took the interactions with other independent and control variables. The results of the fixed effect regression outputs can be seen in Table 7. Table 7 includes the individual regressions with the variable recession and its interactions with other option-based and control variables.

DIV’s interaction with the recession variable is not significant. This may be due to the short-term memory of the market during the recession periods since DIV includes the implied volatilities of two months before return calculations and market participants make investments decisions based on more recent data.

In Model 2.b, the interaction of Skew with the recession variable has a negative and significant coefficient and its total coefficient during the recession periods increase in absolute terms.

CV-PV’s interaction with the recession variable in Model 3.b is also positive and significant and its coefficient during the recession periods also increases. It shows that during the recession periods, investing in stocks with higher call implied volatilities compared to put implied volatilities may yield higher returns for the investors. In Figure 4, one can see that the average CV-PV during the 2008 recession is drastically lower compared to the full period average. Probably taking short positions with low CV-PV valued stocks would’ve yielded extra returns for the investors.

VS, is also a representation of call-put implied volatility difference. Its interaction with the recession variable is also positive and significant and its coefficient during the recession periods increases as well.

IV-RV have a positive but not significant coefficient in Model 5.b while the interaction variable's coefficient has a positive but not significant coefficient estimate.. This shows that picking individual stocks based on IV-RV values during the recession periods does not create extra returns for investors.

The coefficients of CV and PV increase in absolute term and are significant during the recession periods in model 6.b. This shows that going long on stocks with high call implied volatilities and shorting stocks with high put implied volatilities might be more beneficial for investors during the recession periods than during the expansion periods.

On the other hand, one can see that DCOI, which did not have significant coefficient in Model 7.a, becomes a significant predictor during the recession periods with a positive and increased coefficient in Model 7.b.

Recession variable is significant in all models. The variable captures the general market downside return compared to expansion period and also affects the magnitude of the coefficients of the other variables.

Model 8.b presents the regression coefficients for the model, with all the variables. Not surprisingly, the coefficient of recession by itself is significant and has a minus sign. Model 8.b represents the average betas which are being used to make predictions to compare the estimations of an option-based model and previously established factor models. Model 8.b is the Final Model for my performance analysis, which contain the largest number of variables, including recession. Nearly all of the variables which have significant coefficients with the recession variable in Models 1-7.b and also have significant coefficients in Model 8.b.

Also, I ran separate regressions for the full period by only taking the recession variable as 1 only during the 2008 recession period, even though some of the option-based variables' coefficients interacted with recession increase in absolute terms in these models. The predictive power and the signs of the coefficients did not change significantly. The output of these regressions can be seen in Appendix A.

DIV and IV-RV, did not have significant beta estimates when combined with the recession in Models 1.b and 6.b. However, they have positive and significant coefficients in Model 1.c and 6.c. The remaining estimates have the same signs and significance as models 1-7.b

5.3 Individual Regressions

To calculate the average beta estimates, I run regressions for each option-based variable with control variables for every individual security and I take the average of these individual betas. I test whether these averages are greater/less than zero depending on the option-based variable. All the option-based variables are included in the models separately, except CV and PV; DCOI and DPOI.

Results of the mean of individual betas obtained are presented in Appendix B. Except DPOI, every option-based have significant average coefficient with the expected signs in the regressions without the recession variable. On the other hand, only CV-PV and Skews' interaction with the recession period have significant average coefficients.

5.4 Comparison of the Final Model with CAPM and FF Model

Since I use all the variables in both CAPM and FF Model, it is expected that Final Model to outperform these previously established factor models when forecasting future stock returns. The predictions of future returns of the CAPM and FF Model are obtained by using the factors in the same month, I obtained the factor values for each month for both models from WRDS' Fama French library for every month. As the comparative error measure, I used the squared errors and checked whether the mean error of Final Model is significantly lower than both CAPM and FF Model. To calculate a model's average error, I first take the average of squared errors for each stock in the sample and then take the mean of these average individual errors. Then I test whether the difference between the Final Model errors and CAPM, FF Model is significantly lower than zero. As I expected, Final Model's mean squared error term is significantly lower than CAPM. The same holds for the comparison with FF Model. T- stats in table 8 represent the test statistic for the difference between the Final Model errors and CAPM, FF Model is significantly lower than zero or not. The results show that for optionable stocks, my proposed model with option-based variables offers higher information for the future equity returns of optionable stocks compared to the previously established factor models.

Table 7: Results of regressions using the recession variable in addition to option-based variables.

Model	1.b	2.b	3.b	4.b	5.b	6.b	7.b	8.b
DIV	0.087***							0.063***
	7.372							*4.682*
Skew		-0.030***						-0.024**
		-4.358						*-3.173*
CV						0.111***		-0.005
						7.220		*-0.220*
PV						-0.068***		0.078**
						-4.514		*3.129*
CV-PV			0.075***					
			4.965					
VS				0.152***				0.153***
				6.244				*4.015*
IV-RV					0.004***			0.015***
					5.220			*13.227*
DCOI							0.001	0.001
							0.503	*0.452*
DPOI							0.003	0.002
							0.546	*0.501*
recession	-1.796***	-0.998***	-1.508***	-1.491***	-1.941***	-2.795***	-1.873***	-2.721***
	-15.527	*-5.683*	*-12.492*	*-12.345*	*-4.272*	*-9.096*	*-15.910*	*-5.621*
marketreturn	0.117***	0.111***	0.113***	0.109***	0.111***	0.136***	0.116***	-0.024
	12.933	*12.279*	*12.501*	*12.016*	*12.165*	*14.881*	*12.884*	*-2.268*
value	-0.027***	-0.026***	-0.027***	-0.027***	-0.028***	-0.023***	-0.027***	-0.023***
	-13.820	*-13.701*	*-13.951*	*-14.103*	*-14.329*	*-11.689*	*-13.814*	*-12.058*
bookmarket	0.132***	0.137***	0.133***	0.133***	0.136***	0.121***	0.132***	0.115***
	5.718	*5.906*	*5.764*	*5.760*	*5.861*	*5.240*	*5.716*	*4.987*
DIV:recession	0.027							-0.059*
	1.147							*-2.155*
Skew:recession		-0.089***						-0.056**
		-5.320						*-2.698*
CV:recession						0.193***		0.209***
						6.509		*3.559*
PV:recession						-0.179***		-0.145*
						-6.225		*-2.456*
VS:recession				0.223***				-0.082
				4.848				*-0.909*
IV-RV:recession					-0.001			0.007*
					-0.815			*2.508*
marketreturn:recession								0.512***
								25.680
value:recession								0.005*
								2.016
bookmarket:recession								0.076**
								2.668
DCOI:recession							0.248***	0.170*
							3.423	*2.354*
DPOI:recession							0.080	0.179**
							1.164	*2.612*
CV-PV:recession			0.163***					
			5.669					

∗∗∗, ∗∗, and ∗ indicate statistical significance at the 0.1%, 1%, and 5% levels, respectively of the coefficients. The italic numbers below the coefficients estimates represent the t-statistic for each estimation.

One should note that Final Model uses the full period to estimate betas of both control variables and option-based variables while CAPM and FF Model estimates are obtained from past data. As I expected, Final Model's mean squared error term is significantly lower than CAPM. The same holds for the comparison with FF Model. T- stats in table 8 represent the test statistic testing whether the final model has less errors than the other two models. In other words, I test for whether the difference between the Final model errors and the other models is less than zero. The results show that for optionable stocks, my proposed model with option-based variables predicts the future equity returns of optionable stocks more accurately compared to the other two models. One should note that Final Model uses the full period to estimate betas of both control variables and option-based variables while CAPM and FF Model estimates are obtained from past data.

