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摘要

過去許多文獻在探討選擇權隱含波動度偏離與未來標的報酬的關係時採用的是日資料，本研究採用了日內資料以觀察在同一個交易日中，是否有其他的時間區段對於大盤報酬有正向關係。研究發現，在開盤與盤中時的選擇權隱含波動度偏離對於當日的報酬有解釋能力，且其解釋能力在 (i) 極端投資者情緒的區間 (ii) 選擇權流動性高的區間 (iii) 經濟衰退時更為顯著。另外，本研究也利用不同區段的選擇權隱含波動度偏離對日內的大盤報酬進行預測，發現開盤區段的波動度偏離相對其他時間含有更多交易資訊，且其預測能力隨著交易時間而遞減。

關鍵字：S&P 500、選擇權報酬、隱含波動度差、日內資料、投資者情緒、選擇權流動性

Abstract

Numerous studies have investigated the relationship between call-put implied volatility spreads (CPIV) and expected equity returns on daily frequency. While we provide a novel method for calculating the intraday CPIV with moneyness and maturity adjusted weight in order to examine the explanatory power. We observe that the CPIV of open market intervals and mid intervals have both positive links to S&P 500 contemporaneous index returns. This relationship is significantly more intense for the periods during which (i) consumer sentiment measures reach extreme values (ii) option liquidity is relatively high (iii) economic states head to a downturn. In addition, we also examine the predictability of intraday CPIV on intraday half-hours cumulated returns, discovering the open market interval may contain the most information in a single trading day and the predictability decreases as hours decay during the remainder of a day.

Keywords: S&P 500; Option returns; Implied volatility spreads; Intraday data; Investors sentiment; Option liquidity

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1 Introduction

In recent year, the information of the derivatives market plays an increasingly crucial role in financial markets. There are multiple reasons why the option market is vital for investors. One, informed traders may choose to trade in derivative markets since they can camouflage with noise traders by trading different options contracts on one specific security (Easley, O'hara, and Srinivas 1998). Another, authors such as Black and Scholes (1973), Mayhew, Sarin, and Shastri (1995), Fleming, Ostdiek, and Whaley (1996), among others, argue that widened financial leverage and narrowed transaction costs may encourage informed traders to trade in the option market instead of the equity market, Third, unlike the stock market, there are no short-selling constraints in option market. Therefore, the characteristics of an option contract are informational and worthy to investigate. However, to what extent has it been supported by empirical works?

It has been a fierce debate on whether the trading information from derivative markets leads the underlying markets. Prior studies hold different arguments toward this topic. Relevant papers, like Manaster and Rendleman Jr (1982), Anthony (1988), Chakravarty, Gulen, and Mayhew (2004), Cremers and Weinbaum (2010), Xing, X. Zhang, and Zhao (2010) have found that the information from option market takes the lead of the information from stock market. When informed traders receive private information, they prefer to trade in options market since there are several advantages we mentioned in the first paragraph. Furthermore, plentiful literature address that the informed trading in options market elucidates the process of price discovery, and the information contained in option price and volume would eventually get incorporated into underlying prices.While, other studies like Chan, Chung, and Johnson (1993), Stephan and Whaley (1990) find no evidence that option prices can lead to stock prices.

Nevertheless, after the sequential model built in Easley, O'hara, and Srinivas (1998), myriad literature tried to capture the information from options market. Studies like Doran, Peterson, and Tarrant (2007), Doran and Krieger (2010) and Atilgan, Bali, and Demirtas (2015) examined the impact on future asset returns of information contained in the implied volatility skewness. Others like Chan, Chung, and Fong (2002) and Pan and Poteshman (2006) found an ordered imbalance in options volume facilitates the predictability in future asset returns. Apart from that, Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) employ the call-put implied volatility spread (CPIV) to construct portfolios. Moreover, they prove that the deviations of put-call parity contain information about future stock returns. By longing the highest CPIV portfolio and shorting the lowest CPIV portfolio can generate a positive and significant alpha.

In this paper, we provide a comprehensive analysis of the examination of the interrelation between option and index markets. First, rather than investigating on the stock market, we focus mainly on the index – S&P 500. Since most prior literature discusses the informational linkage between option and stock markets, few of them had mentioned about the index market. One literature, Atilgan, Bali, and Demirtas (2015), has investigated on S&P 500 option and index market, however, it employs the way of implied volatility skewness rather than implied volatility spreads. We focus on the latter and discover different results from them. In addition, another reason we choose to explore S&P 500 rather than individual stocks is that index is not allowed to short comparing with stocks, so we believe there are more incentives for investors to trade in options market first from the aspect of liquidity.

Second, the previous studies primarily deliberate over the option information on daily frequency. We would like to investigate the experiments on intraday frequency. Furthermore, prior studies data are mainly constructed by ”highest closing bid price” and ”lowest closing ask price”, which only capture the option information of 5-minutes interval before options market close. Therefore, we would like to test whether the predictability power is stronger in the open period, middle period or close period.

Based on the CPIV proposed by Cremers and Weinbaum (2010), we refine this approach and derive an intraday version. We partition a single trading day to 14 intervals, and each interval we only include 5-minutes long data in case the put-call parity would be unbalanced due to the major difference between the underlying prices in call and put options[1]. In each interval, we examine all the possible option pairs and pick up the valid ones to compose a representative CPIV.

Our main results are simply summarized. To start with, the results display an intermarket relation between quote-data CPIV and contemporaneous index returns. However, there is no predictive power toward one-day ahead index returns[2]. We conclude that these intraday CPIV are enormously informational on index returns during the identical day, but once the market close and open again in next day, the price of S&P 500 would soon be adjusted during the first couple minutes. There-

[1]Apart from the above reason, there are several causes that are responsible for the deviation of put-call parity, short sell constraints, the early exercise value of American options, transaction costs, taxes, to name a few

[2]We also practice a robustness check on trade-data CPIV. Surprisingly, the $CPIV_{10:30}$ has strong predictability to forecast a one-day-ahead index return

fore, it is even harder to generate an information gap from insider to noise trader.

Next, we focus on intraday index returns, and the empirical results express the open interval implied volatility spreads – $CPIV_{08:30}$, has intense predictability toward the intraday half-hours cumulated returns. The adjusted R^2 range from 50.5% to 23.6% as hours decay during the rest of the day. All other intervals CPIV have no such powerful predictability as $CPIV_{08:30}$, the result again proves that the most informational interval is the first interval no matter on the daily frequency and intraday frequency.

Finally, we also conduct tests to yield further evidence for our information-based hypothesis. Following Atilgan, Bali, and Demirtas (2015), our finding presents that the periods with high sentiment index are more sensitive to information distributing between markets. Hence, the relation between CPIV and returns is significantly stronger during the particular periods as previous studies suggested. In Pan and Poteshman (2006), Chang, Z.-Y. Lin, and Wang (2018), they also examine the tests on different stock liquidity and option liquidity periods. They all agree that during the periods with low stock liquidity or high option liquidity, the predictability on future asset returns increases. We segregate the periods by option liquidity, and the empirical results demonstrate the above ideas, where the coefficients of interval CPIV are larger and positive in high option liquidity periods. Overall, these results convey that information explanation is supported by empirical analysis.

The remainder of our research is organized as follows. In Section 2 we describe our research hypothesis, In Section 3, we describe our methodology and data. Section 4 presents the main empirical results on predicting index returns. Section 5 provides additional evidence for the information explanation. Section 6 concludes.