Surprisingly, CAPM outperforms FF Model based on the estimates. The difference between CAPM and FF Model estimates are significant at 1%. This might be due to the extreme values of future returns of some of the observations in the sample. One should note that number of stocks analyzed is quite small compared to all US stocks due to the filtering I made in constructing option-based variables.

As a second test, I tested whether my final model significantly outperforms both CAPM and FF Model in the recession periods. During the recession periods, the mean error term of my final model is significantly lower than both CAPM and FF Model forecasts with significant t-values. The results of both of the tests against CAPM and FF Model is shown in Table 8.

Table 8: Estimation Errors of Final Model, CAPM and FF Model.

Full Period	Final Model	CAPM	FF Model
Mean squared error	144.91	175.29	192.51
Difference between the Final Model		-30.38*	-47.61*
t-stat		-22.48	-19.10

Recession Periods	Final Model	CAPM	FF Model
Mean squared error	240.42	260.80	280.77
Difference between the Final Model		-20.38*	-40.35*
t-stat		-4.89	-7.94

∗ indicate statistical significance at the 1%

5.5 Additional Tests

Grundy and Malkiel (1996) suggest that investors mostly care about downside risk, and a positive surprise compared to the expected return is not actually a risk. Thus, they expect beta to be a useful predictor during the market declines. They show that portfolios with higher betas tend to underperform during recession periods. Their results hold for using both 60 months and 24 months preceding betas.

In this part, I analyze whether Final Model yields higher accuracy to predict for future stock returns for the low beta stocks compared to high beta stocks. I expect that the model predicts the returns of low beta stocks more accurately than high beta stocks since the stocks with lower betas are more defensive. I divided my sample into three groups based on their betas. If a stock's beta is higher than the 80th percentile of the sample beta for the full period, I assign the stock as a high beta stock. If a stock's beta is lower than the 20th percentile of the sample beta, I assign the stock as a low beta stock. Then I tested for the mean sample squared errors for these two groups. Similar to the previous test, I first take the average of individual errors and then take the mean of these average individual errors. The results indicate that the mean error measure of the model for low beta stocks is significantly lower than the high beta stocks with a t-statistics of -7.46 and a p-value lower than 0.1%. The results indicate that forecasting future returns of stocks with high beta is more complex than stocks with low beta since low beta stocks offer less risk and a clearer future outlook.

As a second analysis, I tested whether the Final Model's mean error term during the expansion periods (when the recession dummy is 0) differs from the recession periods. Results show that Final Model's estimation error is significantly lower during the expansion periods. This show that even though the model beats CAPM and FF Model both in expansion and recession periods, high uncertainty during the recession periods does not allow option-based variables to predict stock returns as accurate as they do during the expansion periods.

Table 9: Final Model's performance for low-high beta stocks and expansion period vs. recession periods.

Low-High Beta estimations	Low Beta	High Beta
Mean squared error	121.78	200.63
Difference		-78.85*
t-stat		-7.46

Expansion -Recession estimations	Full Period	Recession
Mean squared error	130.43	240.42
Difference		-109.99*
t-stat		-12.88

∗ indicate statistical significance at the 1%

5.6 Portfolio Construction

As an additional test to see the performance of a strategy of buying or selling stocks based on their option-based variable, I formed five portfolios each month by using the breakpoints of each option-based variables with 20^{th},40^{th},60^{th} and 80^{th} percentile values at that month t. Portfolio 1 represents the lowest quintile portfolio for that option-based variable while Portfolio 5 represents the highest. Average returns, alphas generated on CAPM and FF Model are shown in Appendix B and C for the full period and the recession period, respectively. Long-short portfolios represent the expected return of buying Portfolio 5 and short-selling Portfolio 1. Results can be seen in Appendix C and D.

Results indicate that long-short portfolios of DIV, CV-PV, CV, VS, IV-RV yields positive alphas compared to CAPM FF Model However, their alphas are not statistically significant according to the t-values. Skew’s long-short portfolio, as expected, yields negative alphas compared to CAPM and FF Model, but its t-stat is also insignificant.

During the recession periods, long-short portfolios of CV-PV, CV and PV yield very high alphas compared to the expansion periods, but due to the low number of portfolios formed during the recession periods, t-statistics do not provide any significance. The results indicate that investors which traded based on option-based values could have earned abnormal returns but since the dataset during the recession is relatively small, they are not statistically significant.

One can also find the portfolio returns for the big-valued and small-valued stocks by forming portfolios based on their quintile values for the given option-based variables during full periods and the recession period in Appendix E, F, G and H. Big valued stocks are the ones which are above the 75^{th} percentile among the stocks of that month based on their market values. Small valued stocks are the ones below 25^{th} percentile. Results suggest that forming portfolios based on CV and PV yields very high but not statistically significant returns during the recession periods for both big and small-valued stocks. Portfolios sorted on CV-PV yielded significantly high alphas on CAPM during the recession periods for small sized stocks.

CHAPTER VI

CONCLUSION

Bali, Chabi-Yo and Murray (2022) showed that the previously established factor models do not explain the future stock returns based on their option-based metrics. Thus, they tried to for the simplest factor model with option-based variables and show that difference of implied volatilities and/or realized volatilities are powerful measures as an indicator for future returns.

Fixed effect regression results support the argues of both Bali, Chabi-Yo and Murray (2022) and Easley, O'Hara and Srinivas (1998). According to the results of this study, options market has strong information to predict future equity returns. Nearly all of the variables suggested by Bali, Chabi-Yo and Murray (2022) have a strong predictive power of forecasting future equity returns, while the impact of the open interest changes are relatively weaker. Results indicate that option-based variables are helpful by themselves for predicting future stock returns, but their ability to predict, and the magnitude of their estimated coefficients vary whether the economy is in recession or not.

As expected, predictive models formed with option-based and control variables outperform previously established factor models since they contain more information. But Final Model is not robust to predict the future returns of stock with higher systematic risk as well as compared to the ones with lower systematic risk. Also, the results show that the predictive power of individual option-based variables change during the recession periods but still, it is still hard to forecast future stock returns during the recession periods compared to expansion periods based on the error measures of Final Model. But the predictive model still outperforms CAPM and FF Model during the recession periods.

Over the years, derivatives market becomes more complex. Thus, it is difficult for an individual investor to understand and use all of the derivative instruments. This study supports the argument that information flows from the option market to the equity market due to informed traders first taking position in the options market. Current complex structure of the derivatives market helps large institutional investors to make large profits via options market and individual investors to take risks in the spot market since the institutional investors have the inside information.

The main limitation of this study was out-of-sample testing. Since the 2001 recession was not long enough to train models by itself, I could not conduct out-of-sample test for the 2008 recession. When data is available, training a model with the 2008 recession and testing for the Covid period might be a useful study. Also, another study focusing on predicting stock returns using option-based variables in an emerging market where the derivatives market is not developed as US might yield different results. This might be a potential subject for future studies.

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APPENDICES

APPENDIX A: Fixed Effects model with 2008 recession period

Model	1.c	2.c	3.c	4.c	5.c	6.c	7.c	8.c
DIV	0.082***							0.054***
	7.184							*4.16*
Skew		-0.029***						-0.025***
		-4.337						*-3.333*
CV						0.119***		0.014
						7.951		*0.579*
PV						-0.070***		0.063**
						-4.789		*2.603*
CV-PV			0.077***					
			5.289					
VS				0.143***				0.133***
				6.068				*3.584*
IV-RV					0.003***			0.014***
					3.492			*13.104*
DCOI							0.001	0.001
							0.503	*0.435*
DPOI							0.003	0.003
							0.651	*0.606*
recession	-2.180***	-1.242***	-1.849***	-1.795***	-0.664	-1.982***	-2.270***	-1.555***
	-17.359	*-6.365*	*-14.044*	*-13.589*	*-1.344*	*-5.9*	*-17.736*	*-2.943*
marketreturn	0.113***	0.107***	0.109***	0.104***	0.105***	0.132***	0.112***	-0.013
	12.502	*11.863*	*11.044*	*11.515*	*11.484*	*14.355*	*12.423*	*-1.24*
value	-0.027***	-0.026***	-0.027***	-0.027***	-0.028***	-0.022***	-0.026***	-0.023***
	-13.817	*-13.749*	*-13.961*	*-14.093*	*-14.246*	*-11.558*	*-13.8*	*-11.705*
bookmarket	0.132***	0.137***	0.133***	0.133***	0.136***	0.122***	0.131	0.117***
	5.706	*5.917*	*5.764*	*5.76*	*5.875*	*5.305*	*5.647*	*5.08*
DIV:recession	0.062*							-0.009
	2.396							*-0.315*
Skew:recession		-0.102***						-0.053*
		-5.61						*-2.334*
CV:recession						0.187***		0.156*
						5.853		*2.357*
PV:recession						-0.197***		-0.108
						-6.424		*-1.62*
VS:recession				0.294***				-0.027
				6.01				*-0.262*
IV-RV:recession					0.005**			0.009**

		2.751		*3.062*
marketreturn:recession				0.536***
				25.572
value:recession				0.001
				0.422
bookmarket:recession				0.086***
				2.86
DCOI:recession			0.550***	0.469***
			5.134	*4.375*
DPOI:recession			-0.111	0.042
			-1.313	*0.498*
CV-PV:recession	0.182***			
	5.937			

APPENDIX B: Individual Regressions

Average coefficients obtained from individual regressions

	Model	Average Coefficient	t-value
DIV	1.d	0,1257*	6,798
CV-PV	2.d	0,2101*	8,361
VS	3.d	0,366*	9,516
skew	4.d	-0,0931*	-8,853
IV-RV	5.d	0,01*	8,57
CV	6.d	0,194*	7,595
PV	6.d	-0,228*	-8,953
DCOI	7.d	0,24*	3,08
DPOI	7.d	0,047	0,654

Average coefficients obtained from individual regressions with recession dummy

	Model	Average Coefficient	t-value
DIV	1.e	0.11*	5.723
DIV:recession	1.e	0.026	0.0279
CV-PV	2.e	0.07*	2.55
CV-PV:recession	2.e	1.45*	1.667
VS	3.e	0.139*	3.37
VS:recession	3.e	0.45	0.74
Skew	4.e	-0.042*	-38.365
Skew:recession	4.e	-0.327*	-24.126
IV-RV	5.e	0.005*	4.373
IV-RV:recession	5.e	0.006	0.38
CV	6.e	0.08*	2.872
CV:recession	6.e	-1.444	-0.84
PV	6.e	-0.092*	-32.859
PV:recession	6.e	1.626	0.923
DCOI	7.e	0.133	1.61
DCOI:recession	7.e	2.6	2.1
DPOI	7.e	0.018	0.238
DPOI:recession	7.e	-28.499	-1.358

$*$ indicate statistical significance at the 5% .

Number of positive, negative, significant and insignificant coefficient estimates

	Model	Positive, significant	Positive, insignificant	Negative, significant	Negative, insignificant
DIV	1.d	130	470	52	376
CP	2.d	131	515	53	329
VS	3.d	160	519	35	314
skew	4.d	26	331	133	538
IV-RV	5.d	208	526	17	277
CV	6.d	127	515	46	340
PV	6.d	42	320	154	512
DCOI	7.d	60	476	43	449
DPOI	7.d	50	506	59	413

Number of positive, negative, significant and insignificant coefficient estimates with recession dummy

	Model	Positive, significant	Positive, insignificant	Negative, significant	Negative, insignificant
DIV	1.e	93	490	41	404
DIV:recession	1.e	95	514	74	345
CP	2.e	74	495	53	406
CP:recession	2.e	142	530	62	294
VS	3.e	91	500	58	379
VS:recession	3.e	132	535	54	307
skew	4.e	58	398	87	485
skew:recession	4.e	51	303	139	535
IV-RV	5.e	130	448	96	354
IV-RV:recession	5.e	119	537	64	308
CV	6.e	87	489	50	402
CV:recession	6.e	155	550	62	261
PV	6.e	44	397	86	501
PV:recession	6.e	53	473	162	340
DCOI	7.e	51	474	43	460
DCOI:recession	7.e	110	556	61	301
DPOI	7.e	47	515	45	421
DPOI:recession	7.e	67	549	89	323

APPENDIX C: Portfolio performance for the full period

DIV	1	2	3	4	5	Long-Short
Average monthly return	0.67	0.97*	1.02*	1.19*	0.90*	0.23
	1.63	*2.59*	*2.94*	*3.20*	*2.44*	*0.43*
Alpha on CAPM	-0.41	-0.02	0.05	0.25	-0.12	0.29
	-0.78	*-0.03*	*0.12*	*0.51*	*-0.25*	*0.27*
Alpha on FF Model	-0.54	-0.12	-0.09	0.16	-0.25	0.29
	-1.00	*-0.24*	*-0.20*	*0.33*	*-0.50*	*0.38*
Average value	-4.36*	-1.09*	-0.01	1.07*	-2.08*	-3.22*
	-28.71	*-20.47*	*-0.37*	*21.65*	*-30.06*	*-37.89*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	0.87*	0.77*	1.04*	1.08*	1.39*	0.53
	2.17	*2.10*	*2.86*	*2.94*	*3.54*	*1.01*
Alpha on CAPM	-0.16	-0.23	0.06	0.05	0.34	0.49
	-0.31	*-0.49*	*0.13*	*0.10*	*0.65*	*0.65*
Alpha on FF Model	-0.31	-0.34	-0.08	-0.05	0.37	0.68
	-0.59	*-0.70*	*-0.16*	*-0.10*	*0.69*	*0.98*
Average value	-4.33*	-1.37*	-0.55*	0.18*	1.98*	-1.17*
	-34.11	*-29.26*	*-14.87*	*5.01*	*24.20*	*-15.47*

CV	1	2	3	4	5	Long-Short
Average monthly return	0.72*	0.96*	1.00*	1.09*	1.37*	0.66
	3.14	*3.22*	*2.85*	*2.33*	*2.00*	*0.91*
Alpha on CAPM	-0.06	0.07	0.05	-0.08	0.08	0.14
	-0.21	*0.17*	*0.11*	*-0.13*	*0.09*	*0.09*
Alpha on FF Model	-0.26	-0.16	-0.12	-0.19	0.32	0.58
	-0.83	*-0.41*	*-0.26*	*-0.32*	*0.34*	*0.60*
Average value	24.17*	30.75*	36.79*	44.83*	60.82*	42.50*
	59.15	*61.34*	*62.78*	*62.85*	*62.99*	*80.85*