2 Hypothesis Development

Pan and Poteshman (2006) considers that there is no evidence to prove the informed trading in the index market via performing a regression of the next-day index returns on open-buy put-call ratios. It is a common belief that informed traders tend to hold private information in the firm-specific level rather than market-wide level. Therefore, we first exclude the possibility that the predictability of the index market may come from informed-trading.

In our research, we articulate the intraday CPIV may come from the trading information in the previous day and the news beyond market close. Hence, we would like to see in which interval may also contain information toward the contemporaneous index prices and next-day index prices. Apart from prior studies, which possess the best-bid and best-offer of call and put option price within 5 minutes before market close. On top of that, we apply prior approaches to establish CPIV of distinct interval in a single trading day. We assume that the trading information and news in the previous day would also reflect in other intervals. In fact, we discuss whether it is appropriate to use the last 5-minutes best bid and best offer to represent the option information in daily frequency. Would it be another chance that other intervals may also be crucial roles in price discovery?

Hypothesis 1: The open and mid intervals may also contain important information toward index returns

Bergsma et al. (2018) spans the results from Easley, O'hara, and Srinivas (1998) that intraday signed options to stock ratios (O/S) have strong stock returns predictability especially in the first 30 minutes of market open. They make a statement that the first half hour of trading has predictive power for the remainder of the trading day. In line with this study, we believe CPIV also reflect the market sentiment like O/S. Consequently, we suggest that S&P 500 index options carry information toward expected index returns, and the information would gradually get incorporated into the index market as time flows.

Hypothesis 2: The first 5-minutes CPIV has predictability on intraday index cumulated returns for the remainder of the same trading day

3 Data and Empirical Methodology

3.1 Deviation From Put-Call Parity

The put-call parity relations derived from Stoll (1969) is a classical option pricing concepts in finance. It characterized the relationship that must exist between European put and call options with the identical underlying asset, expiration and strike prices. The equation must hold for European options given on no-dividends paying underlying in a perfect market.

$$C - P = S - PV(K) \tag{1}$$

Where C and P represent call prices and put prices, and S is Stock price. With same maturity and exercise price K, the arbitrage opportunity would exist if the equation does not hold. The Black and Scholes (1973) formula satisfies the put-call parity for an assumed value of the volatility parameter σ, therefore,

$$C^{BS}(\sigma) + PV(K) = P^{BS}(\sigma) + S \tag{2}$$

where $C^{BS}(\sigma)$ and $P^{BS}(\sigma)$ indicate Black-Scholes call and put prices, respectively. Combine the above equation, we can derive the equation

$$C^{BS}(\sigma) - C = P^{BS}(\sigma) - P \tag{3}$$

which implies that the implied volatility of call option and put option should be the same if all equation holds.

$$IV^{call} = IV^{put} \tag{4}$$

Of course, the equation may not hold once the option is American-style. However, our primary studies, SPX option, is European style. Therefore, we do not need to consider the dividend payment or early exercise case in our further research.

Clearly, the larger the implied volatilities, the higher the call (put) options prices claim. Following Amin, Coval, and Seyhun (2004), we refer to the difference between call and put implied volatilities as the call-put implied volatility spreads (CPIV). It is suggested that a positive (negative) CPIV could be viewed as a bullish (bearish) signal regarding the underlying stock.

The aggregate Intraday CPIV are construced as following steps:

1. We first divided a single day into 14 of 5-minutes intervals. Each interval contains the tick data from 2.5 minutes ahead and behind the clock. For example, the 9 a.m. interval, we collect valid data from 08:47:30 to 09:32:30 to represent this interval. As for open (close) interval, we choose to accumulate the full 5 minutes data behind (ahead)[3]

[3] We collect the whole transaction data in 5 minutes for trade data. However, the size of quote data is extremely unbalanced in different intervals, we restricted 1000 to 2000 quotes as maximum for call and put in collecting quote data.

2. Similar to Xing, X. Zhang, and Zhao (2010), in each interval, we eliminate an option from the sample if its time to expiration is less than 10 days or more than a year, if its open interest is negative, if its moneyness[4] is smaller than 0.9 or more than 1.1. Furthermore, the option quotes must not violate basic no-arbitrage relations.

3. Then, in each time interval, there must be several valid option pairs with identical maturity (T) and exercise price (K). For each option pair, we choose only one pair to be the representative. For quote data, we average the best bid (β^*) and best offer (α^*) as the chosen call (put) option price. On the contrary, for trade data, we seize the specific transaction data which is closet to the centering time.

4. After collecting several time interval valid option pairs. we calculated the CPIV by applying,

$$CPIV_t = IV_t^{call} - IV_t^{put} = \sum_{j=1}^{N_t} \theta_{j,t}(IV_{j,t}^{call} - IV_{j,t}^{put}) \tag{5}$$

$CPIV_t$ denotes the implied volatility spread on interval t; $IV_{j,t}$ describe the B-S implied volatility for j^{th} option pair in time t; $\theta_{j,t}$ are the weight for j^{th} option pair in time t, there are N_t valid pairs of options on interval t.

Follow by Holowczak, Hu, and Wu (2013), the aggregation of option information could be adjusted by the level of moneyness and maturity.

$$CPIV_t = IV_t^{call} - IV_t^{put} = \sum_{j=1}^{N_t} w_{j,t}(IV_{j,t}^{call} - IV_{j,t}^{put}) \tag{6}$$

[4]Moneyness is defined as the ratio of the strike price to the stock price.

The equation is identical except for the weights term. Ceteris paribus. $w_{j,t}$ equals to $exp(-(m_j^2)/2-(M_j-1)^2)*\theta_j$ where m_j^2 measures the moneyness and the M_j evaluates the maturity of option contract j. To be more specific, $m_j = (\frac{K_j}{S_j} - 1)$ and K_j represents the exercise price and S_i acts for the underlying price of option j; $M_j = max(1, T_j * 12)$ and T_j represents the maturity of option j in month unit.

3.2 Data

In our analysis, the primary quote and trade intraday data for SPX option originates from CBOE MDR. The sample period studied is from January 2007 to December 2017. The options data includes trade date, trade time, expiration date, put-call code, exercise price, maturities, bid price, ask price, underlying price. The daily price of S& P 500 index is obtained from Bloomberg. The zero-coupon bond (ZCB) rate represent risk-free rate in B-S formula are collected from WRDS with different duration. The size of the sample data is about 1-TB around and the data amount is about 1 billion. After we exclude the tick data fall outside the 14 of 5-minute intervals, it remains about 40 million. Furthermore, we follow the approach from Ofek, Richardson, and Whitelaw (2004) to exclude the invalid option pairs. Finally, we have 1,692,542 valid volatility spreads for SPX option from January 2007 to December 2017.

Following the prior studies Bollerslev, Tauchen, and Zhou (2009), several macroeconomic variables are suggested to be crucial and informative with regard to future returns. Specifically, we collect data of the default spread (between Moody's BAA and AAA corporate bond spreads), the term spread (between the 10-year T-Bond and 3-month T-bill yields) [5] as control variables in our regression analysis. The set of macro-economics controls used in regressions changes as the measurement window of the expected market returns changes.

In our study, the amount of intraday CPIV should be 38,668 (14 Intervals multiply 2,762 Days). However, most of the option quote data are short date contract (less than 10 days) in the middle of the month so that we have multiple values that are not able to calculate by our approach. Meanwhile, our research also winsorized the outliers of intraday CPIV on 1% at the front and end. The amount of final valid interval CPIV of quote data is 27,554, as for trade data is 36,959.

Table 1 presents the descriptive statistics of intraday CPIV. In panel A, we demonstrate the descriptive statistics on CPIV of intervals. The mean (median) CPIV vary from -2.45 % to -3.65 % (-3.32 % to -3.72%), indicating that, on average, S&P 500 index put option has about three percent higher implied volatility than index call option during our sample period. In fact, the results are similar to Atilgan, Bali, and Demirtas (2015), they put forth the observation that on average there are nine percent higher during their sample period. In the index market, the implied volatility to moneyness graph mostly shows a reverse skew, which prior studies (J. E. Zhang and Xiang 2008) claimed it volatility smirk. Our observations also express this phenomenon. In addition, in panel A, we could tell that the CPIV of open interval (08:30) is completely different from other interval CPIV. The mean of $CPIV_{0830}$ is about 1% higher than other intervals, and the standard deviation of $CPIV_{0830}$ is 0.4% higher than others. Furthermore, the amount of positive CPIV is way larger than other intervals. We suggest during the open interval,

[5] The daily data are collected from the public website of the Federal Reserve Bank of St. Louis.

numerous news and trading information flow in and cause the open-interval CPIV more volatile. Furthermore, the call options are more likely to be relatively expensive than put options in the first interval. We suggest that if investors exposure to good news before the market open, they prefer to reflect on option price in the first 5-minutes.

In panel B, we test the population mean among the intervals CPIV.

$$H0 : \mu_i = \mu_j \tag{7}$$

The p-values of pairs are shown in corresponding rows and columns. From the results, we declare that the population means of $CPIV_{0830}$ are significantly different from other intervals, so does the close interval CPIV. In other words, we claim that the population means of mid-interval CPIV are not significantly different from other mid intervals. The mid intervals may gather similar information.

3.3 Empirical Methodology

Our research divided into two parts. The first part we analysis certain option pair characteristics that cause the deviation of put-call parity. The second part we discuss the relationship between CPIV and index returns in different aspects and frequencies.

Firstly, we regress CPIV on options characteristics like moneyness, time non-synchronization, maturity, and controlling on intervals effect. The CPIV term and moneyness term are in absolute form because we care about the level of deviations in put-call parity rather than the direction of deviations.

$$|CPIV_i| = \alpha + \beta_1 TimeDiff_i + \beta_2 |Moneyness_i| + \beta_3 Maturity_i + \beta_j \sum_{j=1}^{13} IntDummy_j + \varepsilon_i \quad (8)$$

$TimeDiff_i$ represents time non-synchronization in option pair i. $Moneyness_i$ stands for the level of divergence between the underlying price and the excersie price of option pair i. $Maturity_i$ symbolizes the maturity date in option pair i. As for $IntDummy_j$, we control the intervals effect where j denote as each interval, for instance, $IntDummy_1$ stands for 09:00. All the t statistics are Newey and West statistics adjusted.

Secondly, we regress contemporaneous index returns, one day ahead index returns, halh-hours ahead index returns on CPIV and other macroeconomic variables respectively.

$$SPX\_Return_t = \alpha + \beta_1 CPIV_t + \beta_2 DEF_t + \beta_3 TERM_t + \varepsilon_t \quad (9)$$

In above equation, SPX_Return_t elucidates the SPX index returns in day t, where $CPIV_t$ could be any interval CPIV within day t. DEF_t explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds in day t, and $TERM_t$ expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill in day t. All the t statistics are Newey and West statistics adjusted.

$$SPX\_Return_{t+1} = \alpha + \beta_1 CPIV_t + \beta_2 DEF_t + \beta_3 TERM_t + \varepsilon_t \quad (10)$$

In equation (9), the only term we change is SPX_Return_{t+1}. We now regress a day forward returns on dependent variables rather than contemporaneous index returns.

$$Intra\_Return_{t,k} = \alpha + \beta_1 CPIV_t + \beta_2 DEF_t + \beta_3 TERM_t + \varepsilon_t, \forall k = 1, 2...13 - n \quad (11)$$

In this part, we would like to discuss the predictability in intraday index returns, where $Intra\_Return_{t,k}$ means k of half-hour ahead cumulative returns. For example, when we'd like to do research on the intraday returns to $CPIV_{0830}$, $k = 1$ means the cumulative returns from 08:30 to 09:00, and $k = 2$ means the cumulative returns from 08:30 to 09:30, and so on and so forth. n represents the n^{th} interval CPIV.

4 Empirical Results

The main results are based on SPX option quote data. We take both Equation 5 (non-adjusted weights) and Equation 6 (adjusted weights) to build intraday CPIV. The results are quite similar, so we only present the results of Equation 6. The non-adjusted version is upon request.

4.1 Relationships Between CPIV and Option Characteristic

Before we explore the relationship between the index returns and CPIV, we need to survey on the option characteristics. From Equation 8, We expect the coefficient of time non-synchronization, moneyness. and maturity to be positive. There should be no deviation in put-call parity given that the underlying price is also identical in theroy. In other words, the larger the time gap between the pair option, the larger the divergence may occur and cause higher CPIV in absolute form. Furthermore, the level of moneyness and time to expiration are crucial to CPIV as well. According to Hentschel (2003), implied volatilities from options away from the money are especially sensitive to measurement errors in option prices and uderlying asset price. Therefore, we estimates that with greater level of moneyness and time to maturities, the measurement errors in implied volatilities would increase.

The results in Table 5 confirm our earlier statements based on regression of CPIV. Column (1) reports the regression of CPIV on time non-synchronization. All the coefficients are highly significant; they imply a positive effect on the deviation of put-call parity. Column (2) of table 5 shows that regression of CPIV on moneyness. The coefficient of moneyness term is also highly significant (0.3833, t-statistic 434.96). Column (3) signifies of CPIV on maturity. The coefficient of maturity term is highly significant (0.0348, t-statistic 296.27) as well. Clearly, the regression results are aligned with previous literature, which indicates the moneyness and maturity have a positive effect on CPIV. Finally, in column (4), we regress CPIV on all option pair characteristics. The outcome is similar to previous regressions. Noticeably, the adjusted R^2 of moneyness term is almost 34%, which stands for the most influential factor.

4.2 Relationships Between Index Return and CPIV

In this subsection, we discuss the relationship between CPIV and index returns in different aspects. The Panel A in Table 6 depict the results of contemporaneous index return regressions, while Panel B acts for the results of one-day ahead index return regressions. The header of columns describes the interval of CPIV, and all the variables are in a percentage format.

In panel A, the CPIV coefficients are all positive and this outcome is aligned with Cremers and Weinbaum (2010) which proves the evidence for a significant positive link between implied volatility spread and expected returns. To be more specific, $CPIV_{08:30}$ and $CPIV_{12:00}$ are significant in 1% and 10% level respectively. However, other intervals are not significant enough under 10% level. The result validates our first hypothesis: The open and mid intervals may also contain important information toward index returns. Apart from that, $CPIV_{08:30}$ has the largest coefficient 8.33[6] (t-statistic 17.84), we believe that most trading information and news of previous days get incorporated into the first interval.

In panel B, we test the one day ahead index returns on CPIV and other control variables to see whether the information spillover from the options market to one day ahead index market. Surprisingly, none of them are significant enough and not all of them are positive. According to Atilgan, Bali, and Demirtas (2015), they assert the volatility skewness of S&P index option may cause a spillover effect to the index market. We find out the implied volatility spreads have no predictability on aggregate index returns in the one-day horizon. This is slightly different from Atilgan, Bali, and Demirtas (2015) since we choose implied volatility spreads rather than volatility skewness as the measures. The implied volatility spreads absorb all possible option pairs information while volatility skewness only include the information from out-of-money (OTM) put options and at-the-money (ATM) call options. Briefly, the implied volatility spreads may be too noisy in forecasting future index returns.