PV	1	2	3	4	5	Long-Short
Average monthly return	0.78*	1.02*	0.91*	1.02*	1.40*	0.62
	3.39	*3.39*	*2.65*	*2.18*	*2.03*	*0.85*
Alpha on CAPM	0.01	0.12	-0.06	-0.14	0.12	0.11
	0.04	*0.32*	*-0.13*	*-0.23*	*0.14*	*0.14*
Alpha on FF Model	-0.17	-0.10	-0.25	-0.22	0.33	0.50
	-0.54	*-0.25*	*-0.55*	*-0.36*	*0.35*	*0.52*
Average value	24.91*	31.44*	37.52*	45.61*	61.98*	43.44*
	58.57	*60.40*	*61.53*	*62.03*	*63.50*	*80.03*

Skew	1	2	3	4	5	Long-Short

Average monthly return	1.29*	1.03*	1.13*	0.86*	0.85*	-0.44
	3.59	*3.03*	*3.01*	*2.15*	*1.98*	*-0.78*
Alpha on CAPM	0.33	0.08	0.13	-0.22	-0.26	-0.58
	0.68	*0.17*	*0.27*	*-0.42*	*-0.48*	*-0.48*
Alpha on FF Model	0.27	-0.05	-0.01	-0.27	-0.33	-0.60
	0.54	*-0.12*	*-0.03*	*-0.51*	*-0.61*	*-0.81*
Average value	-0.47*	3.36*	5.50*	8.03*	14.13*	6.83*
	-2.59	*23.49*	*35.72*	*47.93*	*67.93*	*50.56*

VS	1	2	3	4	5	Long-Short
Average monthly return	0.80*	0.71*	1.12*	1.17*	1.34*	0.54
	1.84	*1.85*	*3.22*	*3.39*	*3.49*	*0.92*
Alpha on CAPM	-0.21	-0.22	0.16	0.12	0.21	0.43
	-0.39	*-0.45*	*0.35*	*0.25*	*0.42*	*0.42*
Alpha on FF Model	-0.22	-0.35	0.03	0.03	0.09	0.30
	-0.39	*-0.69*	*0.08*	*0.07*	*0.16*	*0.41*
Average value	-2.62*	-0.80*	-0.26*	0.25*	1.49*	-0.56*
	-33.07	*-21.69*	*-8.44*	*7.80*	*28.25*	*-11.55*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	0.94	1.02*	1.13*	1.09*	0.99*	0.06
	1.58	*2.20*	*3.08*	*3.50*	*3.89*	*0.08*
Alpha on CAPM	-0.30	-0.06	0.08	0.17	0.19	0.49
	-0.41	*-0.11*	*0.17*	*0.40*	*0.58*	*0.58*
Alpha on FF Model	-0.30	-0.10	-0.05	0.01	0.04	0.35
	-0.38	*-0.16*	*-0.10*	*0.01*	*0.13*	*0.39*
Average value	-263.29*	-216.70*	-193.95*	-174.76*	-148.84*	-206.06*
	-104.61	*-98.05*	*-96.83*	*-94.71*	*-91.50*	*-128.44*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	0.99*	1.08*	1.21*	0.90*	0.95*	-0.04
	2.63	*2.71*	*3.11*	*2.43*	*2.54*	*-0.08*
Alpha on CAPM	0.17	0.19	0.19	-0.22	-0.27	-0.44
	0.34	*0.36*	*0.37*	*-0.46*	*-0.57*	*-0.57*
Alpha on FF Model	0.28	0.25	0.09	-0.43	-0.61	-0.89
	0.55	*0.47*	*0.18*	*-0.87*	*-1.25*	*-1.27*
Average value	-0.43*	-0.12*	0.08*	0.31*	1.67*	0.62*
	-52.07	*-9.89*	*4.84*	*13.41*	*12.54*	*9.31*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	1.07*	1.14*	1.08*	0.89*	0.98*	-0.10
	2.71	*3.03*	*2.86*	*2.39*	*2.62*	*-0.17*
Alpha on CAPM	0.08	0.14	0.10	-0.12	-0.13	-0.22
	0.16	*0.28*	*0.19*	*-0.25*	*-0.28*	*-0.28*

Alpha on FF Model	-0.17	-0.06	0.06	-0.04	-0.19	-0.02
	-0.32	*-0.12*	*0.13*	*-0.09*	*-0.38*	*-0.02*
Average value	-0.44*	-0.11*	0.09*	0.34*	2.28*	0.92*
	-50.33	*-8.92*	*5.19*	*13.19*	*10.52*	*8.49*

Average value represents that portfolio's mean value of the give variable. Italic numbers represent the t-value of the row above for testing against if the mean is different than zero. ∗ indicate statistical significance at the 5%.

APPENDIX D: Portfolio performance during recession periods

DIV	1	2	3	4	5	Long-Short
Average monthly return	-1.10	-0.84	-0.56	-0.39	-0.84	0.26
	-0.61	*-0.54*	*-0.40*	*-0.27*	*-0.53*	*0.14*
Alpha on CAPM	0.76	1.04	1.18	1.53	0.96	0.20
	0.41	*0.62*	*0.75*	*0.85*	*0.57*	*0.57*
Alpha on FF Model	0.08	0.69	0.76	1.19	0.47	0.39
	0.04	*0.42*	*0.49*	*0.66*	*0.28*	*0.17*
Average value	-5.39*	-1.23*	0.02	1.29*	-2.53*	-3.96*
	-9.50	*-7.20*	*0.14*	*7.43*	*-11.20*	*-11.85*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	-0.97	-1.28	-0.41	-0.85	0.31	1.28
	-0.57	*-0.78*	*-0.27*	*-0.58*	*0.20*	*0.56*
Alpha on CAPM	1.02	0.61	1.38	0.88	2.16	1.15
	0.57	*0.33*	*0.84*	*0.54*	*1.20*	*1.20*
Alpha on FF Model	0.32	0.33	1.05	0.44	1.80	1.48
	0.17	*0.18*	*0.65*	*0.27*	*0.98*	*0.55*
Average value	-5.96*	-1.87*	-0.94*	-0.12	2.00*	-1.98*
	-9.89	*-11.17*	*-7.76*	*-1.17*	*6.64*	*-7.40*

CV	1	2	3	4	5	Long-Short
Average monthly return	-0.88	-0.58	-0.91	-1.00	0.21	1.09
	-1.02	*-0.44*	*-0.59*	*-0.55*	*0.08*	*0.40*
Alpha on CAPM	0.06	1.05	0.94	1.08	2.93	2.87
	0.07	*0.74*	*0.57*	*0.55*	*0.98*	*0.98*
Alpha on FF Model	0.07	0.70	0.41	0.44	2.32	2.25
	0.07	*0.48*	*0.25*	*0.22*	*0.75*	*0.74*
Average value	30.98*	40.09*	47.80*	57.33*	77.18*	54.08*
	24.77	*25.36*	*26.67*	*28.18*	*28.76*	*39.51*

PV	1	2	3	4	5	Long-Short
Average monthly return	-0.74	-0.59	-1.11	-0.96	0.21	0.95
	-0.85	*-0.45*	*-0.72*	*-0.52*	*0.08*	*0.35*
Alpha on CAPM	0.24	1.03	0.70	1.13	2.96	2.72
	0.26	*0.74*	*0.44*	*0.54*	*0.99*	*0.99*
Alpha on FF Model	0.25	0.69	0.21	0.51	2.29	2.05
	0.25	*0.48*	*0.13*	*0.24*	*0.75*	*0.67*
Average value	32.09*	41.21*	49.06*	58.75*	79.16*	55.62*
	24.63	*24.71*	*25.76*	*27.41*	*28.61*	*40.08*

Skew	1	2	3	4	5	Long-Short
Average monthly return	0.16	-0.70	-1.02	-0.84	-0.78	-0.94
	0.11	*-0.49*	*-0.62*	*-0.51*	*-0.45*	*-0.40*
Alpha on CAPM	1.86	1.09	0.94	0.97	1.19	-0.67
	1.16	*0.67*	*0.52*	*0.53*	*0.62*	*0.62*
Alpha on FF Model	1.43	0.66	0.57	0.55	0.74	-0.69
	0.89	*0.41*	*0.32*	*0.30*	*0.37*	*-0.26*
Average value	1.00*	5.17*	7.53*	10.15*	16.82*	8.91*

	1.82	*12.71*	*17.62*	*22.21*	*22.96*	*18.33*

VS	1	2	3	4	5	Long-Short
Average monthly return	-0.80	-0.85	-0.99	-0.48	-0.03	0.77
	-0.44	*-0.51*	*-0.67*	*-0.35*	*-0.02*	*0.30*
Alpha on CAPM	1.49	1.23	0.75	0.99	1.60	0.10
	0.75	*0.69*	*0.46*	*0.63*	*0.92*	*0.92*
Alpha on FF Model	1.03	0.90	0.34	0.58	1.08	0.05
	0.49	*0.49*	*0.21*	*0.38*	*0.63*	*0.02*
Average value	-3.91*	-1.29*	-0.62*	-0.04	1.38*	-1.26*
	-10.33	*-8.35*	*-5.49*	*-0.45*	*8.17*	*-5.63*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	-0.97	-0.63	-0.72	-0.36	-0.49	0.48
	-0.43	*-0.33*	*-0.46*	*-0.28*	*-0.49*	*0.19*
Alpha on CAPM	1.20	1.47	1.15	1.39	0.84	-0.36
	0.46	*0.73*	*0.67*	*0.97*	*0.77*	*0.77*
Alpha on FF Model	0.28	0.98	0.74	1.17	0.75	0.47
	0.11	*0.48*	*0.43*	*0.78*	*0.65*	*0.15*
Average value	-305.71*	-255.15*	-228.60*	-205.42*	-173.96*	-239.84*
	-36.65	*-36.10*	*-35.11*	*-33.40*	*-30.76*	*-48.43*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	-0.71	-0.94	-0.57	-0.72	-0.23	0.47
	-0.45	*-0.55*	*-0.37*	*-0.47*	*-0.15*	*0.20*
Alpha on CAPM	1.70	1.35	1.24	0.82	0.94	-0.77
	0.93	*0.74*	*0.72*	*0.51*	*0.55*	*0.55*
Alpha on FF Model	1.92	1.24	0.75	0.11	-0.10	-2.02
	1.04	*0.66*	*0.44*	*0.07*	*-0.06*	*-0.79*
Average value	-0.43*	-0.12*	0.08	0.32*	1.50*	0.53*
	-15.24	*-2.97*	*1.55*	*4.44*	*7.85*	*5.79*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	-0.73	-0.82	-0.36	-0.53	-0.74	-0.01
	-0.44	*-0.51*	*-0.23*	*-0.35*	*-0.49*	*0.00*
Alpha on CAPM	1.33	1.09	1.57	1.15	0.92	-0.42
	0.69	*0.59*	*0.96*	*0.70*	*0.56*	*0.56*
Alpha on FF Model	0.88	0.62	1.19	0.97	0.27	-0.61
	0.45	*0.34*	*0.73*	*0.59*	*0.16*	*-0.27*
Average value	-0.39*	-0.09*	0.10*	0.32*	1.53*	0.57*
	-14.13	*-2.21*	*1.85*	*4.51*	*8.90*	*6.60*

Average value represents that portfolio's mean value of the give variable. Italic numbers represent the t-value of the row above for testing against if the mean is different than zero. $*$ indicate statistical significance at the 5% .

APPENDIX E: Small valued stock portfolios

DIV	1	2	3	4	5	Long-Short
Average monthly return	0.67	0.99	1.38	1.56	0.95	0.28
	1.21	*1.89*	*2.67*	*2.78*	*1.88*	*0.38*
Alpha on CAPM	-0.56	-0.25	0.21	0.39	-0.26	0.30
	-0.81	*-0.39*	*0.34*	*0.56*	*-0.41*	*-0.41*
Alpha on FF Model	-0.66	-0.40	0.13	0.30	-0.40	0.26
	-0.92	*-0.60*	*0.21*	*0.42*	*-0.60*	*0.29*
Average value	-6.16	-1.69	-0.07	1.61	-3.15	-4.65
	-25.27	*-18.23*	*-0.99*	*20.71*	*-26.18*	*-34.18*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	1.18	0.75	1.64	1.19	1.59	0.41
	2.13	*1.37*	*2.74*	*2.39*	*2.89*	*0.51*
Alpha on CAPM	0.00	-0.47	0.44	-0.18	0.43	0.43
	0.00	*-0.74*	*0.62*	*-0.30*	*0.62*	*0.62*
Alpha on FF Model	-0.23	-0.51	0.36	-0.18	0.52	0.75
	-0.33	*-0.75*	*0.49*	*-0.27*	*0.72*	*0.75*
Average value	-6.78	-2.09	-0.82	0.26	2.71	-2.03
	-27.55	*-25.19*	*-14.42*	*4.77*	*21.83*	*-14.64*

CV	1	2	3	4	5	Long-Short
Average monthly return	0.81	1.20	0.85	1.91	1.51	0.70
	2.32	*2.76*	*1.66*	*2.82*	*1.81*	*0.76*
Alpha on CAPM	-0.11	0.11	-0.39	0.58	-0.04	0.08
	-0.27	*0.21*	*-0.62*	*0.70*	*-0.04*	*-0.04*
Alpha on FF Model	-0.40	-0.12	-0.51	0.67	0.28	0.69
	-0.92	*-0.23*	*-0.79*	*0.76*	*0.26*	*0.57*
Average value	33.09	41.67	48.25	55.82	71.74	52.41
	77.46	*77.01*	*74.80*	*71.67*	*74.33*	*95.37*

PV	1	2	3	4	5	Long-Short
Average monthly return	0.81	1.18	1.11	1.68	1.66	0.85
	2.32	*2.69*	*2.11*	*2.55*	*1.95*	*0.96*
Alpha on CAPM	-0.12	0.10	-0.20	0.38	0.16	0.28
	-0.29	*0.19*	*-0.31*	*0.47*	*0.16*	*0.16*
Alpha on FF Model	-0.34	-0.18	-0.31	0.49	0.49	0.83
	-0.77	*-0.34*	*-0.45*	*0.59*	*0.44*	*0.72*
Average value	34.51	42.94	49.33	56.91	73.63	54.07
	73.62	*73.98*	*73.63*	*71.54*	*75.22*	*97.60*

Skew	1	2	3	4	5	Long-Short
Average monthly return	1.10	1.37	0.85	1.56	1.35	0.25
	2.23	*2.95*	*1.62*	*2.48*	*2.20*	*0.32*
Alpha on CAPM	-0.03	0.19	-0.37	0.31	0.05	0.08
	-0.04	*0.31*	*-0.58*	*0.42*	*0.07*	*0.07*
Alpha on FF Model	0.07	0.20	-0.56	0.40	-0.21	-0.28
	0.11	*0.32*	*-0.83*	*0.52*	*-0.29*	*-0.27*
Average value	-1.44	3.10	5.49	8.33	15.44	7.00
	-6.65	*20.61*	*35.77*	*49.55*	*55.99*	*40.92*