[6] The value is shown in a percentage format.

On intraday frequency, we also test the predictability on cumulative half hour index returns in different horizons. We only take $CPIV_{08:30}$ and $CPIV_{12:00}$ as independent variables since they are the only variables significant on daily frequency. However, the results are completely not the same way. From Table 8, the coefficients of $CPIV_{08:30}$ range from 5.63 to 6.57, implying myriad economic significance. The adjusted R^2 of $CPIV_{08:30}$ range from 50.19% to 19.17% as hours decay. The results are consistent with our Hypothesis 2: The first 5-minutes CPIV has predictability on intraday index cumulated returns for the remainder of the same trading day. On the contrary, we did not find predictive power on $CPIV_{12:30}$ for any k. In this paragraph, we demonstrate that the first 5-minutes interval keeps considerable information compared to other intervals, and this information would be incorporated into the index market by hours – not by days. Our empirical results are slightly different from Cremers and Weinbaum (2010), but similar to Kumar, Sarin, and Shastri (1992).

5 Information Explanation

5.1 Consumer Sentiment

In this section, we provide evidence for the intertemporal relationship between CPIV from the options market and index future returns. According to Atilgan, Bali, and Demirtas (2015), the periods of extremely high or low consumer sentiment index are crucial because these are the periods where asset prices are vulnerable to deviate from the fundamental values the most. Therefore, one would expect, during periods of extreme consumer sentiment, the intertemporal relation between CPIV and index returns to be stronger.

$$SPX\_Return_t = \alpha + \beta_1 VSPLUS_t + \beta_2 VSMINUS_t + \beta_3 DEF_t + \beta_4 TERM_t + \varepsilon_t \tag{12}$$

We follow the previous method to define a dummy variable that is equal to one for a given trading day if the consumer sentiment index is greater than its 90^{th} percentile or less than its 10^{th} percentile over the sample period, and 0 otherwise. Hence, follow prior studies, VSPLUS is denoted as CPIV if dummy variable is equal to one and 0 otherwise, while VSMINUS is denoted as CPIV of dummy variable is equal to zero and 0 otherwise. If the information in CPIV to consumer sentiment is essential in the predictive power of the CPIV on index returns, then β_1 is expected to be positive and larger than β_2.

Panel A in Table 9 focuses on Baker and Wurgler (BW) sentiment index[7], while panel B centers around University of Michigan Consumer (UOM) Sentiment Index[8]. Firstly, from panel A, our empirical results show that all the coefficients of VSPLUS are positive and greater than the coefficients of VSMINUS except for the open-interval. Moreover, comparing with the original contemporaneous Equation 9, there are more than two intervals with significant positive coefficients, and 1.2 basis higher than original coefficients on average.

Secondly, from panel B, the results based on UOM sentiment measures are consistent with those based on the BW sentiment measure. Not only all the coefficients of VSPLUS are positive and greater than the coefficients of VSMINUS, but also there are even more significant VSPLUS than the amount of BW sentiment

[7]The data can be found in Jeffrey Wurgler personal website
[8]The data are available on the University of Michigan Website

measure. From the table, the coefficients of VSPLUS of the significant interval is around 0.05%, which are 1.5 times larger than the coefficients of the original regressions.

In summary, these results are consistent with Baker and Wurgler (2006), which argues that prices can deviate from fundamental values because a significant part of the investor class is irrational at the roots of behavioral finance. Hence, the predictability produced by CPIV is found to be more noticeable during the high sentiment periods.

5.2 Option Liquidity

Myriad studies like Easley, O'hara, and Srinivas (1998), Cremers and Weinbaum (2010), Driessen, T.-C. Lin, and Lu (2012) indicated that the predictability will be stronger in options with higher liquidity. In this section, we also follow the method in Chang, Z.-Y. Lin, and Wang (2018) to segregate the high option liquidity periods and others. We use the S&P 500 option daily trading volume to represent the option liquidity, which is available on WRDS. Furthermore, we define a dummy variable that is equal to one for a given trading day if the options volume is greater than its 90^{th} percentile over the sample period, and 0 otherwise. Hence, follow prior studies, VSPLUS is denoted as CPIV if dummy variable is equal to one and 0 otherwise, while VSMINUS is denoted as CPIV of dummy variable is equal to zero and 0 otherwise. Finally, if the information in CPIV to option liquidity is instrumental in the predictive power of the CPIV on index returns, then β_1 is expected to be positive and larger than β_2.

Table 11 describes the regression results on the effect of option liquidity. All the coefficients of VSPLUS are positive and greater than the coefficients of VSMINUS. Moreover, compared with the original contemporaneous Equation 9, there are five intervals with significant positive coefficients, and 3.4 basis higher than original coefficients on average.

In summary, we find out the predictability of contemporaneous index return increases with option liquidity. These results are in line with previous literature.

5.3 Economic States

We also test regressions on the effect of economic states. The economic states are segregated according to NBER business cycles. We believe that during recession time, the stock market liquidity is relatively lower than the options market liquidity since there are short-sell constraints in the stock market. Moreover, our underlying – SPX is not available to short while the economy is going down. In contrast, investors could buy a put option to hedge the risk during the recession. Therefore, we believe that the results of regressions given segregated economic states would be consistent with the sentiment measures and option liquidity.

We utilize economic states from NBER to set apart the overall sample. Then, we define a dummy variable that is equal to one for a given trading day if the economic state bumps into a recession, and 0 if it is expansion. Hence, follow prior studies, VSPLUS is denoted as CPIV if dummy variable is equal to one and 0 otherwise, while VSMINUS is denoted as CPIV of dummy variable is equal to zero and 0 otherwise. If the information in CPIV to economic is critical in the predictive power of the CPIV on index returns, then β_1 is expected to be positive and larger than β_2.

Table 12 describes the regression results on the effect of economic states. All the coefficients of VSPLUS are positive and greater than the coefficients of VSMINUS. Moreover, compared with the original contemporaneous Equation 9, there are seven intervals with significant positive coefficients, including open intervals, mid intervals, and close intervals.

In a nutshell, we suggest that during the recession, prices and volume from the option market are much more informational toward the index market since the periods of consumer sentiments and the periods of option liquidity have high correlations with the periods of economic states.

6 Conclusion

Our research contributes in several ways. First and foremost, we provide a novel method for calculating the intraday CPIV with moneyness and maturity adjusted weights term. Also, we aggregate the sample data across a business cycle including the 2008 financial crisis to validate the stability of our empirical results. Next, we examine the contemporaneous and intertemporal relations between CPIV and expected market returns. In our findings, the open intervals and mid intervals of quote-data CPIV are significantly positively related to the contemporaneous index returns. However, we do not find strong evidence that the intertemporal relation exists. Therefore, if further researchers want to investigate the intertemporal relations between the options market and index market, we suggest to employ volatility skewness rather than implied volatility spreads.

Besides, we also run a battery of tests in intraday SPX index returns on distinct interval CPIV. In empirical results, the open 5-minutes interval CPIV has strong predictability on intraday half-hours cumulated returns. Moreover, the predictive power decreases as hours decay during the remainder of the trading day. We claim that the most informational interval is the first 5-minute interval no matter on the daily frequency and intraday frequency.

Last but not least, we provide several option explanations for the relationship between CPIV and expected index returns. During the periods with high consumer sentiment, the documented relationship is significantly more pronounced compared with the rest of the periods. We also find that given the effect of option liquidity, the relationship becomes formidable during high option liquidity periods, and the results are consistent with the effect of economic states.