VS	1	2	3	4	5	Long-Short
Average monthly return	1.34	0.63	1.07	1.52	1.58	0.24
	2.27	*1.14*	*2.12*	*2.71*	*3.08*	*0.29*
Alpha on CAPM	0.15	-0.57	-0.13	0.24	0.39	0.24
	0.22	*-0.87*	*-0.20*	*0.35*	*0.60*	*0.60*
Alpha on FF Model	0.18	-0.73	-0.40	0.37	0.40	0.22
	0.25	*-1.06*	*-0.59*	*0.54*	*0.59*	*0.22*
Average value	-4.15	-1.25	-0.43	0.31	1.93	-1.11
	-31.78	*-22.71*	*-10.01*	*7.73*	*25.45*	*-14.43*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	1.33	0.83	1.11	1.72	1.23	-0.09
	1.93	*1.30*	*2.03*	*3.50*	*3.13*	*-0.12*
Alpha on CAPM	-0.04	-0.46	-0.17	0.54	0.23	0.27
	-0.05	*-0.61*	*-0.26*	*0.89*	*0.50*	*0.50*
Alpha on FF Model	-0.09	-0.43	-0.37	0.58	0.17	0.26
	-0.10	*-0.52*	*-0.54*	*0.92*	*0.35*	*0.24*
Average value	-288.77	-238.89	-215.51	-193.93	-163.40	-226.08
	-119.20	*-111.95*	*-110.55*	*-109.15*	*-106.95*	*-156.93*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	1.13	1.41	1.37	1.12	1.37	0.24
	2.16	*2.50*	*2.59*	*1.95*	*2.62*	*0.31*
Alpha on CAPM	0.10	0.28	0.08	-0.21	0.08	-0.02
	0.16	*0.40*	*0.12*	*-0.31*	*0.13*	*0.13*
Alpha on FF Model	0.37	0.42	0.07	-0.49	-0.30	-0.67
	0.55	*0.58*	*0.11*	*-0.67*	*-0.45*	*-0.70*
Average value	-0.47	-0.13	0.09	0.37	2.20	0.86
	-58.72	*-13.83*	*8.36*	*23.20*	*7.93*	*6.24*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	1.30	1.19	1.45	1.07	1.42	0.12

	2.57	*2.09*	*2.54*	*1.98*	*2.70*	*0.17*
Alpha on CAPM	0.02	-0.04	0.33	-0.19	0.22	0.20
	0.03	*-0.06*	*0.49*	*-0.28*	*0.35*	*0.35*
Alpha on FF Model	-0.25	-0.13	0.36	-0.14	0.29	0.55
	-0.37	*-0.18*	*0.51*	*-0.20*	*0.45*	*0.58*
Average value	-0.47	-0.13	0.10	0.41	2.79	1.16
	-58.22	*-13.22*	*8.94*	*22.63*	*13.99*	*11.59*

APPENDIX F: Small valued stock portfolios during recession periods

DIV	1	2	3	4	5	Long-Short
Average monthly return	-0.41	-1.08	-1.11	1.54	-0.49	-0.08
	-0.20	*-0.53*	*-0.63*	*0.84*	*-0.26*	*-0.04*
Alpha on CAPM	1.75	1.46	1.51	3.85	1.95	0.20
	0.80	*0.62*	*0.74*	*1.81*	*0.91*	*0.91*
Alpha on FF Model	0.82	-0.29	0.87	2.80	0.77	-0.05
	0.35	*-0.11*	*0.39*	*1.23*	*0.33*	*-0.02*
Average value	-7.23	-1.88	0.04	2.02	-3.56	-5.39
	-7.33	*-5.80*	*0.15*	*7.28*	*-8.97*	*-10.62*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	0.07	-1.41	-0.36	-1.02	2.26	2.19
	0.04	*-0.67*	*-0.16*	*-0.60*	*1.20*	*0.78*
Alpha on CAPM	2.54	0.91	1.70	1.40	4.57	2.04
	1.38	*0.40*	*0.71*	*0.67*	*2.02*	*2.02*
Alpha on FF Model	1.58	-0.39	0.78	0.36	3.60	2.02
	0.79	*-0.15*	*0.31*	*0.16*	*1.49*	*0.63*
Average value	-9.50	-2.77	-1.29	-0.15	2.61	-3.44
	-8.70	*-8.58*	*-6.03*	*-0.84*	*5.16*	*-5.86*

CV	1	2	3	4	5	Long-Short
Average monthly return	-0.44	-1.02	-0.32	0.08	1.76	2.20
	-0.33	*-0.66*	*-0.16*	*0.04*	*0.70*	*0.79*
Alpha on CAPM	1.28	1.00	2.03	2.74	4.59	3.31
	0.91	*0.60*	*0.95*	*1.03*	*1.54*	*1.54*
Alpha on FF Model	0.31	0.36	0.63	1.45	3.64	3.33
	0.21	*0.20*	*0.27*	*0.49*	*1.15*	*0.99*
Average value	40.98	49.95	57.19	66.62	86.56	63.77
	30.02	*32.06*	*32.37*	*31.82*	*34.96*	*41.93*

PV	1	2	3	4	5	Long-Short
Average monthly return	-0.86	-1.14	-0.14	0.45	1.81	2.67
	-0.65	*-0.72*	*-0.07*	*0.20*	*0.72*	*0.82*
Alpha on CAPM	0.84	0.99	2.12	3.20	4.53	3.69
	0.62	*0.59*	*0.97*	*1.18*	*1.56*	*1.56*
Alpha on FF Model	-0.01	0.25	0.88	2.03	3.42	3.43
	-0.01	*0.14*	*0.37*	*0.71*	*1.08*	*0.95*
Average value	43.20	52.08	59.06	68.64	89.47	66.33

	28.72	*30.09*	*31.08*	*31.02*	*34.30*	*37.78*

Skew	1	2	3	4	5	Long-Short
Average monthly return	0.28	0.28	-1.30	0.71	0.18	-0.10
	0.16	*0.17*	*-0.66*	*0.34*	*0.10*	*-0.03*
Alpha on CAPM	2.46	2.66	0.81	3.28	2.54	0.08
	1.22	*1.24*	*0.41*	*1.30*	*1.23*	*1.23*
Alpha on FF Model	1.69	1.26	-0.01	2.30	1.47	-0.22
	0.80	*0.56*	*-0.01*	*0.82*	*0.67*	*-0.06*
Average value	-0.36	4.90	7.57	10.70	18.91	9.28
	-0.40	*10.89*	*16.12*	*20.04*	*15.86*	*12.72*

VS	1	2	3	4	5	Long-Short
Average monthly return	0.58	-0.81	-0.84	-1.09	1.99	1.41
	0.31	*-0.37*	*-0.45*	*-0.60*	*1.00*	*0.50*
Alpha on CAPM	3.08	1.86	1.41	1.06	4.16	1.08
	1.61	*0.74*	*0.66*	*0.53*	*1.81*	*1.81*
Alpha on FF Model	2.34	0.43	-0.09	0.24	3.41	1.07
	1.11	*0.16*	*-0.04*	*0.12*	*1.45*	*0.35*
Average value	-6.11	-1.79	-0.79	0.02	1.86	-2.12
	-9.96	*-8.22*	*-4.88*	*0.13*	*5.90*	*-6.15*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	0.53	-0.68	0.67	-0.67	0.21	-0.33
	0.22	*-0.33*	*0.34*	*-0.38*	*0.16*	*-0.12*
Alpha on CAPM	2.81	1.97	2.79	1.59	2.50	-0.31
	0.97	*0.86*	*1.33*	*0.81*	*1.58*	*1.58*
Alpha on FF Model	1.32	1.11	1.60	0.77	1.73	0.41
	0.44	*0.45*	*0.71*	*0.36*	*1.00*	*0.12*
Average value	-321.4	-270.4	-245.4	-222.0	-188.7	-255.1
	-44.72	*-41.92*	*-40.51*	*-39.56*	*-35.81*	*-61.42*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	0.47	0.52	-0.94	-0.51	0.39	-0.08
	0.23	*0.25*	*-0.49*	*-0.29*	*0.20*	*-0.03*
Alpha on CAPM	3.16	3.38	1.23	1.58	2.21	-0.95
	1.36	*1.45*	*0.61*	*0.81*	*0.99*	*0.99*
Alpha on FF Model	3.28	2.11	0.06	0.24	0.62	-2.66
	1.36	*0.83*	*0.03*	*0.11*	*0.26*	*-0.75*
Average value	-0.47	-0.13	0.11	0.41	1.82	0.68
	-16.92	*-3.77*	*2.54*	*6.34*	*8.27*	*6.06*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	0.60	-0.79	0.22	0.49	-0.34	-0.94
	0.36	*-0.36*	*0.11*	*0.27*	*-0.18*	*-0.39*
Alpha on CAPM	2.83	1.38	2.77	2.64	2.11	-0.71
	1.33	*0.56*	*1.33*	*1.17*	*1.13*	*1.13*
Alpha on FF Model	1.69	0.50	1.96	1.68	0.76	-0.92
	0.77	*0.20*	*0.85*	*0.69*	*0.37*	*-0.27*
Average value	-0.44	-0.11	0.10	0.39	2.00	0.78
	-16.34	*-3.71*	*3.09*	*7.51*	*8.54*	*6.88*

APPENDIX G: Big valued stock portfolios

DIV	1	2	3	4	5	Long-Short
Average monthly return	0.81	0.88	0.71	1.12	0.78	-0.03
	2.43	*2.78*	*2.29*	*3.49*	*2.62*	*-0.08*
Alpha on CAPM	-0.08	0.05	-0.21	0.26	-0.09	-0.01
	-0.19	*0.13*	*-0.49*	*0.65*	*-0.22*	*-0.22*
Alpha on FF Model	-0.10	0.08	-0.37	0.21	-0.11	-0.02
	-0.22	*0.21*	*-0.85*	*0.51*	*-0.28*	*-0.03*
Average value	-2.87	-0.76	0.00	0.76	-1.41	-2.14
	-20.52	*-14.48*	*-0.10*	*15.25*	*-19.62*	*-27.43*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	0.73	0.89	0.92	0.82	1.06	0.33
	2.36	*2.89*	*2.79*	*2.55*	*3.07*	*0.70*
Alpha on CAPM	-0.09	0.02	0.04	-0.05	0.17	0.26
	-0.23	*0.05*	*0.08*	*-0.12*	*0.40*	*0.40*
Alpha on FF Model	-0.11	-0.04	-0.04	-0.15	0.27	0.38
	-0.27	*-0.09*	*-0.10*	*-0.34*	*0.62*	*0.65*
Average value	-2.43	-0.91	-0.35	0.19	1.48	-0.47
	-34.16	*-23.27*	*-9.65*	*4.52*	*17.06*	*-9.02*

CV	1	2	3	4	5	Long-Short
Average monthly return	0.61	0.74	1.03	0.82	1.29	0.68
	2.72	*2.68*	*3.38*	*2.16*	*2.44*	*1.22*
Alpha on CAPM	-0.09	-0.09	0.19	-0.06	0.20	0.30
	-0.33	*-0.24*	*0.48*	*-0.13*	*0.30*	*0.30*
Alpha on FF Model	-0.25	-0.18	0.02	-0.03	0.39	0.64
	-0.84	*-0.47*	*0.05*	*-0.06*	*0.55*	*0.83*
Average value	21.67	25.88	29.30	33.75	43.81	32.74
	53.40	*55.28*	*55.25*	*53.33*	*49.14*	*69.99*

PV	1	2	3	4	5	Long-Short
Average monthly return	0.64	0.84	1.02	0.71	1.20	0.55
	2.81	*3.06*	*3.28*	*1.91*	*2.29*	*1.00*
Alpha on CAPM	-0.05	0.03	0.17	-0.19	0.11	0.16
	-0.19	*0.07*	*0.44*	*-0.41*	*0.17*	*0.17*
Alpha on FF Model	-0.17	-0.06	-0.07	-0.13	0.31	0.49
	-0.57	*-0.17*	*-0.17*	*-0.26*	*0.44*	*0.61*
Average value	22.23	26.36	29.70	34.08	44.07	33.15
	53.54	*55.02*	*54.61*	*52.22*	*48.79*	*64.54*

Skew	1	2	3	4	5	Long-Short
Average monthly return	1.16	0.87	0.89	1.02	0.63	-0.52
	3.68	*2.74*	*2.67*	*3.07*	*1.80*	*-1.06*
Alpha on CAPM	0.32	0.01	0.09	0.08	-0.28	-0.60
	0.81	*0.03*	*0.20*	*0.20*	*-0.61*	*-0.61*
Alpha on FF Model	0.25	-0.05	0.05	0.02	-0.25	-0.50
	0.62	*-0.12*	*0.12*	*0.06*	*-0.52*	*-0.79*
Average value	0.88	4.28	6.32	8.63	13.91	7.39
	4.56	*25.23*	*32.36*	*38.56*	*49.89*	*43.09*

VS	1	2	3	4	5	Long-Short
Average monthly return	0.81	0.83	0.96	0.84	1.14	0.33
	2.38	*2.61*	*3.04*	*2.48*	*3.37*	*0.71*
Alpha on CAPM	0.01	-0.02	0.11	-0.07	0.19	0.18
	0.03	*-0.05*	*0.26*	*-0.18*	*0.44*	*0.44*
Alpha on FF Model	0.08	-0.09	0.07	-0.18	0.14	0.06
	0.17	*-0.21*	*0.17*	*-0.41*	*0.31*	*0.10*
Average value	-1.47	-0.55	-0.18	0.21	1.11	-0.18
	-28.30	*-17.06*	*-5.69*	*6.27*	*20.49*	*-4.88*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	0.90	0.73	0.99	0.99	0.82	-0.08
	1.91	*2.06*	*2.98*	*3.69*	*3.38*	*-0.15*
Alpha on CAPM	-0.09	-0.20	0.08	0.21	0.06	0.15
	-0.16	*-0.42*	*0.20*	*0.59*	*0.20*	*0.20*
Alpha on FF Model	-0.02	-0.18	0.00	0.12	-0.03	-0.01
	-0.03	*-0.38*	*-0.01*	*0.31*	*-0.10*	*-0.02*
Average value	-228.4	-194.7	-178.4	-163.7	-143.1	-185.8
	-84.07	*-85.34*	*-85.07*	*-84.44*	*-81.02*	*-110.81*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	1.13	0.91	1.05	0.86	0.60	-0.53
	3.39	*2.80*	*3.25*	*2.59*	*1.91*	*-1.19*
Alpha on CAPM	0.37	0.08	0.26	-0.07	-0.42	-0.79
	0.87	*0.18*	*0.61*	*-0.17*	*-1.04*	*-1.04*
Alpha on FF Model	0.37	0.08	0.36	-0.07	-0.64	-1.01
	0.83	*0.20*	*0.81*	*-0.17*	*-1.55*	*-1.65*
Average value	-0.31	-0.06	0.10	0.26	0.92	0.30
	-21.63	*-2.85*	*3.50*	*7.51*	*13.45*	*8.77*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	1.00	1.05	1.12	0.65	0.66	-0.34
	2.86	*3.29*	*3.48*	*1.99*	*2.06*	*-0.71*
Alpha on CAPM	0.16	0.17	0.27	-0.24	-0.22	-0.38
	0.37	*0.40*	*0.66*	*-0.56*	*-0.54*	*-0.54*
Alpha on FF Model	0.05	-0.06	0.31	-0.12	-0.23	-0.28
	0.11	*-0.14*	*0.73*	*-0.26*	*-0.57*	*-0.44*
Average value	-0.31	-0.06	0.10	0.28	0.98	0.34
	-19.41	*-2.44*	*3.56*	*7.60*	*12.91*	*8.91*