References

Amin, Kaushik, Joshua D Coval, and H Nejat Seyhun (2004). "Index option prices and stock market momentum". In: *The Journal of Business* 77.4, pp. 835–874.

Anthony, Joseph H (1988). "The interrelation of stock and options market trading-volume data". In: *The Journal of Finance* 43.4, pp. 949–964.

Atilgan, Yigit, Turan G Bali, and K Ozgur Demirtas (2015). "Implied volatility spreads and expected market returns". In: *Journal of Business & Economic Statistics* 33.1, pp. 87–101.

Baker, Malcolm and Jeffrey Wurgler (2006). "Investor sentiment and the cross-section of stock returns". In: *The journal of finance* 61.4, pp. 1645–1680.

Bali, Turan G and Armen Hovakimian (2009). "Volatility spreads and expected stock returns". In: *Management Science* 55.11, pp. 1797–1812.

Bergsma, Kelley et al. (2018). "Intraday option to stock volume ratios and stock return predictability". In: *Social Science Electronic Publishing. Available online: https://papers. ssrn. com/sol3/papers. cfm*.

Black, Fischer and Myron Scholes (1973). "The pricing of options and corporate liabilities". In: *Journal of political economy* 81.3, pp. 637–654.

Bollerslev, Tim, George Tauchen, and Hao Zhou (2009). "Expected stock returns and variance risk premia". In: *The Review of Financial Studies* 22.11, pp. 4463–4492.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew (2004). "Informed trading in stock and option markets". In: *The Journal of Finance* 59.3, pp. 1235–1257.

Chan, Kalok, Y Peter Chung, and Wai-Ming Fong (2002). "The informational role of stock and option volume". In: *The Review of Financial Studies* 15.4, pp. 1049–1075.

Chan, Kalok, Y Peter Chung, and Herb Johnson (1993). "Why option prices lag stock prices: A trading-based explanation". In: *The Journal of Finance* 48.5, pp. 1957–1967.

Chang, Chuang-Chang, Zih-Ying Lin, and Yaw-Huei Wang (2018). "Implied Volatility Spreads and Future Options Returns Around Information Events and Conditions". In: *Available at SSRN 3096877*.

Cremers, Martijn and David Weinbaum (2010). "Deviations from put-call parity and stock return predictability". In: *Journal of Financial and Quantitative Analysis* 45.2, pp. 335–367.

Doran, James S and Kevin Krieger (2010). "Implications for asset returns in the implied volatility skew". In: *Financial Analysts Journal* 66.1, pp. 65–76.

Doran, James S, David R Peterson, and Brian C Tarrant (2007). "Is there information in the volatility skew?" In: *Journal of Futures Markets: Futures, Options, and Other Derivative Products* 27.10, pp. 921–959.

Driessen, Joost, Tse-Chun Lin, and Xiaolong Lu (2012). "Why do option prices predict stock returns". In: *SSRN: https://ssrn. com/abstract* 2400955.

Easley, David, Maureen O'hara, and Pulle Subrahmanya Srinivas (1998). "Option volume and stock prices: Evidence on where informed traders trade". In: *The Journal of Finance* 53.2, pp. 431–465.

Fleming, Jeff, Barbara Ostdiek, and Robert E Whaley (1996). "Trading costs and the relative rates of price discovery in stock, futures, and option markets". In: *Journal of Futures Markets: Futures, Options, and Other Derivative Products* 16.4, pp. 353–387.

Hentschel, Ludger (2003). "Errors in implied volatility estimation". In: *Journal of Financial and Quantitative analysis* 38.4, pp. 779–810.

Holowczak, Richard, Jianfeng Hu, and Liuren Wu (2013). "Aggregating information in option transactions". In: *Journal of Derivatives* 21.3, p. 9.

Kumar, Raman, Atulya Sarin, and Kuldeep Shastri (1992). "The behavior of option price around large block transactions in the underlying security". In: *The Journal of Finance* 47.3, pp. 879–889.

Manaster, Steven and Richard J Rendleman Jr (1982). "Option prices as predictors of equilibrium stock prices". In: *The Journal of Finance* 37.4, pp. 1043–1057.

Mayhew, Stewart, Atulya Sarin, and Kuldeep Shastri (1995). "The allocation of informed trading across related markets: An analysis of the impact of changes in equity-option margin requirements". In: *The Journal of Finance* 50.5, pp. 1635–1653.

Newey, Whitney K and Kenneth D West (1986). *A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix*.

Ofek, Eli, Matthew Richardson, and Robert F Whitelaw (2004). “Limited arbitrage and short sales restrictions: Evidence from the options markets”. In: *Journal of Financial Economics* 74.2, pp. 305–342.

Pan, Jun and Allen M Poteshman (2006). “The information in option volume for future stock prices”. In: *The Review of Financial Studies* 19.3, pp. 871–908.

Stephan, Jens A and Robert E Whaley (1990). “Intraday price change and trading volume relations in the stock and stock option markets”. In: *The Journal of Finance* 45.1, pp. 191–220.

Stoll, Hans R (1969). “The relationship between put and call option prices”. In: *The Journal of Finance* 24.5, pp. 801–824.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao (2010). “What does the individual option volatility smirk tell us about future equity returns?” In: *Journal of Financial and Quantitative Analysis* 45.3, pp. 641–662.

Zhang, Jin E and Yi Xiang (2008). “The implied volatility smirk”. In: *Quantitative Finance* 8.3, pp. 263–284.

List of Tables

Table 1: Descriptive Statistics of Intraday CPIV of Quote Data

This table shows descriptive statistics for call-put implied volatility (CPIV) of each interval. Panel A presents the summary statistics for CPIV. Panel B presents the population means test among CPIV of each interval. In panel A, the first row represents all intervals. # Pos. CPIV is the amount of CPIV above zero, where # Neg. CPIV is the amount of CPIV below zero. Nan Value Rate refers to the rate that CPIV is blank during the sample period due to the reasons like the option prices are out of the boundary, or the maturity is not satisfied with the rules, etc. In Panel B, the first row and column represent all 14 intervals. The values in the table convey the p-value of population mean test between each interval.

(a) Panel A: The Descriptive Statistics of CPIV on Quote Data

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Mean(%)	-2.45	-3.73	-3.65	-3.59	-3.57	-3.57	-3.62	-3.61	-3.60	-3.62	-3.62	-3.58	-3.51	-3.41
Std(%)	1.11	0.71	0.77	0.80	0.79	0.76	0.78	0.82	0.82	0.78	0.77	0.77	0.71	0.80
Min(%)	-51.17	-14.81	-11.38	-14.24	-10.65	-10.65	-11.86	-11.64	-13.95	-11.60	-10.09	-14.39	-11.22	-15.84
Max(%)	43.20	11.69	20.39	3.49	8.91	7.09	6.52	4.38	5.21	4.92	3.51	4.22	5.62	4.67
Median(%)	-3.36	-3.72	-3.59	-3.55	-3.47	-3.49	-3.50	-3.47	-3.46	-3.51	-3.43	-3.41	-3.33	-3.20
# Pos. CPIV	647	47	24	25	19	22	18	20	19	22	14	19	19	32
# Neg. CPIV	1916	2366	2183	2099	2048	1982	1943	1901	1847	1802	1758	1710	1649	1399
Nan Value Rate(%)	3.8	9.1	16.8	19.9	22.1	24.5	26.1	27.6	29.7	31.2	33.2	34.8	37.1	46.0