APPENDIX H: Big valued stock portfolios during recession periods

DIV	1	2	3	4	5	Long-Short
Average monthly return	-0.93	-0.84	-0.58	-0.35	-0.77	0.16
	-0.63	*-0.68*	*-0.52*	*-0.32*	*-0.63*	*0.08*
Alpha on CAPM	0.58	0.55	0.61	1.04	0.65	0.07
	0.36	*0.46*	*0.46*	*0.86*	*0.49*	*0.49*
Alpha on FF Model	0.74	0.72	0.67	0.93	0.77	0.03
	0.45	*0.59*	*0.50*	*0.75*	*0.57*	*0.01*
Average value	-3.66	-0.86	0.01	0.92	-1.77	-2.71
	-10.00	*-6.83*	*0.11*	*6.36*	*-10.05*	*-14.25*

CV-PV	1	2	3	4	5	Long-Short
Average monthly return	-1.07	-1.61	-0.82	-0.46	-0.31	0.76
	-0.79	*-1.43*	*-0.66*	*-0.35*	*-0.22*	*0.50*
Alpha on CAPM	0.53	-0.22	0.42	0.95	1.15	0.62
	0.35	*-0.17*	*0.31*	*0.66*	*0.79*	*0.79*
Alpha on FF Model	0.67	-0.06	0.44	0.88	1.28	0.61
	0.43	*-0.05*	*0.32*	*0.62*	*0.88*	*0.36*
Average value	-3.11	-1.28	-0.70	-0.12	1.70	-0.71
	-11.80	*-12.24*	*-7.77*	*-1.47*	*5.82*	*-3.48*

CV	1	2	3	4	5	Long-Short
Average monthly return	-1.16	-0.89	-0.52	-1.44	-0.17	0.99
	-1.70	*-0.86*	*-0.42*	*-0.96*	*-0.08*	*0.43*
Alpha on CAPM	-0.39	0.19	0.90	0.28	1.90	2.29
	-0.49	*0.18*	*0.64*	*0.17*	*0.78*	*0.78*
Alpha on FF Model	-0.16	0.30	0.79	0.21	2.09	2.25
	-0.19	*0.26*	*0.54*	*0.13*	*0.89*	*0.99*
Average value	27.69	33.62	38.93	45.53	61.01	44.35
	24.02	*23.24*	*23.26*	*22.04*	*20.93*	*31.81*

PV	1	2	3	4	5	Long-Short
Average monthly return	-0.91	-0.48	-0.73	-1.72	-0.39	0.52
	-1.38	*-0.43*	*-0.59*	*-1.08*	*-0.18*	*0.23*
Alpha on CAPM	-0.17	0.62	0.80	-0.04	1.65	1.82
	-0.22	*0.56*	*0.56*	*-0.02*	*0.70*	*0.70*
Alpha on FF Model	0.09	0.66	0.63	-0.10	1.92	1.83
	0.11	*0.54*	*0.43*	*-0.06*	*0.83*	*0.70*
Average value	28.35	34.46	39.67	46.26	61.53	44.94
	24.01	*23.31*	*23.20*	*21.66*	*20.74*	*29.29*

Skew	1	2	3	4	5	Long-Short
Average monthly return	-0.21	-0.77	-1.13	-0.68	-1.24	-1.03
	-0.17	*-0.61*	*-0.89*	*-0.51*	*-0.85*	*-0.44*
Alpha on CAPM	0.95	0.80	0.26	0.93	0.05	-0.90
	0.74	*0.64*	*0.19*	*0.57*	*0.03*	*0.03*
Alpha on FF Model	1.02	0.84	0.33	1.03	0.14	-0.88
	0.79	*0.66*	*0.25*	*0.62*	*0.08*	*-0.37*
Average value	2.27	5.77	7.93	10.33	15.98	9.13
	5.03	*15.27*	*19.23*	*24.30*	*25.24*	*23.52*

VS	1	2	3	4	5	Long-Short
Average monthly return	-1.17	-0.65	-0.89	-0.99	-0.47	0.70
	-0.81	*-0.58*	*-0.70*	*-0.80*	*-0.34*	*0.34*
Alpha on CAPM	0.72	0.77	0.48	0.04	0.89	0.17
	0.45	*0.58*	*0.37*	*0.03*	*0.59*	*0.59*
Alpha on FF Model	0.98	1.08	0.57	-0.14	0.81	-0.18
	0.60	*0.76*	*0.43*	*-0.10*	*0.54*	*-0.08*
Average value	-2.24	-0.94	-0.49	-0.07	1.01	-0.61
	-9.76	*-8.26*	*-6.06*	*-1.02*	*8.28*	*-4.15*

IV-RV	1	2	3	4	5	Long-Short
Average monthly return	-0.95	-1.22	-0.41	-0.65	-1.05	-0.10
	-0.45	*-0.83*	*-0.33*	*-0.63*	*-1.29*	*-0.04*
Alpha on CAPM	0.91	0.33	0.98	0.63	-0.08	-1.00
	0.39	*0.20*	*0.75*	*0.58*	*-0.09*	*-0.09*
Alpha on FF Model	0.82	0.59	0.89	0.70	0.14	-0.68
	0.35	*0.36*	*0.66*	*0.63*	*0.14*	*-0.27*
Average value	-280.4	-233.2	-212.3	-192.3	-165.4	-222.94
	-27.92	*-30.47*	*-30.74*	*-30.27*	*-29.19*	*-38.96*

DCOI	1	2	3	4	5	Long-Short
Average monthly return	-0.63	-0.91	-0.83	-1.17	-0.71	-0.09
	-0.45	*-0.73*	*-0.58*	*-0.90*	*-0.60*	*-0.05*
Alpha on CAPM	1.28	0.69	0.86	-0.09	0.07	-1.22
	0.79	*0.51*	*0.60*	*-0.06*	*0.05*	*0.05*
Alpha on FF Model	1.58	0.84	0.89	-0.05	-0.09	-1.67
	0.96	*0.61*	*0.61*	*-0.03*	*-0.06*	*-0.82*
Average value	-0.33	-0.08	0.09	0.25	0.88	0.28
	-7.84	*-1.22*	*1.17*	*2.77*	*5.33*	*3.54*

DPOI	1	2	3	4	5	Long-Short
Average monthly return	-0.51	-0.09	-0.68	-1.82	-1.16	-0.65

	-0.35	*-0.07*	*-0.55*	*-1.29*	*-0.96*	*-0.31*
Alpha on CAPM	1.08	1.72	0.52	-0.57	0.11	-0.96
	0.71	*1.27*	*0.36*	*-0.39*	*0.08*	*0.08*
Alpha on FF Model	1.15	1.45	0.50	-0.35	0.44	-0.72
	0.74	*1.08*	*0.34*	*-0.23*	*0.31*	*-0.33*
Average value	-0.29	-0.04	0.10	0.25	0.90	0.31
	-6.68	*-0.67*	*1.27*	*2.58*	*5.21*	*3.49*