(b) Panel B: The Population Mean Test Among CPIV of Intervals

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
08:30	1													
09:00	0.00***	1												
09:30	0.00***	0.08*	1											
10:00	0.00***	0.09*	0.91	1										
10:30	0.00***	0.00***	0.10	0.07*	1									
11:00	0.00***	0.00***	0.05**	0.03**	0.77	1								
11:30	0.00***	0.00***	0.22	0.17	0.66	0.46	1							
12:00	0.00***	0.00***	0.13	0.10	0.89	0.67	0.76	1						
12:30	0.00***	0.00***	0.06*	0.04**	0.80	0.96	0.50	0.71	1					
13:00	0.00***	0.00***	0.01***	0.06*	0.93	0.84	0.61	0.83	0.87	1				
13:30	0.00***	0.00***	0.00***	0.01**	0.42	0.62	0.22	0.36	0.59	0.49	1			
14:00	0.00***	0.00***	0.00***	0.00***	0.09*	0.16	0.04**	0.07*	0.16	0.12	0.37	1		
14:30	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.04**	1	
15:00	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	1

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 3: Descriptive Statistics of Intraday CPIV of Trade Data

This table shows descriptive statistics for call-put implied volatility (CPIV) of each interval. Panel A presents the summary statistics for CPIV. Panel B presents the population means test among CPIV of each interval. In panel A, the first row represents all intervals. # Pos. CPIV is the amount of CPIV above zero, where # Neg. CPIV is the amount of CPIV below zero. Nan Value Rate refers to the rate that CPIV is blank during the sample period due to the reasons like the option prices are out of the boundary, or the maturity is not satisfied with the rules, etc. In Panel B, the first row and column represent all 14 intervals. The values in the table convey the p-value of population mean test between each interval.

(a) Panel A: The Descriptive Statistics of CPIV on Trade Data

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Mean(%)	-1.74	-1.84	-1.90	-1.86	-1.93	-1.98	-1.97	-1.94	-1.94	-1.98	-1.97	-1.94	-1.94	-1.78
Std(%)	4.33	1.48	1.34	1.90	2.39	1.63	1.69	1.49	2.84	1.64	1.90	2.30	1.86	3.30
Min(%)	-38.20	-32.80	-16.22	-29.52	-30.79	-28.91	-33.16	-19.60	-50.13	-22.20	-36.12	-41.78	-38.06	-22.06
Max(%)	29.45	7.62	6.26	37.88	81.43	11.01	7.80	6.96	102.54	8.99	13.56	38.66	19.13	139.27
Median(%)	-1.58	-1.77	-1.86	-1.83	-1.89	-1.93	-1.91	-1.94	-1.90	-1.90	-1.88	-1.91	-1.86	-1.76
# Pos. CPIV	586	107	105	120	92	100	97	99	88	101	98	102	96	96
# Neg. CPIV	2139	2647	2635	2601	2586	2540	2474	2453	2409	2412	2477	2495	2573	2631
Nan Value Rate(%)	1.52	0.47	0.98	1.66	3.22	4.59	7.08	7.77	9.76	9.18	6.94	6.14	3.54	1.45

(b) Panel B: The Population Mean Test Among CPIV of Intervals

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
08:30	1													
09:00	0.26	1												
09:30	0.06*	0.11	1											
10:00	0.18	0.62	0.39	1										
10:30	0.04**	0.09*	0.56	0.24	1									
11:00	0.01***	0.00***	0.04**	0.01**	0.34	1								
11:30	0.01***	0.00***	0.08*	0.02**	0.44	0.84	1							
12:00	0.02**	0.01**	0.26	0.08	0.81	0.36	0.49	1						
12:30	0.04**	0.11	0.51	0.24	0.88	0.51	0.62	0.97	1					
13:00	0.01**	0.00***	0.05**	0.01**	0.35	0.99	0.85	0.37	0.52	1				
13:30	0.01**	0.01**	0.12	0.04**	0.50	0.79	0.94	0.58	0.67	0.80	1			
14:00	0.03**	0.05**	0.41	0.16	0.86	0.45	0.57	0.98	0.99	0.46	0.63	1		
14:30	0.02**	0.02**	0.32	0.11	0.82	0.40	0.53	1.00	0.97	0.42	0.61	0.98	1	
15:00	0.72	0.37	0.07**	0.25	0.05*	0.00***	0.01***	0.02**	0.05**	0.00***	0.01**	0.03**	0.02**	1

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5: Regression Results: CPIV and Option Pair Characterisitcs

This table shows the regression results of call-put implied volatility (CPIV) on moneyness, time non-synchronization, maturity with intervals fixed effect. The $CPIV$ term and moneyness term are in absolute form because we care about the level of deviations in put-call parity rather than the direction of deviations. $TimeDiff$ represents time non-synchronization. $Moneyness$ stands for the level of divergence between the underlying price and the exercise price. $Maturity$ symbolizes the maturity date. As for Interval F.E., we control the effect of the intervals. All the t statistics in parathesis are Newey-West t statistics adjusted.

	(1)	(2)	(3)	(4)
Intercept	0.05577***	0.03087***	0.05055***	0.03011***
	(263.91)	(170.91)	(229.42)	(162.73)
TimeDiff	0.0000***			0.0000***
	(89.32)			(7.40)
Moneyness		0.3833***		0.3710***
		(434.96)		(366.56)
Maturity			0.0348***	0.0103***
			(296.27)	(68.17)
Interval F.E.	Yes	Yes	Yes	Yes
No. Obs	1692542	1692542	1692542	1692542
Adj. R^2	0.0473	0.3368	0.0853	0.3402

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 6: Regression Results: Index Return Predictability on CPIV of Quote Data

This table reports from time-series predictive regressions of the daily return of the S&P 500 index on call-put implied volatility (CPIV), and macroeconomic variables. Panel A presents the summary statistics for contemporaneous index returns regression. Panel B presents summary statistics for one-day ahead index returns regression. $CPIV$ elucidates the interval implied volatility spreads. DEF explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds. $TERM$ expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. All the t statistics in parathesis are Newey-West t statistics adjusted. All variable values are in a percentage format.

(a) Panel A: The Contemporaneous Index Return Regression

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.26***	0.15	0.17	0.16	0.14	0.21*	0.13	0.25**	0.17	0.18	0.14	0.16	0.27**	0.31*
	(2.84)	(1.47)	(1.62)	(1.52)	(1.32)	(1.82)	(1.18)	(2.07)	(1.36)	(1.38)	(1.02)	(1.11)	(1.90)	(2.04)
CPIV	8.33***	1.35	1.30	1.84	1.50	2.86	0.41	3.86*	2.24	2.13	1.03	2.57	4.91	-0.25
	(17.84)	(0.85)	(0.83)	(1.07)	(0.85)	(1.48)	(0.20)	(1.83)	(1.01)	(1.09)	(0.51)	(1.21)	(1.91)	(-0.09)
DEF	0.04	-0.06	-0.07	-0.06	-0.06	-0.09	-0.10	-0.07	-0.07	-0.09	-0.11	-0.09	-0.12	-0.28
	(0.52)	(-0.63)	(-0.70)	(-0.61)	(-0.60)	(-0.73)	(-0.81)	(-0.55)	(-0.54)	(-0.73)	(-0.83)	(-0.67)	(-0.83)	(-1.77)
TERM	-0.03	0.00	0.00	0.02	0.02	0.02	0.02	0.01	0.02	0.03	0.04	0.04*	0.03	0.00
	(-1.29)	(0.07)	(0.21)	(0.71)	(0.92)	(0.77)	(1.00)	(0.59)	(0.98)	(1.26)	(1.63)	(1.74)	(1.33)	(0.00)
Adj. R^2	24.33	0.12	0.15	0.17	0.16	0.33	0.20	0.43	0.24	0.32	0.30	0.43	0.84	1.27

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

(b) Panel B: The One-Day ahead Index Return Regression

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.02	0.04	0.12	0.03	0.06	0.02	0.02	0.07	0.08	0.13	0.08	0.11	0.15	0.13
	(0.20)	(0.44)	(1.18)	(0.31)	(0.56)	(0.15)	(0.18)	(0.61)	(0.66)	(1.08)	(0.66)	(0.84)	(1.10)	(0.91)
CPIV	-0.74	-0.54	1.24	-1.65	0.15	0.75	-1.11	1.31	-0.10	0.81	-0.64	-0.18	-0.49	-2.00
	(-1.23)	(-0.36)	(0.80)	(-0.87)	(0.08)	(0.40)	(-0.57)	(0.70)	(-0.05)	(0.42)	(-0.31)	(-0.09)	(-0.22)	(-0.84)
DEF	-0.01	-0.04	-0.05	-0.07	-0.04	0.03	-0.05	0.00	-0.07	-0.09	-0.09	-0.10	-0.14	-0.15
	(-0.15)	(-0.39)	(-0.53)	(-0.67)	(-0.35)	(0.29)	(-0.48)	(0.01)	(-0.61)	(-0.75)	(-0.77)	(-0.83)	(-1.13)	(-1.07)
TERM	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.00	-0.01
	(0.14)	(0.11)	(-0.01)	(0.29)	(0.33)	(0.37)	(0.75)	(0.39)	(0.42)	(0.41)	(0.36)	(0.28)	(0.09)	(-0.19)
Adj. R^2	0.19	0.02	0.10	0.08	0.02	0.03	0.05	0.03	0.07	0.13	0.09	0.12	0.24	0.31

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 8: Regression Results: Intra-day Index Return Predictability on CPIV of Quote Data

This table records from time-series predictive regressions of intra-day half-hour return of the S&P 500 index on call-put implied volatility (CPIV), and macroeconomic variables. The independent variable is $CPIV_{08:30}$. DEF explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds. $TERM$ expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. K means k of half-hour ahead cumulative returns. For example, k = 1 means the cumulative returns from 08:30 to 09:00, k = 2 means the cumulative returns from 08:30 to 09:30, and so on and so forth. All the t statistics in parathesis are Newey-West t statistics adjusted. All variable values are in a percentage format.

	K=1	K=2	K=3	K=4	K=5	K=6	K=7	K=8	K=9	K=10	K=11	K=12	K=13
Intercept	0.18***	0.16***	0.16***	0.19***	0.19***	0.20***	0.20***	0.21***	0.22***	0.22***	0.17***	0.20***	0.18***
	(5.77)	(4.11)	(3.52)	(3.79)	(3.58)	(3.74)	(3.53)	(3.44)	(3.40)	(3.24)	(2.27)	(2.61)	(2.16)
$CPIV_{08:30}$	5.63***	5.77***	5.79***	5.80***	5.75***	5.81***	5.83***	5.93***	5.87***	5.94***	5.96***	6.12***	6.57***
	(30.81)	(27.76)	(24.92)	(24.37)	(21.44)	(22.27)	(21.92)	(22.05)	(20.71)	(19.94)	(19.12)	(17.58)	(16.17)
DEF	0.00	0.02	0.03	0.00	0.01	0.00	0.00	-0.01	-0.03	-0.04	0.01	0.01	0.03
	(-0.13)	(0.67)	(0.64)	(0.06)	(0.23)	(-0.04)	(-0.05)	(-0.26)	(-0.60)	(-0.62)	(0.22)	(0.09)	(0.45)
TERM	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02
	(-1.58)	(-1.43)	(-1.39)	(-1.54)	(-1.81)	(-1.57)	(-1.45)	(-1.07)	(-0.73)	(-0.70)	(-0.43)	(-0.81)	(-0.83)
Adj.R^2	50.19	41.65	36.43	33.14	29.80	28.79	27.25	26.43	24.69	23.11	20.85	19.87	19.37

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 9: Regression Results: Index Return Predictability on the Effects of Investors Sentiment

This table reports from time-series predictive regressions of contemporaneous return of the S&P 500 index on call-put implied volatility (CPIV), and macroeconomic variables given the effect of investors sentiment. Panel A focuses on Baker and Wurgler (BW) sentiment index, while panel B centers around the University of Michigan Consumer (UOM) Sentiment Index. We take the definition of $VSPLUS$ and $VSMINUS$ in Atilgan, Bali, and Demirtas (2015) as a reference. A dummy variable is equal to one if the consumer sentiment index is greater than the 90th percentile or less than the 10th percentile among the observed consumer sentiment values over the sample period. Therefore, $VSPLUS$ is equal to the CPIV if dummy variable is equal to one and 0 otherwise. $VSMINUS$ is equal to the CPIV if dummy variable is equal to zero and 0 otherwise. DEF explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds. $TERM$ expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. All the t statistics in parathesis are Newey-West t statistics adjusted. All variable values are in a percentage format.

(a) Panel A: Baker and Wurgler Sentiment Index

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.26**	0.16	0.18*	0.17	0.15	0.23**	0.15	0.27**	0.19	0.19	0.16	0.17	0.28***	0.33***
	(2.91)	(1.55)	(1.71)	(1.58)	(1.42)	(2.00)	(1.33)	(2.26)	(1.52)	(1.51)	(1.16)	(1.18)	(1.98)	(2.15)
VSPLUS	7.83***	2.12	2.10	2.34	2.39	4.60*	1.83	5.89**	4.13	3.90	2.76	3.83	6.15**	0.56
	(18.16)	(1.19)	(1.14)	(1.08)	(1.08)	(1.89)	(0.73)	(2.27)	(1.49)	(1.59)	(1.04)	(1.44)	(1.99)	(0.18)
VSMINUS	10.62***	0.36	0.50	1.47	0.81	1.61	-0.66	2.28	0.88	0.71	-0.11	1.46	3.66	-1.75
	(7.23)	(0.22)	(0.32)	(0.89)	(0.48)	(0.90)	(-0.35)	(1.19)	(0.44)	(0.40)	(-0.06)	(0.76)	(1.59)	(-0.69)
DEF	0.07	-0.08	-0.08	-0.07	-0.07	-0.10	-0.12	-0.09	-0.08	-0.11	-0.12	-0.10	-0.13	-0.30
	(0.90)	(-0.79)	(-0.82)	(-0.67)	(-0.70)	(-0.89)	(-0.93)	(-0.70)	(-0.68)	(-0.85)	(-0.93)	(-0.75)	(-0.92)	(-1.91)
TERM	-0.04	0.01	0.01	0.02	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.05	0.04	0.01
	(-1.80)	(0.45)	(0.56)	(0.89)	(1.28)	(1.44)	(1.55)	(1.34)	(1.70)	(1.96)	(2.25)	(2.28)	(1.85)	(0.23)
Adj. R^2	24.79	0.18	0.21	0.19	0.21	0.53	0.34	0.73	0.49	0.57	0.50	0.56	0.97	1.35

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

(b) Panel B: University of Michigan Consumer Sentiment Index

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.17**	0.09	0.13	0.13	0.10	0.16	0.11	0.20	0.14	0.12	0.08	0.10	0.19	0.25*
	(2.02)	(0.93)	(1.27)	(1.21)	(0.99)	(1.46)	(0.98)	(1.72)	(1.16)	(0.99)	(0.65)	(0.74)	(1.39)	(1.68)
VSPLUS	12.57***	4.56*	3.80	3.86	3.59	5.74**	1.98	6.38**	3.86	5.73*	3.96	5.79*	9.69***	4.26
	(8.77)	(1.80)	(1.50)	(1.54)	(1.35)	(2.01)	(0.67)	(2.22)	(1.34)	(1.82)	(1.26)	(1.68)	(2.52)	(0.95)
VSMINUS	7.05***	0.63	0.81	1.35	0.88	2.05	-0.01	3.03	1.81	1.26	0.14	1.65	3.50	-1.33
	(19.03)	(0.40)	(0.51)	(0.76)	(0.49)	(1.05)	(-0.01)	(1.41)	(0.77)	(0.64)	(0.07)	(0.79)	(1.39)	(-0.50)
DEF	0.10	-0.01	-0.04	-0.04	-0.04	-0.05	-0.08	-0.04	-0.05	-0.05	-0.08	-0.05	-0.06	-0.24
	(1.35)	(-0.13)	(-0.36)	(-0.35)	(-0.34)	(-0.43)	(-0.66)	(-0.31)	(-0.40)	(-0.41)	(-0.58)	(-0.38)	(-0.44)	(-1.47)
TERM	-0.02	0.00	0.00	0.02	0.02	0.02	0.02	0.01	0.02	0.03	0.04	0.04	0.04	0.00
	(-1.20)	(0.02)	(0.18)	(0.71)	(0.93)	(0.78)	(1.00)	(0.64)	(1.00)	(1.31)	(1.69)	(1.84)	(1.46)	(0.08)
Adj. R^2	26.39	0.32	0.27	0.26	0.26	0.53	0.25	0.60	0.30	0.63	0.53	0.68	1.38	1.69

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 11: Regression Results: Index Returns Predictability on the Effects of Option Liquidity

This table reports from time-series predictive regressions of contemporaneous return of the S&P 500 index on call-put implied volatility (CPIV), and macroeconomic variables given the effect of option liquidity. To estimate the option liquidity, we employ option volume as a proxy referring to Chang, Z.-Y. Lin, and Wang (2018). Then, we take the definition of $VSPLUS$ and $VSMINUS$ in Atilgan, Bali, and Demirtas (2015) as a reference. A dummy variable is equal to one if the options volume is greater than the 90th percentile among the observed option volume over the sample period. Therefore, $VSPLUS$ is equal to the CPIV if dummy variable is equal to one and 0 otherwise. $VSMINUS$ is equal to the CPIV if dummy variable is equal to zero and 0 otherwise. DEF explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds. $TERM$ expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. All the t statistics in parathesis are Newey-West t statistics adjusted. All variable values are in a percentage format.

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.27***	0.17	0.19*	0.19	0.16	0.24**	0.16	0.29**	0.21	0.20	0.15	0.17	0.28**	0.31**
	(3.03)	(1.59)	(1.72)	(1.64)	(1.42)	(1.97)	(1.36)	(2.29)	(1.55)	(1.51)	(1.12)	(1.18)	(1.94)	(2.04)
VSPLUS	9.75***	2.94	2.73	3.46	2.96	5.04**	2.44	6.89***	4.97*	4.25	2.83	4.34	6.79**	1.19
	(13.61)	(1.51)	(1.46)	(1.55)	(1.30)	(1.96)	(0.97)	(2.56)	(1.70)	(1.69)	(1.10)	(1.69)	(2.25)	(0.38)
VSMINUS	7.09***	0.65	0.49	1.22	0.86	2.04	-0.39	2.84	1.39	1.39	0.30	1.59	3.56	-1.60
	(12.99)	(0.39)	(0.29)	(0.70)	(0.48)	(1.08)	(-0.19)	(1.37)	(0.64)	(0.71)	(0.15)	(0.75)	(1.43)	(-0.60)
DEF	0.02	-0.07	-0.09	-0.07	-0.07	-0.10	-0.11	-0.09	-0.08	-0.10	-0.11	-0.10	-0.13	-0.29
	(0.30)	(-0.73)	(-0.79)	(-0.69)	(-0.67)	(-0.82)	(-0.89)	(-0.64)	(-0.61)	(-0.77)	(-0.85)	(-0.69)	(-0.87)	(-1.78)
TERM	-0.03	0.00	0.00	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.03	0.04	0.03	0.00
	(-1.37)	(-0.06)	(0.10)	(0.57)	(0.80)	(0.57)	(0.80)	(0.37)	(0.75)	(1.07)	(1.47)	(1.62)	(1.26)	(-0.01)
Adj R^2	25.00	0.24	0.27	0.30	0.27	0.55	0.40	0.85	0.59	0.55	0.49	0.65	1.13	1.48

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 12: Regression Results: Index Returns Predictability on the Effects of Economic States

This table reports from time-series predictive regressions of contemporaneous return of the S&P 500 index on call-put implied volatility (CPIV), and macroeconomic variables given the effect of economic states. The economic states are segregated according to NBER business cycles. Then, we take the definition of $VSPLUS$ and $VSMINUS$ in Atilgan, Bali, and Demirtas (2015) as a reference. A dummy variable is equal to one if the economic state in recession, and 0 if it is expansion. Therefore, $VSPLUS$ is equal to the CPIV if dummy variable is equal to one and 0 otherwise. $VSMINUS$ is equal to the CPIV if dummy variable is equal to zero and 0 otherwise. DEF explicates the change in the difference between the yields on BAA- and AAA-rated corporate bonds. $TERM$expounds the difference between the yields on the 10-year Treasury bond and one-month Treasury bill. All the t statistics in parathesis are Newey-West t statistics adjusted. All variable values are in a percentage format.

	08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Intercept	0.27***	0.17	0.19*	0.19	0.16	0.24**	0.16	0.29**	0.21	0.20	0.15	0.17	0.28	0.31**
	(3.03)	(1.59)	(1.72)	(1.64)	(1.42)	(1.97)	(1.36)	(2.29)	(1.55)	(1.51)	(1.12)	(1.18)	(1.94)	(2.04)
VSPLUS	9.75***	2.94	2.73	3.46	2.96	5.04**	2.44	6.89***	4.97*	4.25*	2.83	4.34*	6.79**	1.19
	(13.61)	(1.51)	(1.46)	(1.55)	(1.30)	(1.96)	(0.97)	(2.56)	(1.70)	(1.69)	(1.10)	(1.69)	(2.25)	(0.38)
VSMINUS	7.09***	0.65	0.49	1.22	0.86	2.04	-0.39	2.84	1.39	1.39	0.30	1.59	3.56	-1.60
	(12.99)	(0.39)	(0.29)	(0.70)	(0.48)	(1.08)	(-0.19)	(1.37)	(0.64)	(0.71)	(0.15)	(0.75)	(1.43)	(-0.60)
DEF	0.02	-0.07	-0.09	-0.07	-0.07	-0.10	-0.11	-0.09	-0.08	-0.10	-0.11	-0.10	-0.13	-0.29
	(0.30)	(-0.73)	(-0.79)	(-0.69)	(-0.67)	(-0.82)	(-0.89)	(-0.64)	(-0.61)	(-0.77)	(-0.85)	(-0.69)	(-0.87)	(-1.78)
TERM	-0.03	0.00	0.00	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.03	0.04	0.03	0.00
	(-1.37)	(-0.06)	(0.10)	(0.57)	(0.80)	(0.57)	(0.80)	(0.37)	(0.75)	(1.07)	(1.47)	(1.62)	(1.26)	(-0.01)
Adj. R^2	24.79	0.18	0.21	0.19	0.21	0.53	0.34	0.73	0.49	0.57	0.50	0.56	0.97	1.35

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.